BEARING PROGNOSTICS USING NEURAL NETWORK UNDER TIME VARYING CONDITIONS

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ABSTRACT

Bearing Prognostics using Neural Network under Time Varying Conditions

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Condition based maintenance (CBM) aims to schedule maintenance activities based on condition monitoring data in order to lower the overall maintenance costs and prevent unexpected failures.

Effective CBM can lead to reduced downtime, less inventory, reduced maintenance costs, reliable operation and safety of entire system. The key challenge in achieving effective CBM is the accurate prediction of equipment future health condition and thus the remaining useful life. Existing prognostics methods mainly focus on constant loading conditions. However, in many applications, such as some wind turbine, transmission and engine applications, the load that the equipment is subject to changes over time. It is critical to incorporate the changing load in order to produce more accurate prognostics methods. This research is focused on the bearing prognostics, which are key mechanical components in rotary machines, supporting the entire load imposed on machines. Failure of these components can stop the operation due to machine down time, thus resulting in financial losses, which are much higher than the cost of bearing.

In this thesis, an artificial neural network (ANN) based method is proposed for equipment health condition prediction under time varying conditions. The proposed method can be applied to bearing as well as other components under condition monitoring. In the proposed ANN model, in addition to using the age and condition monitoring measurement values as an inputs, a new input neuron is introduced to incorporate the varying loading condition. The output of the ANN model is accumulated life percentage, based on which the remaining useful life can be calculated once the ANN is trained. Two sets of simulated degradation data under time varying load are used to demonstrate the effectiveness of the proposed ANN method, and the results show that fairly accurate prediction can be achieved using the proposed method.

The other key contribution of this thesis is the experiment validation of the proposed ANN prediction method. The Bearing Prognostics Simulator, after extensive adjustment and tuning, is used to perform bearing run-to-failure test under different loading conditions. Vibration signals are collected using the data acquisition system and the Labview software. The root mean square (RMS) measurement of the vibration signals is used as the condition monitoring input for the validation of the proposed ANN prediction method. Two bearing failure histories are used to train the ANN model and test its prediction performance. The results demonstrate the effectiveness of the proposed method in dealing with real-world condition monitoring data for health condition prediction. The proposed model can greatly benefit industry as well as academia in condition based maintenance of rotary machines.

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Acronyms

CBM	Condition Based Maintenance
ANN	Artificial Neural Network
FFNN	FeedForward Neural Network
RMS	Root Mean Square
ALT	Accelerated Life Testing
AI	Artificial Intelligence
HFRT	High Frequency Resonance Technique
MLP	Multi Layer Perceptron
RBF	Radial Basis Function
SOM	Self Organizing Map
GA	Genetic Algorithm
SVM	Support Vector Machines
RPROP	Resilient Back Propagation Algorithm
PPRL	Progression-Based Prediction of remaining life
IRLS	Improved Redundant Lifting Scheme
AE	Acoustic Emission
DWNN	Dynamic Wavelet Neural Network

AR	Auto Regression Model
ADT	Accelerated Degraded Testing
MSE	Mean Square Error

Chapter 1

Introduction

The main objective of this research is to build a prognostic model for bearing under time varying conditions. Bearings are often subjected to different operating conditions, like variation in load, temperature, pressure and speed. Less effort has been made in this area, and normally prognostic work has been done with assumption of no change in working parameters of bearings. In this work, data generated through accelerated life failure tests of bearings, under time varying conditions, are used to predict remaining useful life of bearings.

1.1. Background

Prognosis is the art of presentation of the remaining useful operational life of component. This can be achieved through analysis of present working condition of existing systems, through condition monitoring data. The benefit of accurate prognosis include reduce downtime, less inventory, reduced maintenance costs, reliable operation and safety of entire system.

Bearings are considered to be a fundamental type of mechanical components. Their safe and reliable operation is necessary for the operation of whole equipments. Therefore, manufacturers and system operators always look forward to developing and implementing condition based maintenance plan, for these components in order to check their existing health condition and predict remaining useful life. Unscheduled maintenance of the equipments, especially due to bearing failure, is an economical burden for organizations. Losses due to no production, spare wages for workers, or some times over time payments in order to meet schedule consignments, are much higher than the cost of bearings.

1.2. Condition Based Maintenance

Condition Based Maintenance (CBM) techniques are approaches for performing maintenance activities during the operational activities of components subject to their working conditions, irrespective of the time frame, or accumulation of certain cycles or hours. It is a type of preventive maintenance. This is a dynamic approach to achieve production without unnecessary down time. Jardine et al (2006) have given a detail review on CBM for rotating machinery implementing diagnostics and prognosis. CBM provides a maintenance process and decision making maintenance schedule by using the information collected through condition monitoring. It captures the multiple degraded states of equipments during operation before they get failed. This health monitoring information can be used for the prediction of optimal maintenance plan that can have capability to prevent equipment breakdown and minimize total operation and maintenance costs. Tian et al. (2009) proposed a model for CBM to avoid unnecessary maintenance tasks by taking maintenance actions only when there are significant impended failures seen. CBM program is consisted of two approaches, diagnostics and prognostics. Diagnostics is a fault detection method. If fault occurs and properly detected in time, maintenance operations can be effectively done. Diagnostic activities are related to fault detection, isolation and identification that are to detect a fault, isolate the defective area, and identify the nature and extent of fault. A prognostic is a prediction of future health condition of components.

CBM program comprised of three steps: Data acquisition, data processing and maintenance decision making, as shown in Figure 1. In data acquisition, operational data of equipments are collected through sensors. Data processing is the transformation of raw data into useful information for analysis and feature extraction. Maintenance decision making is the last step in which all the information are transformed for effective maintenance policies required to be taken (Jardine et al., 2006).

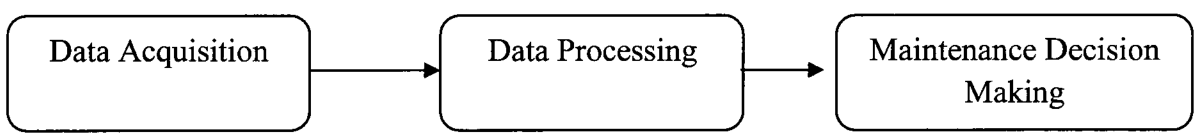

Figure 1: CBM process steps

1.3. Research Motivation

Modern era is time of competition in terms of reputation, financial growth and survival for organizations. Every industry wants to have realistic, prolific and dependable maintenance plan for their entire production. Maintenance of the equipments is vital in terms of steady operation. Now a day's industries are looking for cost effective maintenance practices, in order to optimize their maintenance plan. They want to know the exact threshold figure for their equipments failure, so that necessary actions can be taken at correct and scheduled time. This practice also benefits the safety for both humans and equipments and asset availability.

This research focuses on prognostics of bearings under time varying condition. Bearings are fundamental components of rotary machines. They support the entire load imposed on machines. If these components get failed, the operation of whole equipment can be stopped. As they are located in central position of rotating parts, access to them is only available after stripping the components most of the times.

Remaining useful life (RUL) prediction of bearings under time varying load condition is itself a challenge as a research work. The existing RUL prediction work is limited to fixed operating conditions (e.g., pressure, temperature, humidity, rotating speed, and load). However, in many applications, such as some wind turbine, transmission and engine applications, the load that the equipment is subject to changes over time. It is critical to incorporate the changing load in order to produce more accurate prognostics methods

1.4. Research Contribution

In this thesis, an artificial neural network (ANN) based method is proposed for equipment health condition prediction under time varying conditions. The proposed method can be applied to bearing as well as other components under condition monitoring. In the proposed ANN model, in addition to using the age and condition monitoring measurement values as inputs, a new input neuron is introduced to incorporate the varying loading condition. The output of the ANN model is life percentage, based on which the remaining useful life can be calculated once the ANN is trained. Two sets of simulated degradation data under time varying load are used to demonstrate the effectiveness of the proposed ANN method, and the results show that fairly accurate prediction can be achieved using the proposed method.

The other key contribution of this thesis is the experiment validation of the proposed ANN prediction method. The Bearing Prognostics Simulator, after extensive adjustment and tuning, is used to perform bearing run-to-failure test under different loading conditions. Vibration signals are collected using the data acquisition system and the Labview software. The root mean square (RMS) measurement of the vibration signals is used as the condition monitoring input for the validation of the proposed ANN prediction method. Two bearing failure histories are used to train the ANN model and test its prediction performance. The results demonstrate the effectiveness of the proposed method in dealing with real-world condition monitoring data for health condition prediction. The proposed model can greatly benefit industry as well as academia in condition based maintenance of rotary machines.

1.5. Thesis Organization

The rest of the Thesis is organized as follows:

- In Chapter 2, a detailed literature review is given on bearings and rotary machines condition monitoring methods. In the last part, some previous work on RUL prediction under time varying operating conditions is also discussed.
- In chapter 3, we discuss data analysis and feature extraction techniques, like time domain and frequency domain analysis, basic theory of artificial neural network, bearings and vibration analysis, and parameter used in this research to collect bearing operating characteristics for RUL prediction.
- In Chapter 4, we have discussed in details, our proposed neural network approach for RUL prediction, and validation with simulated data.
- In Chapter 5, experimental setup, data acquisition method and validation of proposed model are presented, to demonstrate the capability of new method.
- Finally in Chapter 6, we draw conclusions from our research and set out our future tasks for ongoing research.

Chapter 2

Literature Review on Bearing Condition Monitoring

Bearings are considered to be as a fundamental part of mechanical equipments, due to the widespread application of rolling element bearings, and it is necessary to effectively monitor their health condition for safe, reliable and cost effective operations. This literature review is comprised of previous research work on diagnosis and prognosis of bearings. Diagnostic research work is discussed, along with artificial intelligence techniques. Two different methods for prognosis, that is, physics based and data driven methods, are briefly discussed with previous work. In the last section of this literature review, remaining useful life of components under time varying condition is also discussed.

2.1. Bearing Diagnostics

Bearings play an important role for the integrity of machines as they are imposed to the most severe working condition. Despite the fact they are not expensive in comparison with the whole cost of equipments, their failure can interrupt the production in a plant, causing unscheduled downtime and production losses. The subject of rolling bearing diagnostics has been studied over past three decades. With the rapid increase in technology and increased in manufacturing of equipments, the need of fault detection in bearings, specifically in industries, has been realized, so that any impended fault if occurs can be rectified without disruption to entire plant production. The main objective of bearing diagnostics is to isolate and identify the different types of defects that occurred in bearings during operation. It is accomplished with the help of technology, developed through physical and statistical means, which involve measuring and processing of defects induced in bearings for any reason.

The most common methods in bearing diagnostics, for the detection of anomalies for feature extraction, are time domain and frequency domain analysis of raw signals of bearings, mainly in form of vibration and acoustic emissions through sensors. In time domain analysis, some statistical features like root-mean-square (RMS), peak, kurtosis, crest factor, impulse factor, shape factor, and clearance factor of vibration or acoustic emission signals, are often used for analysis of data, collected from accelerometers or acoustic emission sensors mounted on the bearing sleeves or machine casings. Kim et al. (2007) studied time domain features for condition monitoring of low speed rolling element bearings for incipient fault detection, by using an acoustic emission (AE) sensor and an accelerometer.

From statistical point of view, kurtosis value of bearing, which is a fourth order deviation from mean, is a good representation of bearing condition. Dyer and Stewart (1978) introduced a statistical parameter, Kurtosis, to measure bearing conditions. Mc-Fadden and Smith (1984) discussed the high-frequency resonance technique (HFRT) to evaluate the bearing condition by using anti aliasing filters. E.D. Price et al. (2001) combined both acoustic emission and vibration data with those from the wear debris analysis to detect impending failure in bearings.

Lee and White (1998) used the impulsive sound and vibration signals and passed these signals to two stage adaptive line enhancer, one to remove tonal and other to remove broadband noise from the signals. In addition to this sometimes other associated components of entire system produces noises which can mingle with bearing vibration signals causing difficulties in interpretation. Khemili and Chouchane (2005) proposed a classical approach to clean noisy signal by passing it through filters. Zhang et al (2008) proposed bearing anomaly detection through envelope signal spectrum, and as the fault dimension increases it shows a monotonic decrease trend. Early failure indication is usually detectable at higher frequencies. Therefore, waveform analysis and demodulation at these frequencies can be performed for time/frequency domain processing. Every time the defect rolls over the race bearings generate an impulse, and the demodulation process can be used to detect these impulse events.

Tandon and Choudhary (1997) proposed an analytical model for predicting the vibration frequencies of rolling bearings and the amplitude of significant frequency components due to localized defects on outer race. Their model can predict a discrete spectrum having peaks at the characteristic defect frequencies and their harmonics. Yu et al. (2002) used high-gain displacement transducers, to measure outer race deflection, resulting as a defected signal spikes in the time based deflection.

A diagnosis system monitors a finite number of fault modes that are conveniently ranked and selected according to a Failure Modes, Effects, and Criticality Analysis. These defects could be the reason of improper installation, misalignment of races, or improper loading of subsequent assemblies. The failures associated with these defects could appear in form of wear, which is a result of indentation on the raceways on the rolling element, flaking and smearing due to overloading and inadequate lubrication. Corrosion inclusion of water between bearing elements leads to pitting of the race ways and the surface of the bearing and cracks propagation for any reasons (Patil et al, 2008). The dominant mode of failure of rolling element bearings is spalling of the races or the rolling elements, which is an initiation of fatigue crack below the surface of the metal and propagates towards the surface until a piece of metal breaks away to leave a small pit or spall. Marble and Morton (2006) conducted research on the spall growth trajectory and presented a physics-based model for bearing condition monitoring.

2.1.1. Application of Neural Network for Fault Diagnostics

Artificial intelligence (AI) is the automation of intelligent behavior, in which an algorithm is made to assist machines while performing cognitive tasks. With the help of Artificial Intelligence, intelligent agents are designed, which are actually a system itself that can perceives their existing environment and can take actions that can maximized their chances of success. Working principle of artificial intelligence is simply learning, adaption and storage of knowledge and phenomena, and built in capability to use this information to solve the problem, and acquire new knowledge through experience. Several AI techniques are applied for rotary machines diagnostics, and some of the common are expert system, fuzzy logic, neurofuzzy, and neural network techniques. Artificial Intelligence techniques are getting popular among the researcher for rotating machines fault diagnosis. In this literature review some of the techniques and contribution will be discussed in general and application of neural network is discussed in particular as this technique is utilized in this research.

