Failure Diagnosis and Prognosis of Rolling – Element Bearings using Artificial Neural Networks: A Critical Overview

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Abstract: Rolling – Element Bearings are extensively used in almost all global industries. Any critical failures in these vitally important components would not only affect the overall systems performance but also its reliability, safety, availability and cost-effectiveness. Proactive strategies do exist to minimise impending failures in real time and at a minimum cost. Continuous innovative developments are taking place in the field of Artificial Neural Networks (ANNs) technology. Significant research and development are taking place in many universities, private and public organizations and a wealth of published literature is available highlighting the potential benefits of employing ANNs in intelligently monitoring, diagnosing, prognosing and managing rolling-element bearing failures. This paper attempts to critically review the recent trends in this topical area of interest.

Keywords: Rolling element bearings, failure diagnosis; prognosis; Artificial Neural Networks, critical review

1. Introduction

The primary function of a bearing is to constrain relative motion between two or more moving parts. Bearings are classified according to the type of motion, operation and directions of applied loads they handle. There are many types of bearings such as: Rotary bearings, Plain bearings, Jewel bearings, Fluid bearings, Magnetic bearings, Flexure bearings, and others.

A ball bearing is a type of rolling-element bearing that uses balls to maintain the separation between the moving parts of the bearing. The purpose of a ball bearing is to reduce rotational friction and support radial and axial loads. It achieves this by using at least two races to contain the balls and transmit the loads through the balls. Usually one of the races is held fixed. As one of the bearing races rotates it causes the balls to rotate as well. Because the balls are rolling they have a much lower coefficient of friction than if two flat surfaces were rotating on each other. There are several common designs of ball bearing, each offering various trade-offs. They can be made from many different materials, including: stainless steel, chrome steel, and ceramic (silicon nitride (Si₃N₄)). A hybrid ball bearing is a bearing with ceramic balls and races of metal. Ball bearings are found in almost every engineering application. These bearings are capable of taking both radial and thrust loads, and are usually found in applications where the load is light to medium and is constant in nature (i.e. not shock loading).
Roller bearings are normally used in heavy duty applications such as conveyor belt rollers, where they must hold heavy radial loads. In these bearings the roller is a cylinder, so the contact between the inner and outer race is not a point (like the ball bearing above) but a line. This spreads the load out over a larger area, allowing the roller bearing to handle much greater loads than a ball bearing. However, this type of bearing cannot handle thrust loads to any significant degree. A variation of this bearing design is called the needle bearing. The needle roller bearing uses cylindrical rollers like those above but with a very small diameter. This allows the bearing to fit into tight places such as gear boxes that rotate at higher speeds.

Thrust ball bearings are mostly used for low-speed non precision applications. They cannot take much radial load. Roller thrust bearing support very large thrust loads. The helical gears used in most transmissions have angled teeth. This can cause a high thrust load that must be supported by this type of bearing. Taper roller bearing designed to support large radial and large thrust loads. These loads can take the form of constant loads or shock loads.

The object of this paper is to highlight some new contribution to the knowledge of applying the Artificial Neural Networks in diagnosing and prognosing roller element bearings failures to achieve world class performance and the associated global competitive advantage. Judicious implementation of the artificial intelligence technology should be considered as an “investment” that yields an added value generating a real profit to the companies. Some new contribution to the knowledge is highlighted.

The paper is structured under the following headings: (a) Basic Terminology and Engineering Physics of Rolling – Element Bearing, (b) Characteristic of rolling-element bearing frequencies, (c) Factors affecting the performance of rolling-element bearings, (d) Faults/Defects in rolling-element bearings, (e) Causes of rolling-element bearing failures, (f) Cost-effective and other benefits of employing rolling-element bearings, (g) A note on feature detection, selection, extraction and classification process, (h) A brief background to ANNs, (i) Application of ANNs in failure diagnosis and prognosis of rolling-element bearings, (j) Some challenges and innovative issues, (k) Conclusion and (l) References and Bibliography
1. Basic Terminology and Engineering Physics of Rolling – Element Bearing

ASTM's rolling element bearing standards provide the specifications and test methods pertinent to the design, property, and performance requirements of the mechanical component known as the rolling element bearing. These rolling element bearing standards allow product manufacturers, industrial plants, and other producers and end-users of such mechanical parts to test ball bearings to ensure acceptability towards safe installation and use. List of rolling element bearing standards developed by ASTM is available at: (http://www.astm.org/Standards/rolling-element-bearing-standards.html). The terminology of rolling element bearing is shown in Figure 1.