Rolling element bearings are important components, therefore fault diagnosis in the earlier stages is necessary to prevent further damages in future operational work. Neural network has so far become very promising for fault diagnosis of bearings. Lots of research has been conducted for fault detection in bearings, through seeded faults and also real life industrially used bearings data. Comparison has been made through new ones for pattern recognition and isolation of defective region. For the analysis of spectral signatures attained from bearing through sensors, neural networks may be used both as classifying and clustering systems, for classification purpose. It is important to label the signature at any instantaneous point to the data taken from machine in order to check the operational state of machine. The input to the network is a spectrum, or its compressed version, and the output is the class label. The network is trained to identify an arbitrary pattern as a member of a state among a set of possible states. Clustering involves the grouping of patterns according to their internal similarity thus requires no labels. The aim of clustering is to distribute the set of patterns into classes such that the patterns in each class have similar statistical and geometrical properties (Israel. et al, 1993).

Several researchers have contributed their work for application of neural network to fault detection and diagnosis of rolling element bearings. Samanta & Balushi (2003) presented a procedure for bearing fault diagnostics using time domain features and ANN with fast training capability. They used time domain features like crest factor, kurtosis and peaks values after normalization, so that even if the signals changes in magnitude due to change in speed or quality of sensor mounting, the diagnostic results are unaffected as long as the signal patterns remain unchanged. The training speed of ANN is enhanced after using the relevant features of the signals characterizing the bearing conditions. Paya et al (1997) studied both bearing and gear faults. They modeled driveline wear consisting of a number of rotating parts both separately and simultaneously. The vibration signals acquired from the driveline were first pre-processed using wavelet transform, and then they used ANNs to differentiate between each fault and established the exact position of the fault occurring in the driveline.

Li et al (2000) discussed several bearing vibration features in time and frequency domain. With the help computer aided software they simulated the data to study and design the neural network for motor bearing fault diagnosis algorithm, and then they used actual vibration data collected in real time to perform initial testing and validation of approach and got effective results in the diagnosis of various motor faults through appropriate measurement and interpretation of motor bearing vibration signals.

Sreejith et al (2008) used feed-forward neural network with back propagation training algorithms for fault diagnosis rolling element bearing from vibration data. The time domain parameters, the Weibull negative log-likelihood values, and the normal negative log-likelihood values of the time domain vibration signals were used as input features. The proposed procedure used ANN classifier and required data measured from only one measurement point. The signal was not pre-processed before the feature extraction. The algorithm used less number of input features resulting in faster training.

Samanta et al (2004) presented a procedure for the diagnosis of bearing condition using three classifiers, namely, MLP, RBF, and PNN with Genetic Algorithm (GA) based feature selection from time-domain vibration signals. GA is used to optimize the classifier parameters and performed successfully for six input parameters of time domain signals. Another important thing they found regarding neural network is that although the classification performance of MLP was comparable to that of PNN with six features, the training time of MLP was much higher than PNN.

Subrahmanyam & Sujatha (1997) used time domain features, like RMS, kurtosis, crest factor etc, along with frequency domain features of bearing like prime spike region and high frequency region. They trained two neural networks: a multi-layered feed forward neural network trained with Error Back Propagation (EBP) algorithm, and an unsupervised Adaptive Resonance Theory-2 (ART2) based single layered competitive neural network, by knowing the fact that these neural networks have an edge over conventional monitoring methods in that they can classify the condition of machine components, even in the absence of explicit input to output relationships. They got better performance with EBP, but faster learning time around 100% with ATR2 type of neural work. Taha & Khusnun (2009) used feed forward back propagation neural network to detect bearing defect through acoustic emission measurements. They used function approximation and pattern recognition tasks for anomaly detection in bearings.

2.1.2. Application of Other Artificial Intelligence Techniques for Diagnostics

Several other artificial intelligence techniques are gaining importance in the field of rotary machines diagnostics. Fuzzy logic has shown prolific results in this area of diagnostic research. Fuzzy logic sets along with statistical data assessment and some pre-defined sets of standards have proven to be effective, but still a question raised is about the human subjectivity and adaptive learning of this technique.

Mechefske (1998) investigated the use of basic fuzzy logic techniques as a machinery fault diagnostic technique. He used fuzzy logic technique to classify frequency spectra according to likely fault condition. He used membership function domain limits that are linked to the variability of group spectra of particular type of faults. Fuzzy logic optimum limits were manually adjusted in this work. Zeng & Wang (1991) used fuzzy logic technique by fault clustering and fault assignment techniques. From the previous failure history, they developed fault pattern data base for every type of fault, and established set of classified clusters, with each cluster representing one type of machine fault. Any kind of fault signature was passed to this cluster for identification of faults.

Another artificial intelligence technique is expert system. Expert Systems are computer programs, established through domain knowledge and it utilizes logical operators like "IF-THEN-ELSE". An expert System is a knowledge based system which stores faults in its data base, but its limitation is that it cannot figure out new problem, which is not stored in data base. This non learning capability of expert system is its limitation.

Another problem associated with expert system is to obtain knowledge from data base. Shao & Nezu (1996) applied the principle of expert system to perform monitoring and diagnosis of bearings. They used recurrence tracing method to minimize accidental variation in monitoring of bearings. They proposed a degree of credibility of parameter value variation (DCPV) factor, which can tackle the online variation of intrusive vibration signals. Jack & Nandi (2000) used six input feature to train a genetic algorithm for bearing vibration diagnostics and found better accuracy after combining it with ANN.

Samanta (2004) presented a procedure for detection of gear condition using ANN and support vector machines (SVM) with GA-based feature selection from time-domain vibration signals. With the help of genetic algorithm he optimized the selection of input features and the appropriate classifier parameters. He collected different vibration signals under both normal and light loads, and at low and high sampling rates. He showed that classification accuracy of SVMs is better than of ANNs, without GA. With GA-based selection, the performance of both classifiers was comparable at nearly 100%, even with different load conditions and sampling rates.

2.2. Bearing Prognostics

In present days, reliable estimation of bearings remaining useful life presents the most challenging aspect in maintenance optimization and catastrophic failure avoidance. So far the two basic methods deployed for prognostics of rotary machines are Physics Based and Data Driven.

2.2.1. Physics Based Prognostics

A physics-based prognostic involves building of mathematical models based on physical phenomena of operation of equipments and their internal relationship with each other. As defects grow within the system and lead towards failure, the failure mechanism and modes are studied to form physics based models, and that can define defect growth trajectory, stress/strain relationship of the defects. Using these models, remaining useful life of the system can be predicted.

Bearing prognostics specifically depends upon the nature of anomalies associated with different types of bearings and their operational characteristics. Fault projection is tracked in order to develop prognostics algorithm for RUL prediction. Lybeck et al (2007) developed a prognostics algorithm for remaining life prediction of bearings and validated their algorithm, with vibration based diagnostic data. In order to check diagnostic severity metrics, after feeding this information into proposed model for prognosis for future spall propagation, they calculated the remaining useful life of bearing. David & Bechhoefer (2007) developed bearing diagnostics and prognostics tools using health and usage monitoring system (HUMS) condition indicators. In their model, physical damages of bearings are correlated with condition indicators for fault diagnosis and prognosis like nearest neighborhood points from real vibration data.

Janjarasjitt et al (2008) analyzed vibration data corresponding to the operation of test bearing in an accelerated life experiment, and used partial correlation integral computed dimensional exponent. They found that this dimensional component was different for healthy bearing and bearings close to failure, it tended to increase. They also proposed computational scheme for bearing condition monitoring using the dimensional exponent integrated with a surrogate data testing technique. Normally the nature of defect growth does not follow a linear relationship. Noises in the wide spectrum of a bearing's vibration signal make this task even more difficult. William et al. (2001) presented a signal processing method, which attempted to emphasize defect signals over background noise and built a model for defect growth. Li et al. (1999) presented the formulation of a bearing prognostic methodology based on the in process adaptation of defect propagation rate with vibration signal analysis. It utilizes a deterministic defect propagation model and an adaptive algorithm to fine tune the predicted rate of defect propagation in a real-time manner.

2.2.2. Data Driven Prognostics

Data driven approaches for bearing prognosis relies on condition monitoring data. Instead of building physical models, only the current and past state features are used to predict remaining useful life. During the operation of components, whenever characteristics features like vibration, acoustic emission, temperature and pressure etc are change, their sequence of points forms some trajectory and data driven methods use these points to predict remaining useful life. Some of the measure data driven methods are ANN, hidden Markov method, auto regressive models etc. Gebrael et al (2005) used the reliability characteristics of a device's population and real-time sensor information from the functioning device to periodically update the distribution of the bearing's residual life. They developed a Bayesian approach for updating their estimates of the stochastic parameters in exponential random-coefficient models and then used these models with their updated parameters to develop residual-life distributions for partially degraded components.

Neural network is a widely used tool in the application of data driven prognosis for rotary machines and equipments. It has shown so far prolific results towards prognosis or prediction of remaining useful life of bearings. For bearing prognosis research work, normally there are different ways to collect bearings data. Mostly researchers have used either vibration or acoustic emission data for most of the research works. The data can be taken from industrial equipments, through computer aided simulation programs at different set of conditions, or from lab experiments. This information is then used to train the neural network on predicting bearing operating times. Bearing sensors data from a set of validation bearings are then applied to these network models, and thus resulting predictions are then used to estimate the bearing failure times.

Gebraeel et al (2004) investigated the fatigue process for a group of identical bearings to calculate variation in bearing life. They performed accelerated life testing on identical bearings and calculated six harmonic frequencies of bearing which are multiple integers of defective frequency, and fed the vibration magnitude at these frequencies to train a set of feed forward back propagation neural network. Their approach was to develop two classes of models, which were single bearing and cluster of bearing networks relying on data base of degradation signals to predict failure time of a partially degraded bearing at any time during its service life and got satisfactory results.

Tian & Zuo (2009) proposed an extended recurrent neural network (ERNN) for health prediction of gearbox based on the vibration data collected form gear box. Fulong et al (1993) proposed a neural network to implement maximum likelihood method. They developed bearing likelihood estimation algorithm in real time and demonstrated their results analytically and through simulation as well. Satish & Sarma (2005) developed a technique for the detection of bearing condition in induction motors, by combining both ANN and fuzzy logic, to take the advantages of non linear mapping through ANN and classification of linguistic and ambiguous information through fuzzy logic. They developed a Fuzzy BP (Back Propagation) in order to avoid the disadvantages of individual artificial intelligence techniques.

Huang et al (2007) presented a method for the prediction of a ball bearing's remaining useful life. Their model was based on self-organizing map (SOM) with unsupervised learning, and back propagation neural network with supervised learning. To identify the current operating time of a bearing, they used six vibration features and developed a new degradation index for performance degradation assessment. Wu et al (2007) developed an integrated neural-network based decision support system for predictive maintenance of rotational equipment. They developed a vibration data base and trained a feed forward back propagation neural network to predict remaining useful life of bearing. They also constructed a cost matrix and probabilistic model to optimize the expected cost per unit time.

Tian (2009) modified the model proposed by Wu et al (2007), and proposed a new ANN based model for achieving more accurate RUL prediction. He presented the model that can take the age and multiple condition monitoring measurement values at discrete inspection points that is at current point and previous point as the inputs and the life percentage as the output. He used generalized Weibull-FR function to fit each condition monitoring measurement series for a failure history. He trained ANN with these fitted measurement values got better result than Wu's method of prediction for remaining useful life.

Tian et al (2009) used ANN for remaining useful life prediction from suspension histories rather than only from failure histories of equipment. They realized the potential of suspension history data that is when equipment is removed from service due to any reason before it gets failed. For each suspension history they determined optimal predicted life, which can minimize the validation mean square error. Mahamad et al (2010) used feed forward neural network with Levenberg-Marquardt training algorithm for the prediction of RUL of bearings. Their model used time and fitted measurements with Weibull hazard rates of root mean square (RMS) and kurtosis from its present and previous points as inputs, and presented the normalized life percentage as an output in order to minimize the noise of degradation signal from target bearings. Vachtsevanos (2001) used dynamic wavelet neural network (DWNN) for the prediction of bearing failures and compared their result with auto regression model (AR) to predict RUL.

2.3. Prognostics under Time Variant Conditions

Bearings are normally subjected to time variant conditions imposed through either environment, or the operating condition of equipment in which they are installed. Current methods for RUL prediction have considered fixed operating environments, like temperature, pressure humidity, speed and load. Usually load imposed on bearing are considered to be stationary. Accurate RUL prediction under time varying conditions is a challenging and critical work. A recommended solution is to figure out the degradation characteristics of the unit under operation at several varying conditions, and apply artificial intelligence techniques, such as neural networks and fuzzy logic to predict RUL prediction under these conditions. Not much research work has been conducted in this area, but still research is going on to build the good physical models with capability to predict RUL under time varying conditions.

Shao & Nezu (2000) proposed a new concept called progression-based prediction of remaining life (PPRL). For accurate prediction of remaining useful life this model used different prediction methods to different bearing running stages. They used online measurements to check level of deterioration during run to failure test and apply PPRL via a compound model of neural computation. They demonstrated that their model has the capability to automatically adjust varying environmental factors. Lao & Saleh (1993) used the frequency features of vibration signal, Power Spectral Density (PSD) and Discrete Fourier Transform (DFT), to analyze a bearings' vibration characteristics under unbalance load in common operation conditions. They developed 2-layer neural network for RUL prediction of bearings. Their model tracked the fault's feature patterns due to unbalance faults identified by a set of time based vibration frequency spectrum, contained in the vibration signal.

Zhang, et al(2002) conducted a research to predict remaining useful life of bearings, by accelerated fatigue test under a corrosive environment with the application of inverse power law. Their theory lies under the fact that RUL prediction model can effectively work under normal or any other accelerated operating conditions, as long as the stress level fall within the designed range. They performed bearing life tests under several corrosion stress levels, and for their model verification, they conducted separated test under normal conditions for validation purpose. Carey and Koenig (1991) conducted an accelerated data testing at higher operating temperature levels, to check the reliability of an integrated logic family under normal operating conditions.

Gebraeel and Pan (2008) have recently developed a prognostic approach for updating the RUL of a single unit under time-varying environment. They used a linear degradation and the multivariate normal distribution model to utilize a conjugate prior distribution for updating the model parameters and RUL prediction. But there proposed approach is still insufficient to handle complex cases, where degradation stress/strain relationship is nonlinear. Meeker et al. (1998) presented an approximate maximum likelihood method for their nonlinear mixed-effects ADT model.

Chapter 3

Data Analysis and Feature Extraction

Data analysis is the transformation of raw sensor data into useful information for decision making. Feature extraction is a procedure of handling raw data in way to reduce curse of dimensionality, as the data collected is normally consisted of several thousand points. Therefore in order to classify them, we need suitable methods for transformation and at the same time, we do not want loose the information available in the data. Several data analysis techniques are used for feature extraction of bearing defects. Most of the prominent techniques are time domain, frequency domain, and time-frequency domain analysis. Time domain analysis mainly comprise of statistical analysis of time varying data, captured through sensors. While frequency domain analysis is the conversion of time domain signal into its frequency components for the detection of defective frequencies. Several techniques are available, already used by researchers. Some of the prominent and promising techniques are high frequency resonance technique (HFRT), power spectral density, cepstrum analysis, spectrum analysis, and so on. All these techniques have their own advantages and disadvantages. Therefore on individual basis each technique can be considered as independent, rather complementing each other in several ways. The most common techniques discussed in this chapter are time domain and frequency domain analysis, spectral analysis with Fourier transform and neural network based methods.

3.1. Time Domain Analysis

Time domain analysis is one the prominent approach for both bearing diagnosis and prognosis. Some of the basic time domain features are root mean square (RMS), Standard deviation, Kurtosis value, Crest factor, Clearance factor, Impulse factor and Shape factor etc.

Sreejith et al (2008) utilized time domain features for their research on bearing diagnostics. Kim et all(2007) also used time domain feature while conducting research on low speed bearings by a low speed fault simulation test rig, specially developed to simulate common machine faults, with shaft speeds as low as 10 rpm under loading conditions. The simplest method is to measure the overall RMS level of the bearing vibration, and compare from previous or pre set values for the health monitoring condition of bearings.

Tandon & Nakra (1993) studied RMS technique along with other techniques to detect bearing defects through simulation. Another point of consideration for RMS is that, it never shows appreciable changes in the early stages of bearing life, therefore some time another measurement called crest factor is used, and it is the ratio of the peak level of the input signal to the RMS level. Higher peaks in the time series signal will increase the crest factor. When defect occurs, it increases the peak level of vibration signal resulted in short burst of high energy. Therefore crest factor is a good indication of faults when it is generated.

Kurtosis is also a common method for signature analysis. It is the statistical indicator used in time history data of bearings signatures, to calculate impulsive character of the signals. It is a fourth statistic moment of the distribution of data from mean. Dyer & Stewart (1978) initially introduced its application to bearing fault detection. Sawalhi & Randall (2005) presented an algorithm for the optimization of spectral kurtosis that can help choose the best filter. In another work they also proposed a pre-whitening method for power spectral density of signal prior to the application of spectral kurtosis.

Another technique shock pulse method is also used. It measures maximum amplitude of sensor's resonances in the time domain. The shock pulses are produced due to impacts in the bearings, which initiate damped oscillations in the sensor at its resonant frequency, condition of bearings is indicated by measuring the maximum value of the damped transient pulses. Zhen et al (2008) proposed new approach for improved redundant lifting scheme (IRLS), by adding the normalization factors in time domain features to avoid error propagation of decomposition results. Some of the basic time domain features were briefly given with their mathematical representation.

3.1.1. Root Mean Square Value (RMS)

As described earlier, The RMS is the most common statistical tool to evaluate the overall performance of bearings vibration level its rapid response detection characteristics makes it more suitable to use in accelerated failure life testing of bearings. During the experiment for quick judgment, practically for good bearings initially this indicator remains steady, and starts increasing gradually and then shows rapid increase in last hours of experiments till bearing get failed. The RMS value is given by the following equation:

$$\text{Signal (RMS)} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(S_i)^2} \tag{3.1}$$

Where N is the total number of data points captured during sampling in one history of entire signal and S_i is the i_{th} member of data set S. We used the above equation for our calculation of RMS of the data, captured during failure tests through accelerometer and we processed them in Matlab.

3.1.2. Kurtosis

Kurtosis is a fourth moment of the distribution and measures the relative peakedness or flatness of a distribution. We can estimate the sharpness of distribution of vibration data with the help of this function. Normally, vibration signals of healthy bearings follow Gaussian distribution. It does not depend upon the load and revolutions. Therefore the value of the kurtosis is close to three for the vibration signals of healthy bearings. As the propagation of cracks rises, this will increase the kurtosis value a lot more than three. As damage becomes severe, kurtosis values starts decreasing practically near three. Therefore, the extent of bearing damage may be assessed by examining the distribution of the kurtosis in selected frequency ranges.

Mathematically Kurtosis can be expressed as

$$\text{Kurtosis}=\frac{1}{N}\sum_{i=1}^{N}\left(\frac{S_i-\mu}{\sigma}\right)^4 \tag{3.2}$$

Where N is the total numbers of data points captured during sampling in one history of entire signal, S_i is the i_{th} member of data set S, σ is the standard deviation, and μ is the mean of all points in data set S

3.1.3. Peak Value

Peak value of time series data is often useful for investigation of peak amplitude of entire signal, especially in later part of accelerated life testing when there are sudden changes in vibration amplitudes. During the test, in case if damaged occurs, its relative amplitude during the accelerated life test can also be a good representation.

Peak value is represented as

$$\text{Peak Value} = (1/2)\,[\max(S_i)\text{-}\min(S_i)] \tag{3.3}$$

Where S_i is the i_{th} member of data set S.

3.1.4. Crest Factor

The crest factor is the ratio of peak amplitude of entire signal and RMS value. Crest factor can provides a quick idea of how much impact is occurring in vibration signal. This impact is often associated with bearing wear or any other damage. Another point is that RMS value has a little variation during early stages of bearing running cycles.

Therefore in case of damages, peak values will increase and eventually crest factor will increase, which indicates the running condition of bearing. For normal bearing, its accepted value is 2 to 6. Values more than 6 can be considered as an indication of defective bearings.

Mathematically

$$\text{Crest Factor} = \frac{PeakValue}{RMS} \tag{3.4}$$

3.2. Frequency Domain Analysis

For bearing fault diagnosis and prognosis, Frequency domain also called Spectral analysis has become more significant and prolific approach due to its features. In this technique, characteristics frequencies of rolling element bearing components are collected in the form of impulses from the wave form of signals. Most prominent techniques are high frequency resonance technique (HFRT), spectrum analysis, cepstrum analysis, synchronized averaging, etc.

HFRT is the technique that utilizes envelope detection of bearing signatures. In this technique, vibration signatures are either attenuated or preamplified, and then these processed signals are routed to a band pass filter, set for an appropriate carrier frequency. These filtered signals are then rectified and demodulated to develop the envelope, the frequencies of this envelop are analyzed through frequency spectrum analyzer. Rolling element bearing components have their own defective frequencies which appears in this envelops for any kind fault detection.

Shiroishi et al (1997) used HFRT along with adaptive line enhancer for fault detection in bearings. They used two accelerometers and acoustic emission sensors to detect bearing defects in outer and inner races. Martin and Thorpe (1992) presented the concept of normalization of the envelope-detected frequency spectra. They compared signal of both faulty and healthy bearing to give rated numbers, thus ensuring more sensitivity to the detection of defect frequencies. Ho & Randal (2000) simulated bearing fault signals and investigated the efficient application of self-adaptive noise cancellation (SANC) in conjunction with envelope analysis in order to remove discrete frequency masking signals. They suggested Hilbert transform or either band-pass rectification technique for combination of these signals. Cepstrum is defined as the spectrum of the logarithmic power of spectrum. Tandon (1994) used cepstrum along with several time domain features to detect of different sizes in bearing.

3.3. Spectral Analysis with Fast Fourier Transform

Bearing Vibration signature are captures through mounted sensors or transducers. These signals are normally captured in time varying conditions or in time domain. Therefore in order to analyze these signals, it is important to select a proper technique in order to analyze those signals to conclude the ongoing problem or condition of bearings at the prevailing stages. Spectral analysis is used to transform a signal from the time domain to the frequency domain and vice versa. With The application of Fourier Transform function we can get the spectral content of a periodic function.

The Fourier transform of function X (t) is given by as follows:

$$X(f) = \int_{-\infty}^{\infty} x(t) e^{iwt} dt \tag{3.5}$$

Transformation of X (t) to X (f) is from time to frequency, and the whole transformed function is the sum of sine and cosine of different frequencies, and w is rotational component which is equals to 2πf.

FFT or Fast Fourier Transform splits time signals into sub components with amplitude, a phase, and a frequency. Every associated frequency reflects its characteristics. Its amplitudes can be useful to work out the problems. Theoretically all waveforms, irrespective of their complexities can be expressed as sum of sine and cosine waves of different amplitudes, phase, and frequencies. FFT performs this function by breakdown, the complex time waveform into components and eliminate time axis, resulting in demonstration of graph that can represent frequency versus amplitude.

3.4. Neural Network

An artificial neural network (ANN) has now become the more popular for pattern recognition of mechanical components, especially for rotary machines. Artificial neural networks map the input data into selected output categories using artificial neurons similar to biological nervous system. ANN works in a layer pattern, the input layer, hidden layer, and output layer. Each layer consists of nodes. The lines between the nodes indicate the flow of information between the nodes. For the feed forward neural networks, the information flows only from the input to the output. The nodes of the input layer are passive, which mean they cannot modify the data. The nodes of the hidden and output layer are active. The values in a hidden node are multiplied by weights. The weighted inputs are then added to produce single results. Before leaving the node, this result is passed through a nonlinear mathematical function called a transfer function. The active nodes of the output layer combine and modify the data to produce the output values of the neural network (Sorin, 2001).

Neural networks are designed to classify input patterns in some selected classes or to create categories that group patterns according to their similarity. They can model processes and systems from actual data. The neural network is supplied with data and then "trained" to find the input-output relationship of the process, or system. Neural networks also have the ability to respond in real time to the changing system state descriptions provided by continuous inputs. Therefore, when there are lots of inputs or the system is complex neural network can provide a realistic solution.

Architecture of Neural networks is comprised of simple elements operating in parallel, similar to biological nervous systems. As in nature, the connections between elements largely determine the network function. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements.

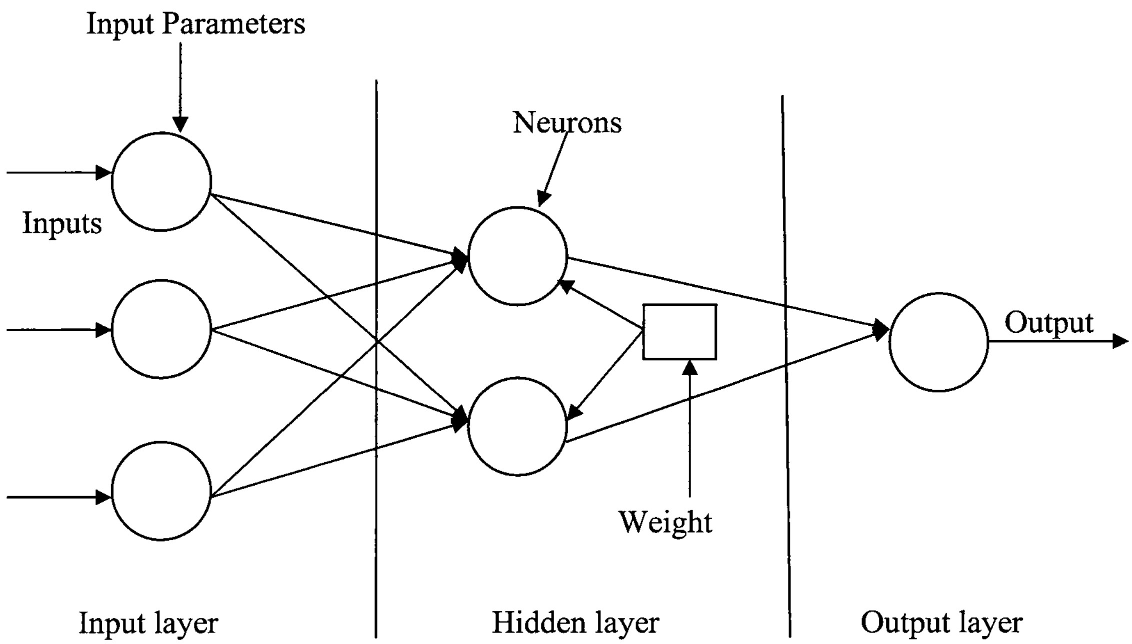

Figure 2: Basic structure of neural network with one input, hidden and output layer.

The two methods for pattern recognition in neural network training are supervised and unsupervised learning. A supervised learning scheme can detect, locate damage and indicate severity of damage. Supervised model defines the effect of input on output of the trained network. Unsupervised learning can be used for cluster analysis. These clusters are sets of data which represent meaningful categories, such as damage types. If the inputs are available, these models are not desired. But in case of missing inputs, it is impossible to infer anything about output. Unsupervised learning is useful for building larger and more complex models than with supervised learning. Normally supervised learning finds the connection between two sets of observations. The difficulty of the learning task increases exponentially in the number of steps between the two sets and that is why supervised learning in practice cannot learn models with deep hierarchies.

The Artificial neural network has gained lot of success in RUL prediction for bearing prognosis model by virtue of their capability of learning the behavior of nonlinear systems. Collection of time series data from accelerated of natural life data of bearings are used as an input to train the neural networks.

For CBM purposes, all the pertaining information are fed to ANN as inputs and ANN produces a decision result as an output. Therefore feeding of an appropriate data regarding the condition of data is important while using ANN and the rest of the job is performed automatically by ANN. ANN has been used fault diagnostic and prognostic of rotary machines, where the degradation process of the equipments are most of the times nonlinear, and sometimes statistics based rules are failed to predict the degradation trajectory. Several kinds of neural networks are now used for bearings prognosis, already discussed in literature review. The most common types of ANN are feed forward neural network and recurrent neural network. A feedforward neural network is that type of ANN in which connections between the units do not form a direct cycle. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes, and to the output nodes. There are no cycles or loops for feedback within in the network. Recurrent neural network are those type of ANN in which output from the neurons are feed to adjacent neurons, to themselves or may be to neurons on preceding network layers.

3.5. Ball Bearings

Ball bearings are one of the main types of rolling element bearings. They support another moving machine element, by permitting a relative motion between the contact surfaces of the members while carrying the load, and at the same time offers less friction, often termed as antifriction bearings. The main advantages of these bearings are low cost of maintenance, reliability, easy installation, low starting and running friction.