![Ball bearing diagram](image)

Figure 1: Basic Terminology.

A brief history of rolling element bearing is published by Hamrack and Anderson (1983). They have described geometry and kinematics, as well as the materials they are made from and the manufacturing processes they involve. Unloaded and unlubricated rolling element bearings, loaded but unlubricated rolling element bearings and loaded and lubricated rolling element bearings are considered. Also see references Eschmann P, Hasbargen L, Weigand K. (1958), Gohar R and Akı̈r N. (1998), Harris, T.A. (1991), Kiral, Zeki (2002), Raymond, J. and A. Guyer. (1996).

2. Characteristics of Rolling – Element Bearing Frequencies

Fundamental train frequency, \( f_{FTF} \)

\[
\frac{f_s}{2} \left[ 1 - \frac{D_{ball}}{D_{pitch}} \cos \phi \right]
\]

Ball spin frequency, \( f_{BS} \)

\[
\frac{f_s}{2} \left[ 1 - \left( \frac{D_{ball}}{D_{pitch}} \right)^2 \cos \phi \right]
\]

Outer race frequency, \( f_{OR} \)

\[
f_{OR} = N f_{FTF}
\]

Inner race frequency, \( f_{IR} \)

\[
f_{IR} = N (f_s - f_{FTF})
\]

Where, \( f_s \) is the rotational frequency of the shaft in revolutions per second, and \( N \) is the number of rollers or balls. (http://zone.ni.com/reference/en-XX/help/372416A-01/svtconcepts/cal_frqs_ords/)
3. Factors affecting the Performance of Rolling – Element Bearings

Cyclical external forces can be applied to the bearing in a number of ways, such as due to:

- Misalignment
- Improper bearing installation
- Rotor imbalance
- Pump cavitations
- Flow induced vibration

Factors affecting bearing fatigue life are: material properties, lubricant properties, speed, load, size, number of rolling elements, etc.

The effects and importance of frequency resolution during the diagnosis of inner and outer race bearing faults are equally important. The bearing faults create impulses and results in strong harmonics of the fault frequencies in the spectrum of vibration signals. These fault frequencies can sometimes be smeared by the adjacent frequencies in the spectra due to their little energy.

4. Faults/Defects in Rolling – Element Bearings

Bearing faults can be categorized into distributed and localized defects. Distributed defects affect a whole region and are difficult to characterize by distinct frequencies. In contrast, single-point defects are localized and can be classified according to the following affected element (Vas (1993), Tandon and Choudhury (1997), Nandi and Tolitat (1999), Stack, Habetler and Harley (2004)).

- Outer raceway defect
- Inner raceway defect
- Ball defect and Cage fault
- Surface irregularities, misaligned races, cracks, pits and spalls on rolling surfaces

5. Causes of Rolling – Elements Bearing Failure:

Some of the major causes for the failure of REBs are attributed to 1) Spalling-subsurface fatigue, Excessive load Peeling surface fatigue, 2) Wear, 3) Fretting/Surface Corrosion, 4) Improper mounting, 5) Entry of foreign particles/Contamination, 6) Inadequate or improper lubrication, 7) Blockage, passage of electrical current/electrical discharge, 8) Excessive speed, vibration and shock, ineffective seals, overloading, 9) Abrasion/scoring/smearing/pitting/fluting/brinnelling, 10) Seals Brinneling/Localized Fretting, 11) Excessive load Denting/Excessive Point load. It is well known that the single-point defect can produce four predictable characteristic fault frequencies based on the knowledge of the bearing’s geometry and motor shaft speed (Benbouzid [2000], Li et al. [2000]). It should be noticed that this prediction is based on the assumption of pure rolling races, however, in reality, some sliding motion may occur which causes deviations of characteristic frequencies (Tse et al. (2001) and Rao (1996)).