Ball bearings are normally compact type bearings in installation, but they are also fabricated in loosed assembled form. Typical ball bearing is comprised of

- Inner race which is mounted on the shaft,
- Outer race which is usually fixed in bearing housing or sleeves
- Balls as rolling elements,
- Cage, for proper location of balls at fixed distance along the periphery, sometimes also accompanied by retainer to fix the whole assembly.

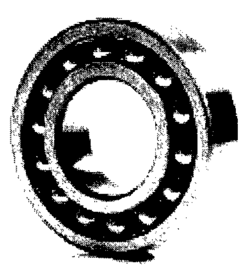

Figure 3: Ball Bearing

3.6. Bearing Health Parameters for Prognostics

Different features of bearing prognosis data can be taken, like vibration, acoustic emission (AE), temperature, and spectrometric oil analysis. Two measure techniques used are acoustic emission and vibration analysis for bearing fault detections. Acoustic emission (AE) is the phenomena of transient elastic wave generation due to a rapid release of strain energy produced by structural components under different kinds of stresses. Generation and propagation of cracks are among the primary sources of AE in bearings. It is dependent on the basic deformation of bearing rolling elements. AE sensors are designed to capture these energies up to 450 KHz. Their normal parameters are peak amplitude, number of counts, and the main advantage taken by AE is the detection of sub surface cracks, which cannot be detected by vibration analysis. Among all of them vibration has become the most widely used tool for the collection of bearing signatures. This research is focused on vibration signature attained from bearings. In this research for the prediction of remaining use full life of bearing, we have used vibration data attained from bearing prognostic simulator.

3.6.1. Vibration Analysis

Vibration analysis can give better information about progressive malfunctions and their patterns. A defective rolling element generates vibration at different frequency levels according to their physical behavior, whenever a defect occurs, their individual defective frequencies can be separately characterized for defect detection. Chaudhary and Tandon

(1998) presented a detailed discussion about the calculation of frequencies of different element of rolling element bearings.

Collection of vibration data is one of the measure tasks. It is usually performed by acquiring an accurate time-varying signal from vibration transducer (accelerometer). Normally these signals are in analogue form, with the help of computer aided software these analogue signals are transformed into digital signals. Theoretically if any type of damage occurs in bearing, like in accelerated life test for prognosis work, when we are going to accelerate the bearing failure, the vibration level supposed to be increased, therefore appropriate methods were needed to compare those signatures from current to previous ones, in order to detect sign of failure in bearings.

Large variation in data made this comparison even more difficult. Therefore we used neural network for the extraction of features from vibration signatures for pattern recognition of bearing failures.

3.6.2. Causes of Vibration in Bearings

Vibration is the mechanical oscillation of equipment subject to loading about a fixed point. It can either periodic or random. Vibrations are unavoidable in any rotating component, and cause waste of energies and production of unnecessary noises in the system. From bearing condition monitoring prospects, vibration analysis is very vital as it is a useful tool to analyze equipment's health at prevailing condition. Vibration thus being an integral phenomenon of bearing rotation needs to be specified for its relative component degradation.

Some of the main reasons that can cause undue vibration are typically but not limited to misalignment of bearing on shafts, unbalancing, bending loads, resonance, internal defect, aerodynamic and gyroscopic forces, etc. Several researchers have done some studies to detect causes of vibration in bearings. Volker & Martin (1984) studied the phenomena of electrical pitting and cracks caused by excessive shock loading in different types of bearings.

If any defect occurs in bearings, it can severely increase the vibration level. These defects can be grouped as 'distributed' or sometimes 'local'. Distributed defects are usually waviness, misaligned races, and off size rolling elements. Meyer (1980) and Wardle & Poon (1983) have studied some causes of these defects. Sunnersjo (1985) and Washo (1996) also studied the phenomena of distributed defects caused due to improper installation, abrasion and manufacturing discrepancies. The other category of defect is termed as 'local', typically but not limited to pitting, spalling and cracks. These are usually occurs due to overloading during operation, or at time of installation. One of the severe categories of defect is spalling in which a layer of metal get break down from races or rolling element. Marble & Morton (2006) has studied these phenomena in detail for vibration purposes.

Chapter 4

Neural Network Model for RUL Prediction

This chapter presents the RUL prediction model, based on feedforward neural networks. Neural Networks are data driven prognostic techniques. For CBM purpose, they are trained by providing input of actual working parameters and condition monitoring data, analyzed through time domain analysis, frequency domain analysis, or both as illustrated in Chapter 2. For prognostics purpose, all these features are incorporated with neural networks to form a degradation trajectory of components. FeedForward neural networks are considered to be more developed for bearing prognostics.

4.1. Remaining Useful Life Prediction

The RUL prediction schema is given by procedure below in Figure 4. It shows the ball bearing, and accelerated life test vibration data collection for feature extraction in time domain analysis, where RMS is chosen as an indicator of overall health condition of bearing during accelerated life test, under time variant conditions during these tests. A feedforward neural network (FFNN) model is developed and trained for remaining useful life prediction of ball bearings under time variant condition.

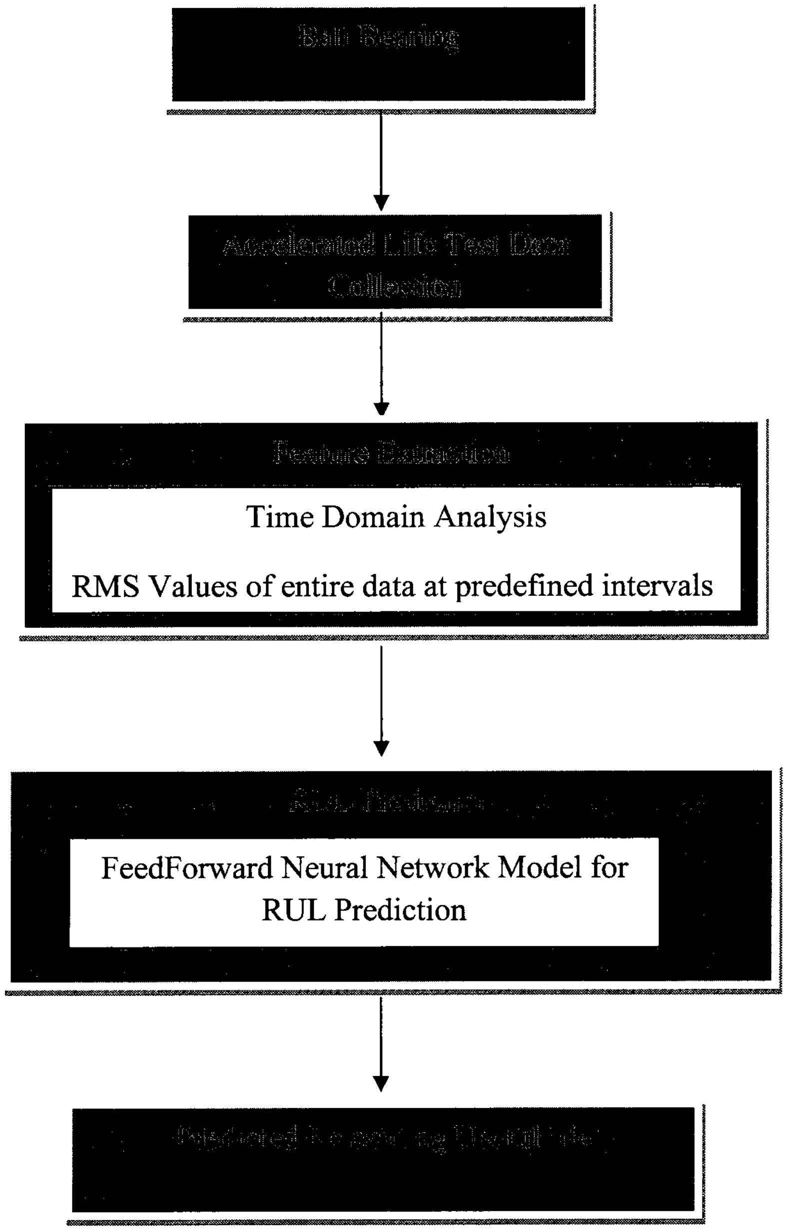

Figure 4: Remaining Useful Life Prediction Procedure

4.2. The Artificial Neural Network Model for RUL Prediction

This section presents the ANN model used in this research work. We have used a feedforward neural network for RUL prediction of rolling element bearing. FeedForward ANN is preferred for providing better training algorithm, and effective methodology for the construction of truly nonlinear system degradation processes. Rolling element bearing degradation process is non linear and most of the physics based models have failed to predict the exact degradation trajectory. The capability to learn itself with little prior input knowledge makes them more useful for prognostics works. Training FFNN is a complex problem and it is essential to verify that network has the capacity of learning and generalization. Another important consideration is the number of neurons to be used. More neurons can increase the complexity of network, as more input parameters are provided for training purposes. This can result in slow training and reduced network performance.

4.2.1 The FeedForward ANN Model

An example of the architecture of the proposed model is shown in Figure 5. The model is comprised of one input layer with five neurons, an output layer with one output neuron, which presents the life percentage of bearings, and two hidden layers. The first hidden layer is comprised of three nodes and the second layer has two nodes. Initially we used single hidden layer, but the training results were not satisfactory in terms of prediction due to randomness of the training algorithm. Therefore, we decided to include the second layer with less number of processing neurons and found reliable and more accurate results with the same experimental and simulated data. We propose our neural network in two versions. Figure 5 shows the basic architecture of our first model for rolling element bearing prognostics. Even though three neurons and two neurons are used in Figure 5, the hidden neurons numbers can actually take any value depending on the size of the problem.

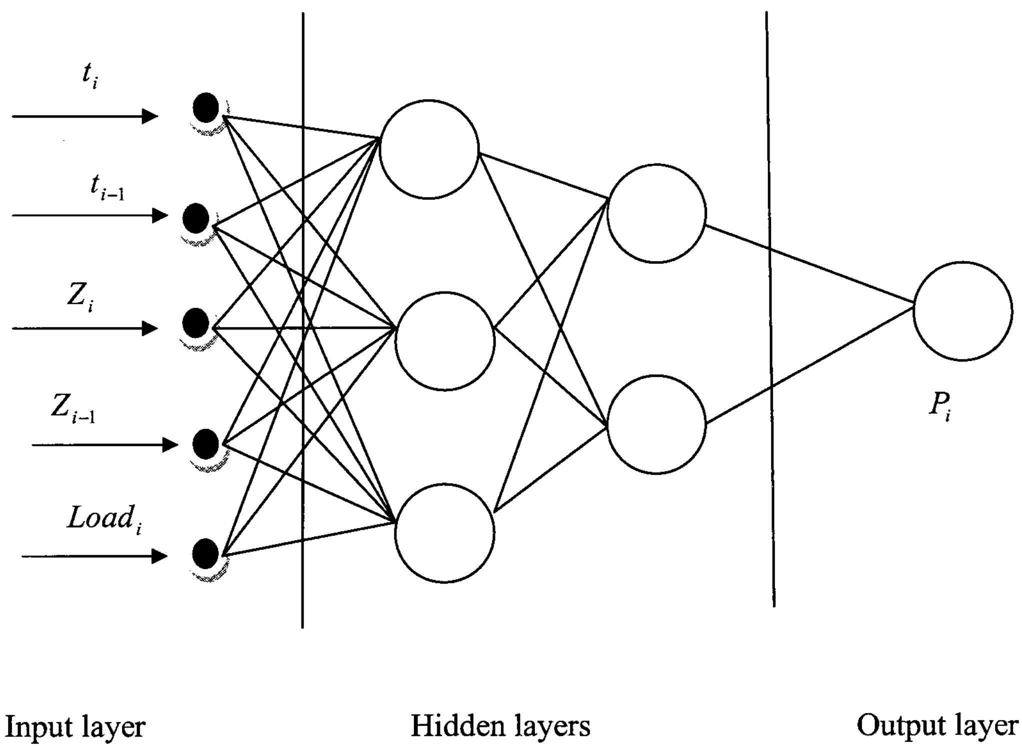

Figure 5: Architecture of first FFNN model for prognostics of rolling element bearing

The inputs to this neural network are condition monitoring measurement 'Z', time 't' and the load. This research is based on RUL prediction under time varying conditions, and the inputs to this network include health monitoring signature of bearing from vibration sensors. During accelerated life test under load, appearance of defect is shown in the overall vibration amplitude over time. Therefore RMS indicator is selected to present the condition monitoring parameter of bearing during tests. RMS indicator is considered to be more effective parameter for degradation trajectory analysis. This parameter is stable in early hour of test with little variation and slightly increased as the defect propagates in the bearing. There is a sharp rising when bearing is close to failure. Detailed of RMS indicator is discussed chapter 3. Second input is the bearing test life in terms of time. Both this values are given as an input from current and previous points of accelerated life failure data. RMS_i and t_i present the values of RMS and time of bearing life at the current point, and RMS_{i-1} and t_{i-1} at previous inspection point. Input of data at two time points can be better to track the rate of change of condition of components from previous to current point. For the training purposes we can training more robust ANN with better generalization capability, as the number of input neurons are less which are resulting in less number of trainable weights. For training purpose we also check the option of feeding three time points input, but got better result with two points input. The final input to this network is the load applied during the tests. In previous work of Tian et al (2009) they considered only condition monitoring and time measurements, but in this work we introduced a new input neuron of load as time varying factor that can affect the bearing remaining useful life prediction. With the addition of load input during the training we can map the performance of ANN according the inclusion of load that affects the overall vibration of entire system. Theoretically application of load input occurs in terms of entire RMS value, with more load higher characteristics vibration induced in the system resulting in higher RMS values and vice versa. Therefore at this point we can say that entire RMS value of vibration signatures represent the condition of equipment at prevailing loading, why we need another input of load to train the neural network, but problem associated with this is to figure out the relationship between RMS value and load which is theoretically very complex as with the application of more load, more vibration from components and other associated structure occurs which can also increase the noises in RMS value, and changing load factor has no linear relationship with RMS value, therefore it is reasonable to include load factor as an input to train the ANN.

Revolution of bearings were kept constant at 2000 during all tests, and the load is the only time variant factor, affecting the length of experiment. Therefore we decided to use this factor as input to train the neural network. This model can be used for discrete inspection points. That is, if the interval of inspection points is not constant, it is appropriate to use this model as the inputs include the current and previous points. The advantage of feeding data at current and previous is that, we can train our network by providing rate change of these parameters from the previous to the current point.

In the second version of our model, we made some changes comparing to the first model, as during the accelerated life tests all the data is generated at constant intervals using Lab View software. Therefore it is more appropriate to use the age at current inspection point only to train the neural network. The reason behind this is data collected at fixed interval and time factor has no significant impact on degradation trajectory. Figure 6 shows the modified architecture of our second model for rolling element bearing prognostics.

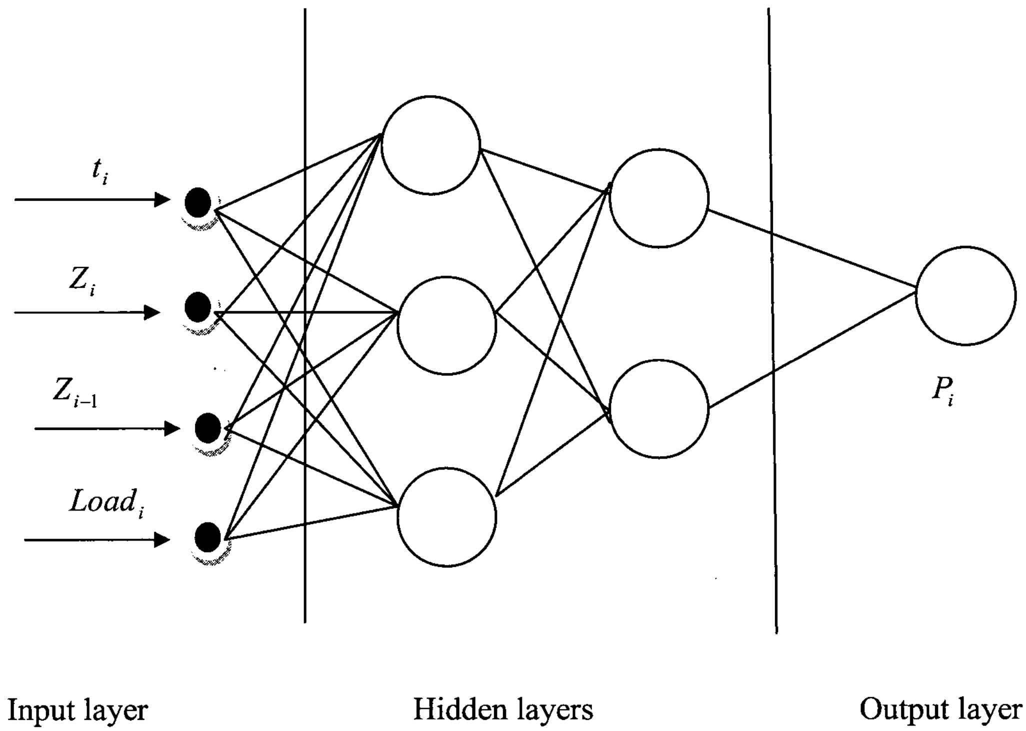

Figure 6: Architecture of modified FFNN mode for prognostics of rolling element bearing

The output of this model is the accumulated percentage life. In our case, dynamic rated life of ball bearing is 3000 lbs, which is based on one million revolutions under rated load. This model presents the life already used in terms of accumulated percentage life, which gives the remaining useful life of this bearing. Suppose the life of bearing is 800 days, and at inspection point 'i', is 620 days, then the life percentage at the time of inspection would be:

$$P_i = \frac{620}{800} * 100\% = 77.5\% \quad (4.1)$$

This indicates that 77.5% life is accumulated, and the remaining useful life will be (1-77.5) %, or 180 days.

4.2.1.1 Transfer Function

Neurons in neural network convert their input to output after processing through some pre selected logical rules. These rules are often termed as transfer function or activation functions. We selected hyperbolic tangent sigmoid function for both of the hidden layers and pure linear function for output layer neuron.

The hyperbolic tangent sigmoid function from hidden layer takes the value of neuron j "N_j ", and give its output value as "Y_j".

$$Y_j = 2/(1 + e^{-2N_j}) - 1 \quad (4.2)$$

For the computation of N_j , following equation is used

$$N_j = \sum_{K=1}^{K_j} W_{kj} Y_k + \delta_j \quad (4.3)$$

where

- Y_j is the output value of neuron j "N_j ",
- K_j is the number of neurons with output connections to N_j ,

- W_{kj} is the weight value of the connection from neuron k to N_j and
- δ_j is the bias value of N_j .

Linear transfer function is used for output neuron N_j , and gives its output value as

$$Y_j = N_j \tag{4.4}$$

Where N_j is again computed by Equation (4.3)

Therefore, after determining the values of weight and bias during training, with the input of accelerated life test data of ball bearings, we can calculate life percentage of bearings from Equations (4.2), and (4.4).

4.3. Neural Network Training

In this section detailed of training neural network with actual accelerated life data of failed bearings and its validation with simulated data is discussed.

4.3.1. The Neural Network Training Algorithm

Training of neural network is done by providing input of accelerated life failure data along with corresponding output values. In this way weights and the bias values of the ANN model are adjusted to minimize the error between the model outputs and the actual outputs.

During the training it is necessary to minimize the training error which is termed as mean square error (MSE). This is also called performance function, and it is calculated by formula as given below

$$F = MSE = \frac{1}{N}\sum_{K=1}^{N}(e_k)^2 = \frac{1}{N}\sum_{K=1}^{N}(y_k - d_k)^2 \tag{4.5}$$

where

- N is then number training input and output pairs,
- d_k is the actual output,
- y_k is the model output. Calculated by using Equations. (4.2), (4.4).
- e_k is the corresponding output error.

For RUL prediction we need to use the validation mechanism, or the early stopping method, during the training process to improve the network generalization. Therefore appropriate training algorithms required that can handle the training requirements. Resilient back propagation algorithm (RPROP) is selected for this purpose due to its reported capability of better handling validation mechanism. This training algorithm is used to avoid harmful effects of the magnitude of partial derivatives, and the direction of the weights update is determined by sign of the derivatives (Mathworks).

4.3.2. The Neural Network Validation

Neural network validation is necessary to check the generalization capability of neural network. Therefore during the training process it is desired to model the mapping between the input vector and the output without modeling the noise in the data. For the application of RUL prediction, it is very important to ensure the generalization performance of neural network to avoid "over fitting", which occurs if the error on the training set is very small, but with the presentation of new data it comes out to be high.

To improve neural network generalization capability, we use network validation method. In this method we use the validation data set by dividing the available data into the training set and the validation set. Data in the training set is used to adjust the ANN weights and bias values, while the data in the validation set is not. In this work, in the training process, we need a performance measure to indicate how good the trained ANN is, given a certain set of available data. We divided available data into the training set and the validation set. In order to check the performance of neural network model, we select the MSE on the test data set, i.e., the test data MSE which gives better generalization performance of ANN among a number of networks strained using the same data sets. The test MSE is the best measure for this purpose. The lower the test MSE, better the trained network. In order to check the performance of our model, we use physics based generated data for validation of model in order to ensure that it can predict accurate RUL.

4.3.2.1. Generation of Simulated Data

We use method proposed by (Liao, & Tian) for the simulation of model degradation data. They developed a linear degradation- stress relationship model in which initial degradation measure x_0 is taken fixed at arbitrary value along with diffusion parameter sigma (σ_x), which is considered to be a mechanical property of equipment and it is considered to be identical for all products of the same type. The drift parameter is a linear function of stress 'Z'. That is the degradation is considered to be linear with stress.

In this model piece wise constant stress level is considered and it shifts during simulation after specific hours. This shifting is done by increasing stress level 'Z'. The reason behind this is the generation of simulated data under varying stress condition, which is a measure concern in this research. In this model, before simulation a threshold value is selected and equipment is considered to be failed when the degradation value reaches or crosses the threshold value. We performed two simulations for the generation of data, and use the data for the validation of our proposed neural network model. Details of the simulation and ANN model prediction is given in next section

4.3.2.2. ANN Model Prediction Results for the First Simulation Data Set

In the first simulation of the generation of accelerated life failure data under time varying condition, we set the threshold value to be 450. That is, a unit is considered failed when the measurement crosses 450 for this simulation. The diffusion parameter sigma (σ_x) is set at 0.5, considered identical across all units. As discussed in the previous section, the load is constant for a few hours of simulation and switched to the next value by increasing the stress level "Z". The drift parameter which is a linear function of stress level in this computer based simulation program, switches the stress level to next value for few hours and again shift to the third value till a unit gets failed. From the simulation, we find that unit fails at 94 hours. Figure 7 shows the first set of simulated data.

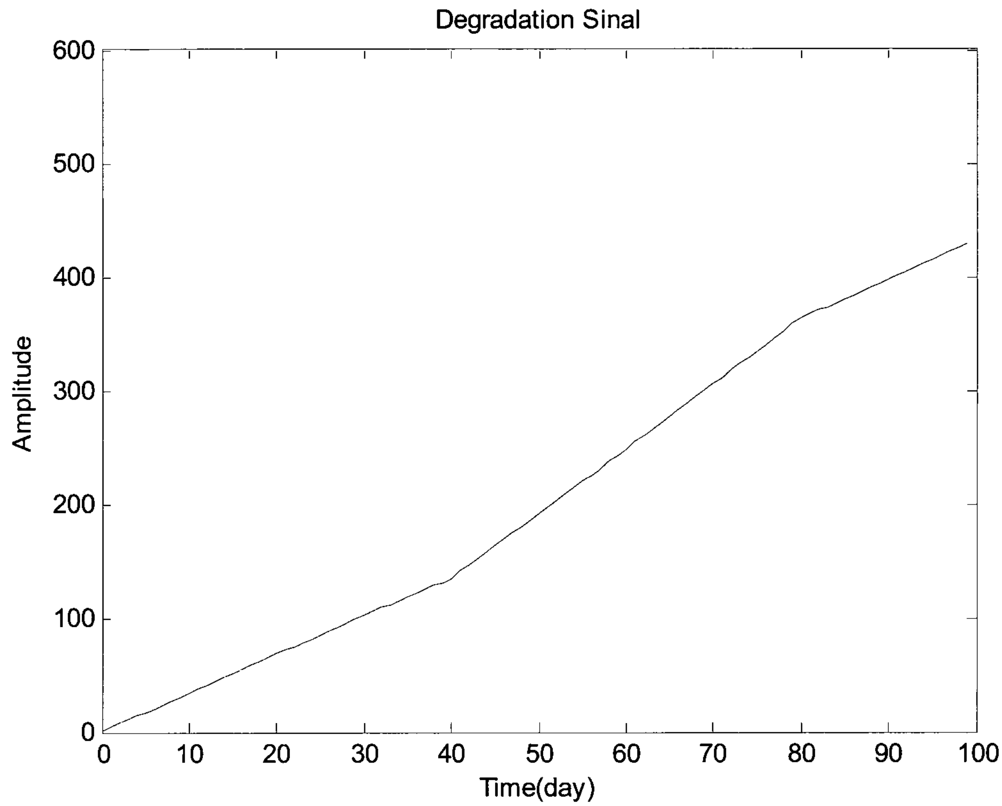

Figure 7: Failure data generated at sigma level of 0.5 at 450 threshold value

The next step is to use this data to test our proposed model's performance and its generalization capability. Due to randomness in the training algorithm, we cannot get the same trained ANN model, and the same prediction results. As previously discussed in section 4.2.1, the life percentage value at any point is equal to the age value divided by the failure time of the component. We use 25% of the available data as the validation set, 25% as the testing set, and the other 50% as the training data set. Data distribution is done in matlab code in such a way that it should be distributed in an even way throughout the whole data. In a programming loop, we divided all the data points by four, and segregate them according to the remainder. For zero remainder data is labeled as test data, and if the remainder is 1 & 2, data is labeled as training data, and the rest is the validation data. In order to get the best results of our trained model, we repeat the training for 30 times. During each run test MSE is recorded, as discussed in previous section lower the test on MSE, and it improves the generalization performance of trained neural network. Figure 8 shows the result of ANN model for first simulation

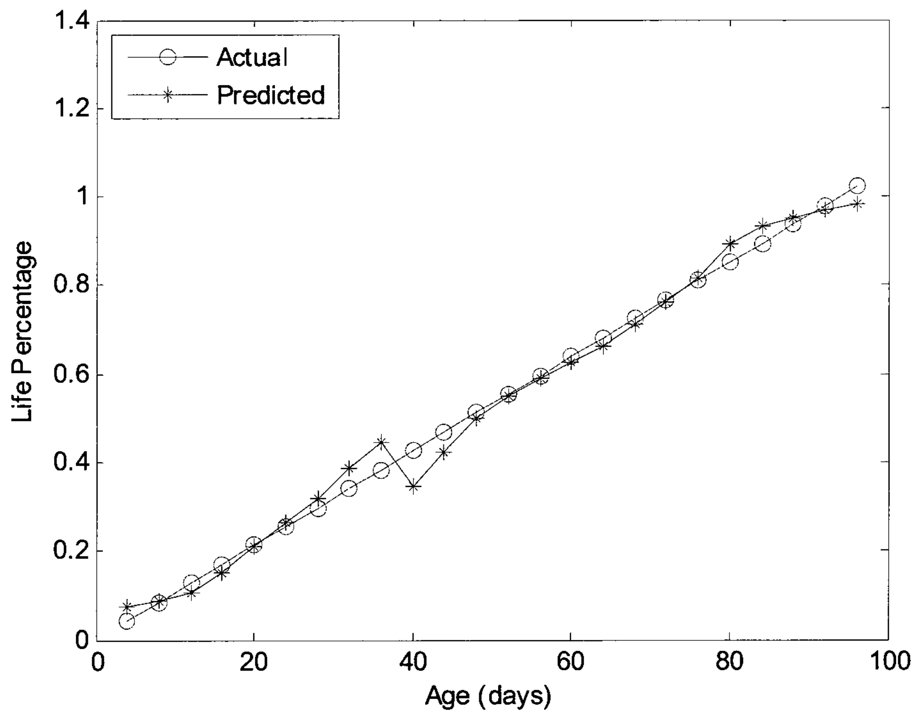

Figure 8: Predicted life of first simulation

We found good results after first simulation data, as the actual and predicted life of our model is very close with test MSE of 0.0267 that is the best point our neural network trained has only 2.67% error from actual failure life of this unit. From figure it can be seen that ANN prediction is not accurate at few points. The reason is the abrupt increase and decrease of the stress level the age point 40 and 80 till it fails. This there is a sudden shift at point 40, where stress level during simulation is increased, and ANN during generalization process consider this shift as a sudden change in input parameters and give short time errors, but soon after it takes successive normalized values it reduces the error, again on age point 80, where there is decreased in stress level ANN has shown error, because of same problem.