Even when operating correctly, rolling element bearings will eventually fail as a result of a surface fatigue phenomenon. Rolling element bearing surface fatigue is characterized by spalling. It starts after some variable time of service as embryonic particles that are liberated from the surface of a race or rolling element in the load zone. Surface fatigue leaves craters that act as stress concentration sites. Subsequent contacts at those sites cause progression of the spalling process. The duration of satisfactory performance depends largely on the durability of bearing surfaces. Generally, there are three types of surface contact damage that can occur under proper operational conditions: surface distress, fatigue pitting, and fatigue spalling.

Other surface damage can occur due to improper mounting or improper operating conditions. Surface distress appears as a smooth surface resulting from plastic deformation in the asperity dimension. This plastic deformation causes a thin work-hardened surface layer (typically less than 10 µm). Pitting
appears as shallow craters at contact surfaces with a depth of, at most, the thickness of the work-hardened layer (approximately 10 µm). Spalling leaves deeper cavities at contact surfaces with a depth of 20 µm to 100 µm. It must be noted here that no common definitions have been established to distinguish spalling from pitting in the literature. In most of the literature, spalling and pitting have been used indiscriminately, and in some other literature, spalling and pitting were used to designate different severities of surface contact fatigue. For instance, Tallian (1992) defined “spalling” as macroscale contact fatigue caused by fatigue crack propagation and reserved “pitting” as surface damage caused by sources other than crack propagation. One of the reasons for the confusing definitions is probably due to the fact that the physical causes of pitting and spalling have not yet been established. To discuss spalling and pitting on a common ground, the following discussion rests on the definitions according to the phenomena as described in the foregoing: that is, pitting is the formation of shallow craters by surface-defect fatigue, and spalling is the formation of deeper cavities by subsurface-defect fatigue.

The normally expected mode of failure of rolling element bearings is by flaking. The bearing surface becomes scaly and literally peels off due to contact loading as pothole-like flaws develop.

Seizing is one of the most common failure modes when bearings are first put into service. The lack of rolling element rotation results in a rapid and excessive rise in temperature. The surface hardness of the bearing races and rollers or balls is reduced, and the bearing is quickly rendered unsuitable for use.

Improper mounting, insufficient internal clearance among bearing parts, or shock loads can result in fracture of bearing races. Retainers are spacing bands or cages that enclose and separate the rolling elements of a bearing. These assemblies may be damaged by foreign matter such as dirt that has entered the bearing. There is one predominant cause of bearing rusting: improper care during storage, maintenance, or when the associated machine is not operating.

All bearings normally go through a wear period of several hours after initial operation, after which the rolling elements and raceways are “broken in,” and perceptible wear ceases. Electrical Erosion - Electrical currents can damage and eventually destroy bearings.

Foreign material intrusion into a bearing lubricant leads to roughening of the load carrying surfaces. Dropping a bearing, or subjecting it to some other form of excessive impact, will drive the rolling elements against the raceways hard enough to create indentations at the points of contact. The term for this condition is brinelling. False brinelling is one of a variety of terms associated with the condition. The other names are fretting, friction oxidation, and slipping damage. Smearing is a condition which occurs after balls or rollers have begun to slip instead of roll. Slippage of a bearing race on its mounting surface is termed creeping.

Approximately two thirds of the bearings that failed early in life had installation defects. Among the defects found most frequently were increased radial tension and misalignment of the fixed bearing race. Many of the failed bearings (about half) had been operating outside specified operating conditions for some period of time. There were also cases where the machine was overloaded, operated at excessive temperatures, with water or other contaminants in the lubrication system and other similar conditions (Barkov and Barkova, http://www.vibrotek.com/articles/sv95/part2/index.htm).

Lai and Reif (1989) have predicted ball bearing failures. Hoeprich (1992) has investigated rolling element bearing fatigue damage propagation.

In 2002, Har Prashad conducted an investigation into the diagnosis of rolling-element bearings failure by localized electrical current between track surfaces of races and rolling-Elements. The diagnosis and cause analysis of rolling-element bearing failure have been well studied and established in literature.
Failure of bearings due to unforeseen causes were reported as: puncturing of bearings insulation; grease deterioration; grease pipe contacting the motor base frame; unshielded instrumentation cable; the bearing operating under the influence of magnetic flux, etc. These causes lead to the passage of electric current through the bearings of motors and alternators and deteriorate them in due course. But, bearing failure due to localized electrical current between track surfaces of races and rolling-elements has not been hitherto diagnosed and analyzed. The author reports the cause of generation of localized current in presence of shaft voltage. Also, he brings out the developed theoretical model to determine the value of localized current density depending on dimensional parameters, shaft voltage, contact resistance, frequency of rotation of shaft and rolling-elements of a bearing. Furthermore, failure caused by flow of localized current has been experimentally investigated.