4.3.2.3. ANN Model Prediction Results for the Second Simulation Data

In the second simulation of the generation of accelerated life failure data under time varying condition, we set the threshold value at 700. That is a unit is considered failed when stress level crosses 700 for this simulation. The diffusion parameter sigma (σ_x) is set at 0.9. Again the stress level is increasing in this simulation the same way as we did in the first simulation and the unit fails at 99 days. Figure 9 shows the second set of simulated data. As can be seen, with larger sigma value, the fluctuation of the sigma becomes larger, and more noise is introduced in the signal.

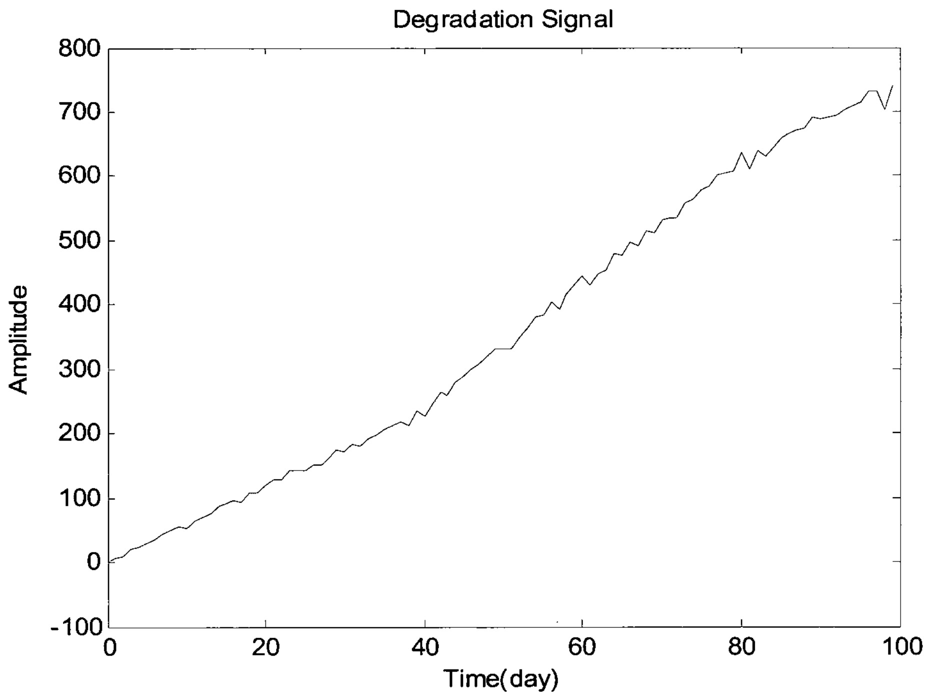

Figure 9: Failure data generated at sigma level of 0.9 at 700 threshold value

The training procedure is same as the previous one. Figure 10 shows the result of ANN model after training. Again we obtain good prediction results, and the actual and predicted life of our model is very close with test MSE of 0.0331. That is the best neural network model trained has only 3.31% error from actual failure life. From figure it can be seen that there is some prediction errors at few points during the entire history. The reason is same as discussed in previous section.

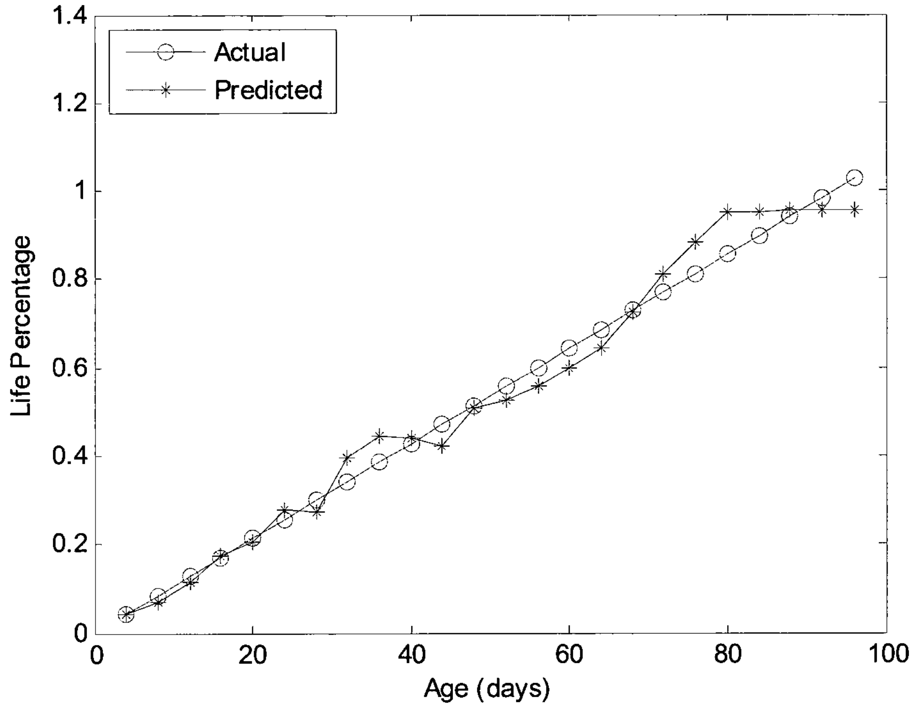

Figure 10: Predicted life of Second simulation

4.4. Summary

In this chapter, we discussed our RUL prediction scheme, and the proposed feedforward neural network model. We proposed a model with two versions. The first version with five inputs can handle the discrete data points, where the interval of inspection is not constant. In the second version, we modify the model. For this research purpose as the interval of sampling is constant, we do not need to feed previous data time as an input. Therefore instead of five we feed only four inputs in this model. We discuss the training of neural network model and its validation with simulated data. This proposed model is not only applicable to bearings but also it can be applied to other rotary components, like gears. The only thing need to be done is the selection of condition health monitoring parameters, also input of health condition monitoring parameters can also be increased with less modification and the same model can be used for RUL prediction.

Chapter 5

Experiments Setup and Validation of ANN Model

This chapter contains detailed information of our experiment setup for bearing prognostics, and validation of our neural network model with the data generated through run to failure tests. We used bearing prognostic simulator for failure tests. Some detailed are provided for this equipment along with data acquisition system of our research work, and results of accelerated life failure tests. In the last section we have demonstrate the results, we validate the proposed ANN prediction approach using the real signals collects from the experiments.

5.1. Bearing Prognostics Simulator

Bearing prognosis requires bearing failure data at certain interval for the calculation of remaining useful life. In practices if we take data from industry, it will be a time consuming process. We decided to conduct our research using Bearing Prognostics Simulator of Spectra Quest Company, so that we can perform accelerated life testing of bearings for our research purposes. Figure 11 gives the basic picture of our simulator

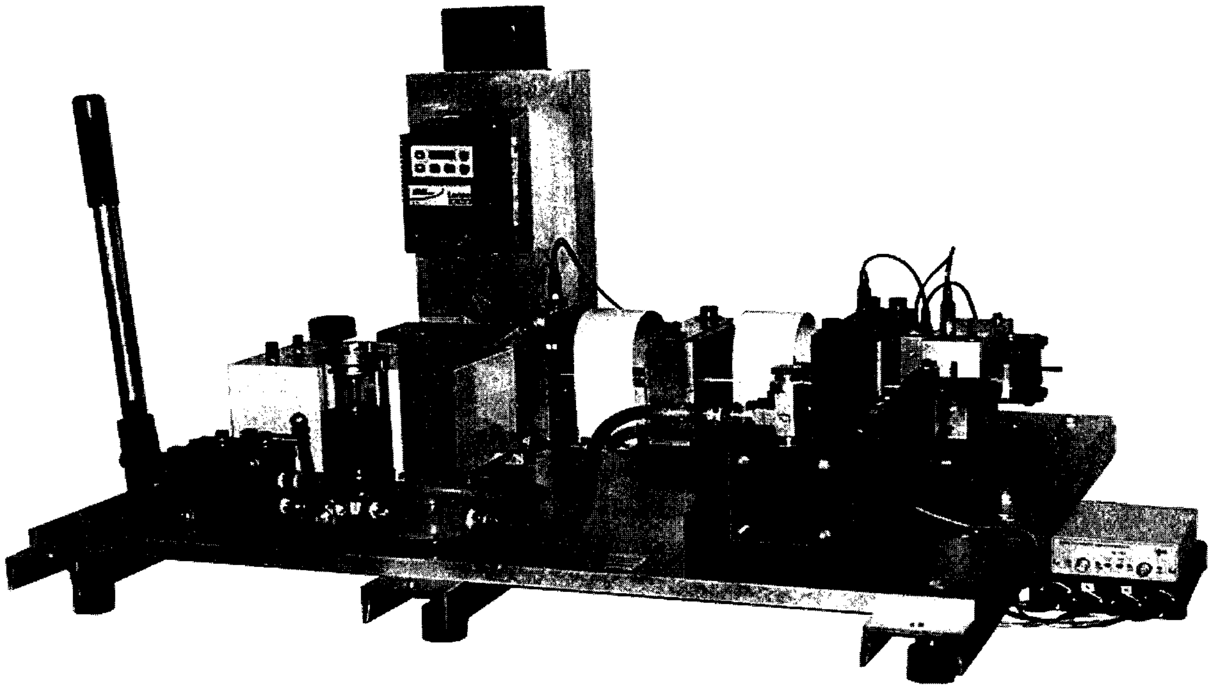

Figure 11: Bearing Prognostics simulator

Spectra Quest's Bearing Prognostics simulator (BPS) is specially designed to conduct fundamental research in bearing wear, and modeling bearing damages and failures evolution process. It provides an opportunity to develop a predictive model of bearing remaining life based condition monitoring measurement. Working phenomena of this equipment is application of load in radial direction, and this load can be measured by frictional torque measuring system. This equipment can be driven in either a constant speed, or purely oscillatory motion and oscillatory excitation superimposed on rotation through stepper motor.

We conduct our research on constant speed mode. Our BPS equipment is comprised of three main subsystems:

- Motor and its controlling system
- Hydraulic loading system
- Bearing shaft rotating system.

This simulator testing system can incorporate one test bearing at a time. Our bearing installation is shown in Figure 12 and 13. The bearings can run at speeds up to 5000 rev/min. In this study, we conduct all of our experiment at fixed 2000 revolution per minute (rpm).

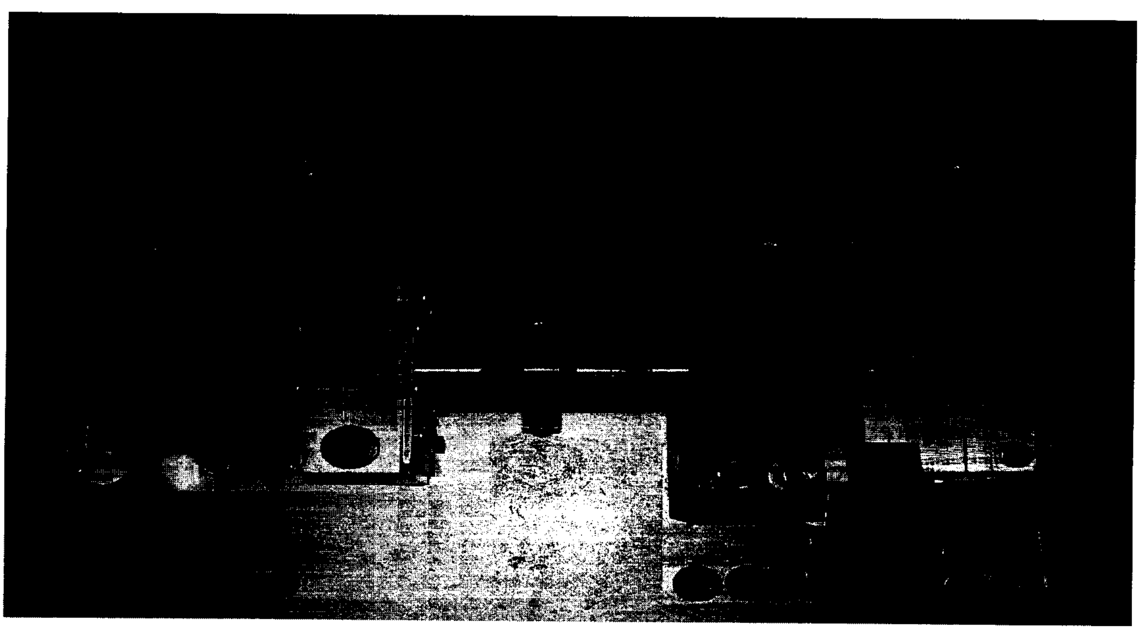

Figure 12: Ball Bearing accelerated life failure test

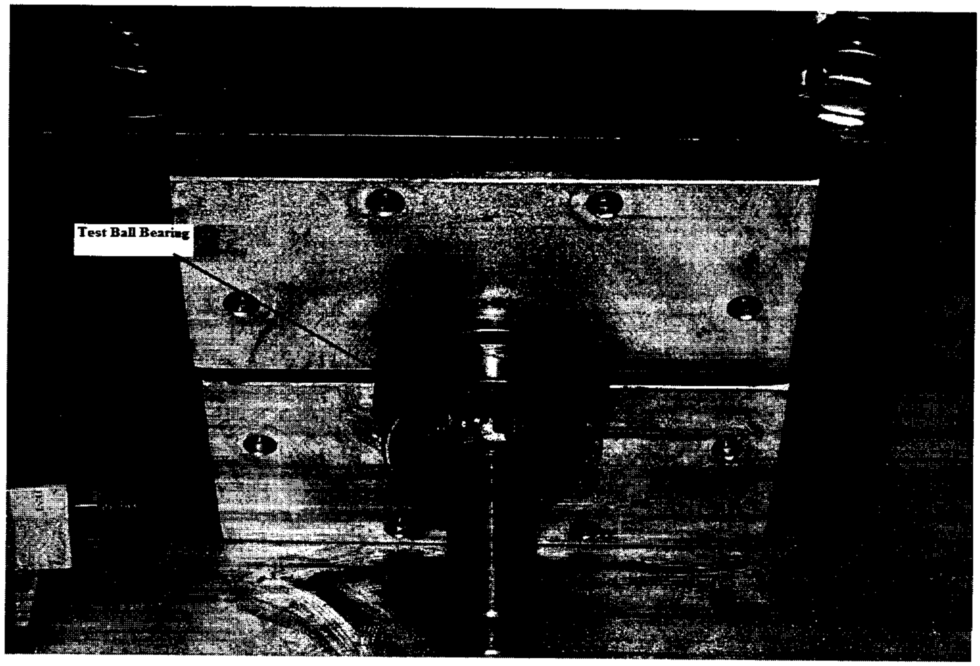

Figure 13: Failed ball bearing after test

5.1.1. Load

We conduct two test at 2500 and 3000 lbs at fixed rpm to investigate the bearing failure time under varying load conditions. In these tests both load and rpm were fixed from start to end of the test till bearing get failed. Data is collected for estimation of bearing RUL under time variant conditions.

5.1.2. Test Bearings

The test bearings used in our experiments are single groove SKF ball bearings, 62052 RSC3, as shown in Figure 14

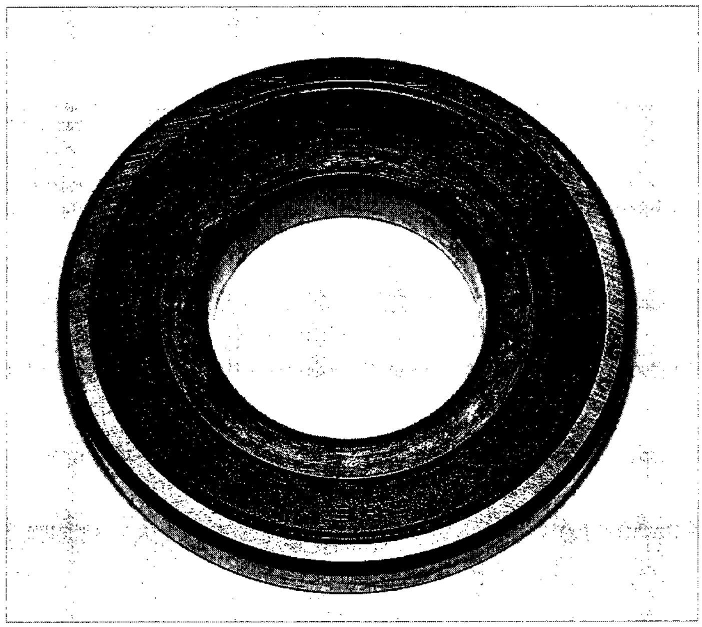

Figure 14: KOYO 62052 Ball Bearing used in the research

With the application of load, which is beyond the normal operating condition of bearings, after only few hours of operation, damage starts with small cracks. These cracks are located between the surface of the flat track and the rolling elements, usually referred to as spall propagation, as previously discussed in literature review. The spalls gradually propagate till the failure of bearing signed is observed and experiment is finished.

5.2. Data Acquisition and Signal Processing

Data acquisition is the process of acquiring information of equipment existing health condition, through method of continuous sampling at selected intervals. Normally data is collected in an analog form through sensors. Then with the help of special software, it is converted into digital format for further processing and feature extraction. Signal detection algorithm for bearing condition monitoring is important part for predictive maintenance of equipments. Selection of desired features and their relevant features plays a vital role for both diagnostic and prognostics purposes. Accurate prediction of bearing impended faults can lead to proper time of adjustment and replacement in order to avoid catastrophic failures of the whole equipment.

The basic purpose of data acquisition of vibration or any other signals is to measure the changes in equipments conditions. Whenever structural distress occurs, it appears in form of relative motion of entire components in the form of vibration. Thus with the help of sensors, this variation is measured and processed in order to build either the fault diagnosis models or prognosis models. This research work is dedicated to prognosis of rolling element bearing under time variant conditions. Figure 15 shows the basic layout of the work followed in this research. Normally bearings are selected, based on life calculation as per their industrial application and operating factors, and their actual life is affected by operation and environmental effects.

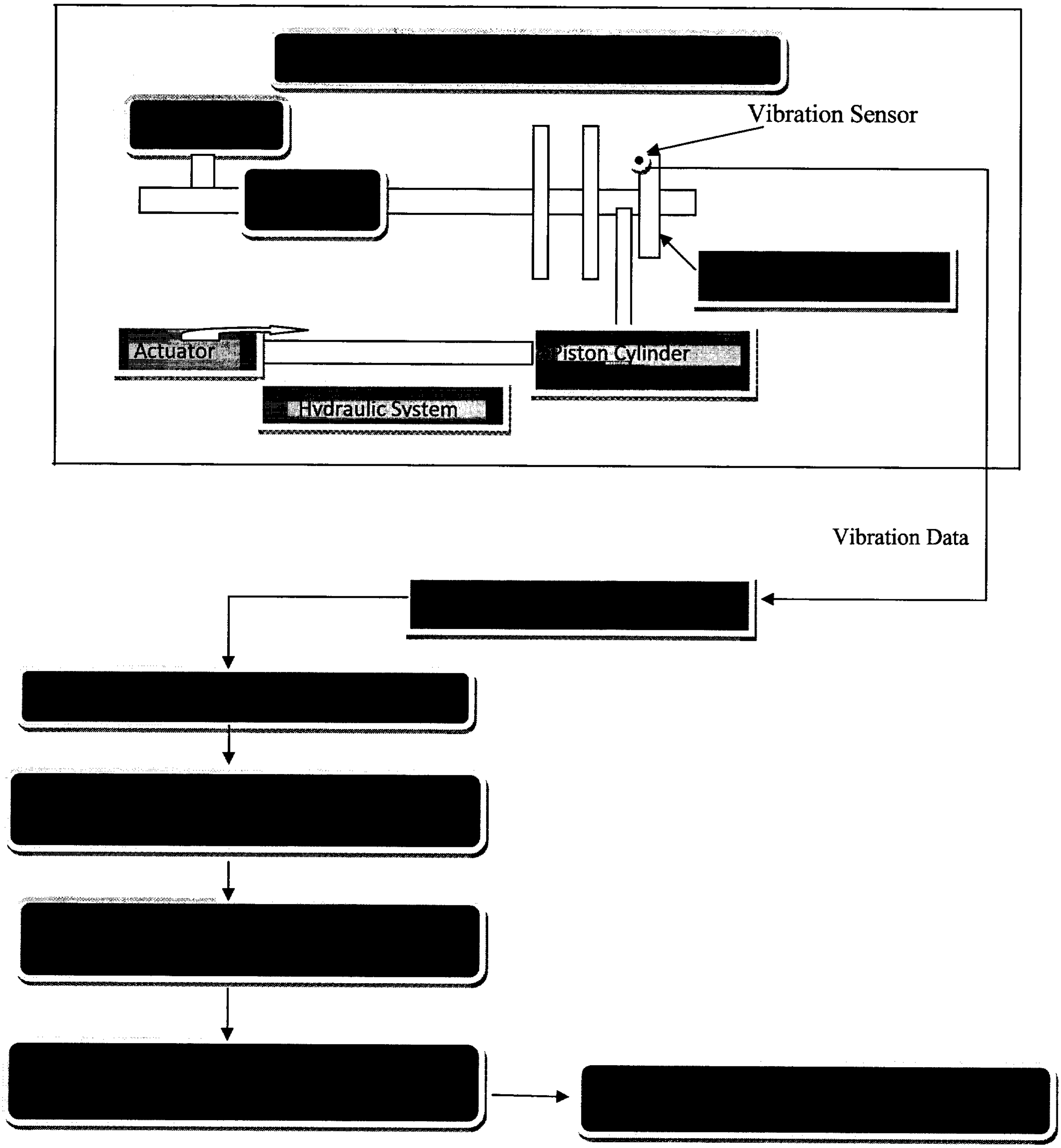

Figure 15: Proposed approach for bearing prognostics

5.2.1. Vibration measuring Sensor

We use piezoelectric sensor, which is case mounted to our test bearing support housing. It was an IMI 608 A11 model sensor as shown in Figure 11.

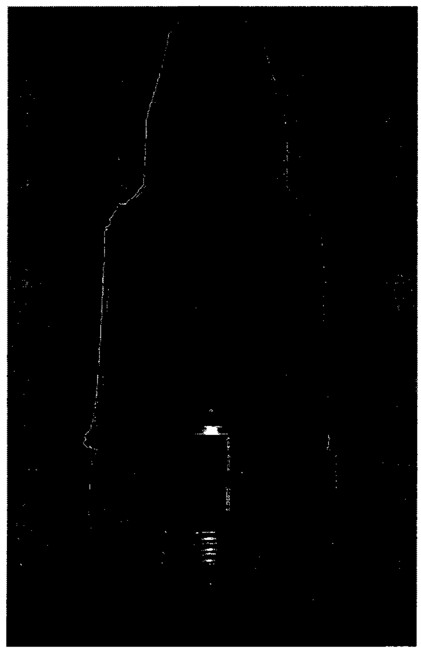

Figure 16: Vibration Sensor

5.2.2. Data Acquisition unit

We used National Instrument "High speed USB carrier NSI USB-9162" unit for collection of data through vibration sensor. The sampling frequency of this unit 25 KHz, therefore it can sample 25000 data points of vibration amplitude for one second, shown in Figure 17.

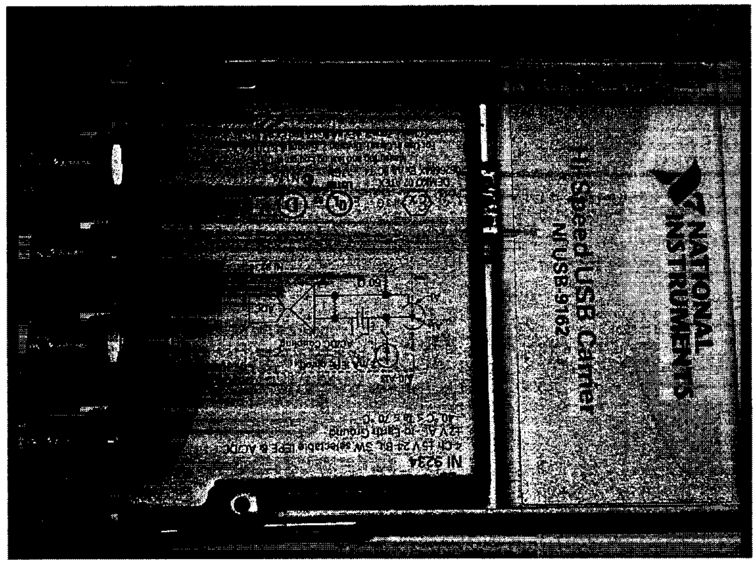

Figure 17: Data Acquisition unit

5.2.3. Signal Processing Software

We use National Instruments Lab View Signal Express 2009, software for the collection of vibration data. We utilize its function for capturing time domain data and pre selected sampling time and interval. The rest of the processing and analysis are performed through Matlab programs for signal processing and neural network training.

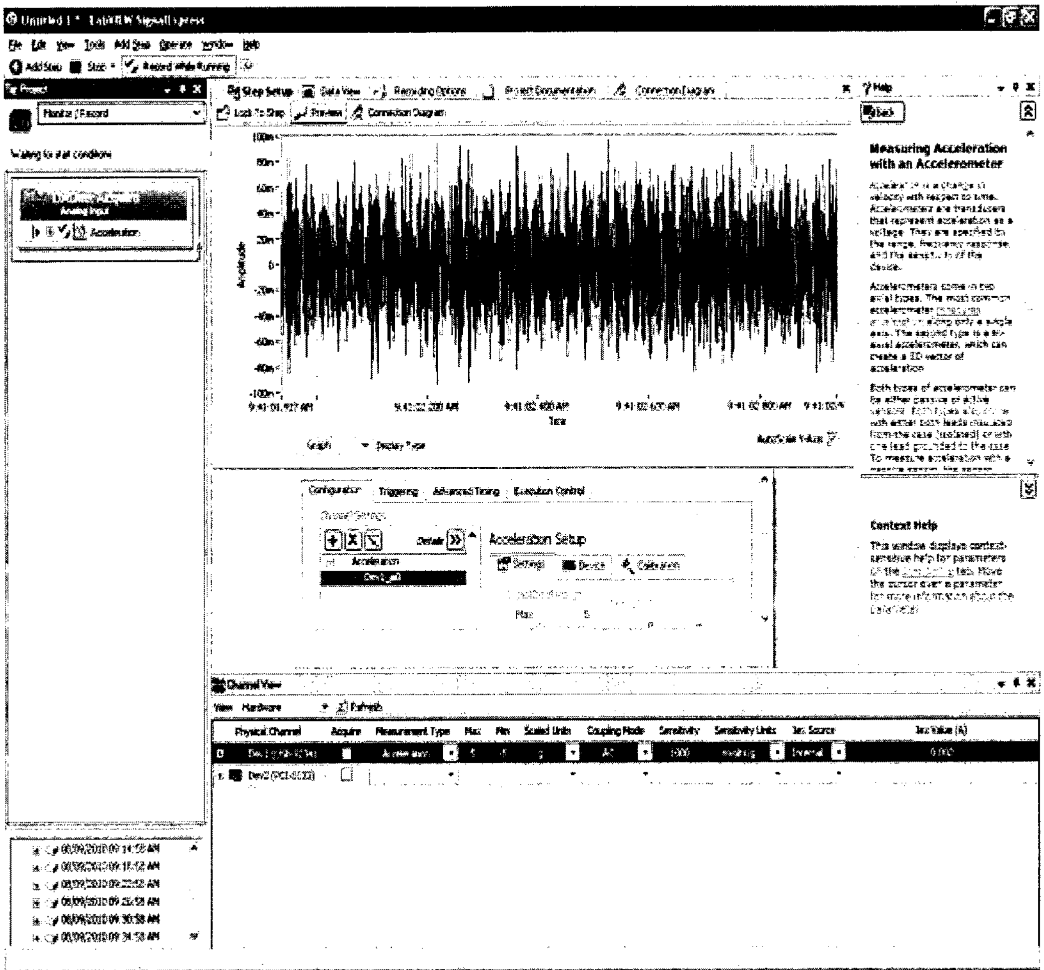

Figure 18: Vibration amplitude data collection for Prognostics test

5.2.4. Sampling

During accelerated life tests of bearings we collected samples after every four minutes for the duration of two seconds, in order to get overall amplitude of bearing vibration signatures at inspection points.

5.3. Validation of the Proposed ANN Prediction Approach Using the Experiment Data

In our proposed algorithms for prediction of remaining useful life of the bearing, we monitored the overall vibration level in time domain, specially root mean square values (RMS) of collected samples, and used these RMS to train the neural network for RUL prediction under time varying conditions.

RMS value is calculated using the definition outlined in the chapter 3, in MATLAB environment. Let's consider the following bearing vibration data taken during the experiments:

Table 1: Data Points

#	**Data points**
1	0.03108
2	0.041739
3	0.047671
4	-0.0052
5	0.01846
6	0.030373
7	0.007574
8	-0.00302

Using the definition:

$$\text{Signal (RMS)} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(S_i)^2}$$

Table 2: RMS Calculation

S_i	0.03108	0.03108	0.03108	0.03108	0.03108	0.03108	0.03108	0.03108
$(S_i)^2$	0.000966	0.000966	0.000966	0.000966	0.000966	0.000966	0.000966	0.000966
	$\sum_{i=1}^{N}(S_i)^2 = 0.006578$ N=8							
	Signal (RMS) = $\sqrt{\frac{1}{8} * 0.006578}$ =0.02867							

5.3.1. The First Experiment

First experiment is conducted at the load of 2500 lbs, at 2000 rpm. Data is collected through vibration sensor and processed in lab view. Theoretically RMS value of bearing is generally constant when it has no defect and it starts increasing gradually when fault occurs. We practically observed these phenomena during the test. When it is close to fail, there is sharp increase in overall amplitude of bearing vibration causing RMS value to increase, till a point where weird noises start and severe vibration show in the equipment. We set a threshold value of 0.12 RMS for bearing to be considered failed during the training of our neural network. The total duration of bearing failure under this condition is 952 minutes. Figure 19 shows the overall RMS value of entire test.

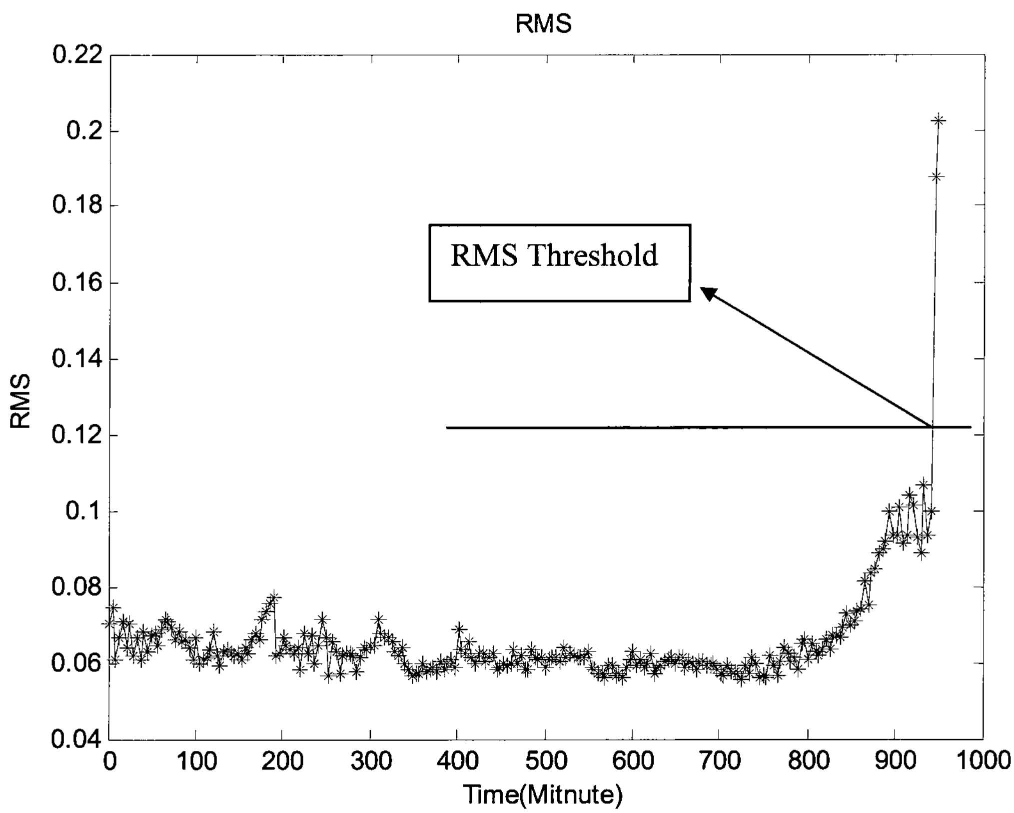

Figure 19: RMS values of first experiment at 2500 lbs of load

5.3.2. Second Experiment

During second load is increased to 3000 lbs, but rpm remains fixed at 2000. Again we set a threshold value of 0.12 for bearing to be considered failed. It took 616 minutes for bearing to fail under this condition. Figure 20 shows the overall RMS value of second test.

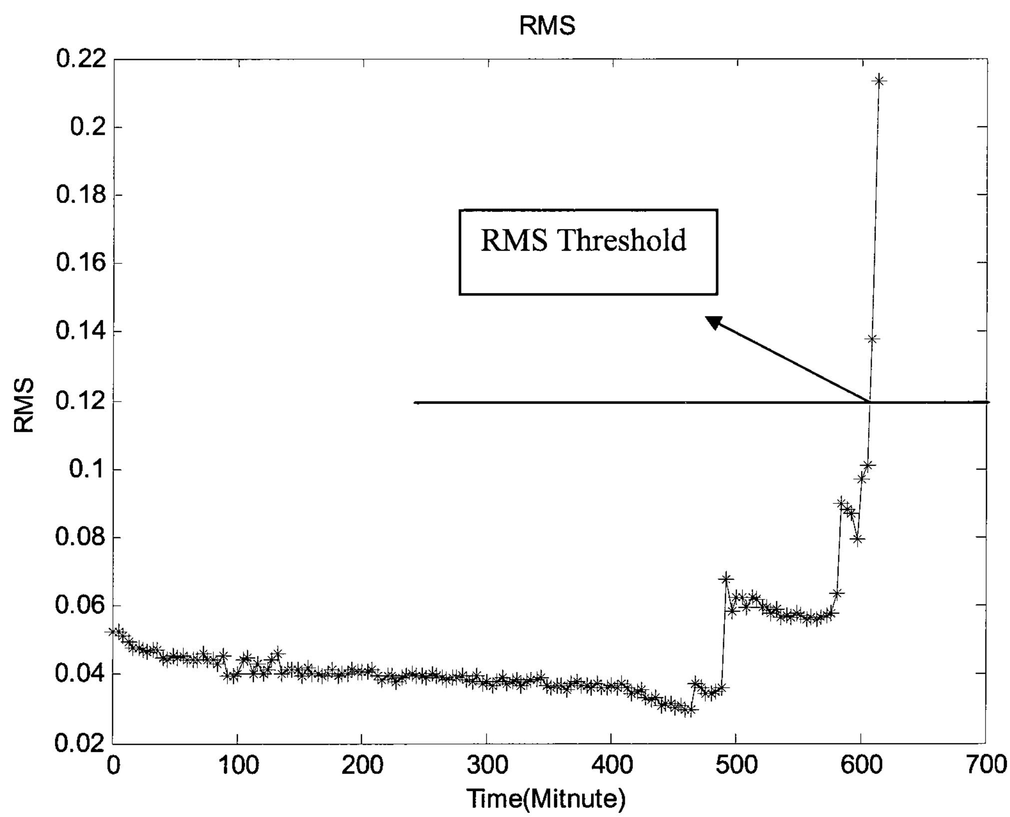

Figure 20: RMS values of second experiment at 3000 lbs of load

5.4. Prediction results with Proposed Neural Network Model

The training method use for experiment data is same as we did with simulation data. That is to improve neural network generalization capability, we use network validation method by dividing the available data into the training set and the validation set. Data in the training set is used to adjust the ANN weights and bias values, while the data in the validation set is not. For training purpose, we combine the two failure histories of accelerated life test, and set a threshold RMS value of 0.12. This means in both of the failure histories under varying time condition, bearing are considered failed if their RMS values reached 0.12. Therefore in the histories RMS values of the vibration signature are determined and fed to our neural network model in Matlab. We input 238 inspection points in the first failure history at 2500 lbs, and 154 inspection points in the second history at 3000 lbs of load to our neural network model. Failure time for the first history was 952 minutes and for the second history it was 616 minutes. We check their age values at the corresponding RMS value of 0.12, and fed these values in our training model to set a threshold for individual histories with respect to RMS value of 0.12. Again we divide the available data into the training set, the validation set, and the test set. We use 25% of the available data as the validation set, 25% as the test set, and the other 50% as the training data set. In order to check the performance of neural network model, we select the MSE on the test data set. During training for better generalization performance, we ran it for 30 times in order to get the best ANN model corresponding to the lower validation. Result of our model with the time varying data of actual bearing accelerated life failure is shown in figure 21.

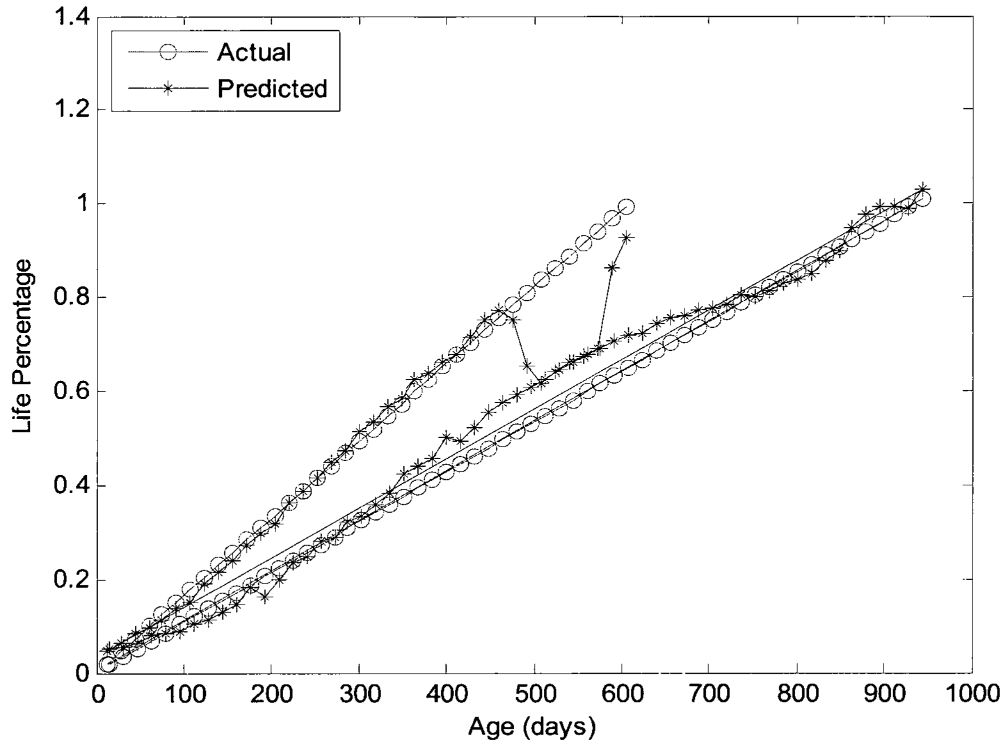

Figure 21: Predicted life of time varying data with neural network model

The result shows a significant progress towards the goal of creating a model of a prognostic system for bearings. Two sets of failure histories were feed to train the ANN. Both the failure histories are under different loading conditions, the result demonstrates, that proposed ANN model, with the input of RMS as a condition monitoring data, time and load factor has the capability to forecast bearing remaining useful life under time varying condition. As the training criteria were set at lowest test MSE, our proposed model has predicted the RUL with test MSE of 0.04. This shows the error of only 4% from actual versus predicted life from our model. Two time points input for training purpose of ANN has give better generalization performance. Another aspect of this model is its training algorithm, we use resilient back propagation algorithm for RUL prediction, and it has shown good results. Our result reflects that this model has good capability to handle the data for this specific research for RUL prediction under time varying conditions. Our proposed methodology can handle both linear and non linear degradation data, to determine the current state bearings in terms of accumulated life, and a future state of forecasting technique, to predict the time to failure when components are subjected to different loading conditions during their operation. The results also demonstrate the effectiveness of the proposed method in dealing with real-world condition monitoring data for health condition prediction. The application of this model is not limited to bearings, but it can be applied to any other rotary equipment, once the health condition indicators are selected.

Chapter 6

Conclusions and Future Work

6.1. Conclusions

This research work is done on prognostics of bearings under time varying condition. Bearings are key mechanical components of rotary machines. Failure of these components can stop the operation and result in financial losses, which are much higher than the cost of bearing. Remaining useful life prediction of bearings under time varying condition is a challenging task as a research work. The existing RUL prediction work available is limited to fixed operating conditions (e.g., pressure, temperature, humidity, rotating speed, and load). However, in many applications, such as some wind turbine, transmission and engine applications, the load that the equipment is subject to changes over time. It is critical to incorporate the changing load in order to produce more accurate prognostics methods.

A data-driven life prediction model for rolling element bearings failure under time varying condition has been developed using neural network. The proposed method can be applied to bearing as well as other components under condition monitoring. In the proposed ANN model, in addition to using the age and condition monitoring measurement values as inputs, a new input neuron is introduced to incorporate the varying loading condition. The output of the ANN model is life percentage, based on which the remaining useful life can be calculated once the ANN is trained. Two sets of simulated degradation data under time varying load are used to demonstrate the effectiveness of the proposed ANN method, and the results show that fairly accurate prediction can be achieved using the proposed method.

The other key contribution of this thesis is the experiment validation of the proposed ANN prediction method. The Bearing Prognostics Simulator, after extensive adjustment and tuning, is used to perform bearing run-to-failure test under different loading conditions. Vibration signals are collected using the data acquisition system and the Labview software. The root mean square (RMS) measurement of the vibration signals is used as the condition monitoring input for the validation of the proposed ANN prediction method. Two bearing failure histories are used to train the ANN model and test its prediction performance. The results demonstrate the effectiveness of the proposed method in dealing with real-world condition monitoring data for health condition prediction. The proposed model can greatly benefit industry as well as academia in condition based maintenance of rotary machines.

6.2. Future Work

Based on the research work in this thesis, we can further explore the following research topics:

- Conduct more experiments on different types of bearings for RUL prediction.
- Study remaining useful life prediction of bearings under other time varying operating condition like speed and temperature.

- Investigate the acoustic emission technology for RUL prediction of rolling element bearings and other equipments.
- Develop other data driven and physic based models for prognostics of rolling element bearings.

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