6. Cost – Effective and other Benefits of employing Rolling – Element Bearings

Implementing a condition assessment program for rolling element bearings provides the user with considerable economic benefits including:

- A significant reduction, perhaps total elimination of unexpected bearing failures.
- Eliminating the necessity for visual inspection during maintenance.
- Improved quality control in areas such as bearing installation, alignment, lubrication and loading.
- A more orderly and cost effective process for purchasing replacement bearings.

Other Factors to be considered are:

- Availability is more important than reliability;
- Rather than minimizing maintenance costs, our objective should be to minimize maintenance cost per unit of production; pursuit of reduced unit energy costs (improved efficiency);
- Pursue a throughput rate (load level) which is the maximum sustainable without causing disproportionate increases in maintenance costs or decreases in availability.

Dennis H. Shreve of IRD Balancing LLC says: Industry spends $200 Billion annually on maintenance in the United States alone. In most applications, maintenance represents fully 15%-40% of the operating cost of a plant. According to several independent studies, somewhere between 28% and 35% of all maintenance spending is unnecessary. This spending excess is hidden in activities that are reworked/redone, excessive stores, unnecessary maintenance, poor quality/scrap, inaccurate analysis, etc. (http://www.irdbalancing.com/downloads/ICMTech.pdf). Basim Al-Najjar of Linnaeus University (formerly Vaxjo University), Sweden, maintains that Maintenance is a profit contributor from different perspectives. (http://dynamite.vtt.fi/conference_pres/maintenance_tq_main_al_najjar_2007.pdf). Rao (2009) has traced the progress of the proactive multidiscipline of COMADEM and its associated benefits. Conde, Fernandez and Arnaiz (2010) presented a simple cost-effective analysis cycle to optimise maintenance by following a systematic procedure. There are many Industrial Application Notes from reputable Condition Monitoring vendors highlighting the cost effective benefits of proactive maintenance. (http://www.tortoiselogic.com/NSK/PDF/E7005a_Bearing%20Doctor.pdf).

7. A note on Feature Detection, Selection, Extraction and Classification (FDSEC) Process

Rolling element bearing failure is one of the foremost causes of breakdown in rotating machinery. These bearings do operate in harsh environmental conditions such as high/low temperatures, poor lubrication, severe vibration/noise, high/low altitudes, etc. We know that the raw data contains all the symptoms of ‘health’ and ‘ill-health’ of Rolling – Element Bearings under the above mentioned operating conditions. We also know that there are considerable advantages to be gained by separating these symptoms from the bulk of the raw data before processing them any further. Fortunately, techniques do exist to transform the raw data into reduced representation set of features. The process of transforming the input data into a set of features (also called features vector) is called feature
extraction. Expert knowledge and general dimensionality reduction techniques are needed to detect, select and extract application-dependent features. In principle, any feature detection, selection, extraction and classification (FDSEC) process should involve dimensionality reduction techniques that generate a subset of new features from the original set by means of some functional mapping, securing as much intelligent information in the data as possible. This way FDSEC process results in a much smaller and richer set of attributes. Fundamental goals of FDSEC are compactness, discrimination power, low computation complexity, reliability and robustness. A number of feature detection, selection techniques and tools have been developed and successfully employed. Some of these techniques include: (1) Vibration analysis: (a) time domain (peak, rms, kurtosis, clearance factor, impact factor, crest factor), and (b) frequency domain (Spectrum analysis, Envelope analysis, High frequency resonance technique (HFRT), (c) Time-frequency (Wavelets transforms, Continuous wavelet transforms, Discrete wavelet transform), (2) Data fusion methods (data-level fusion, feature-level fusion, decision-level fusion), (3) Statistical analysis (Multivariate statistical methods, Principle components (PCA), Linear and quadratic discriminant, Partial least squares (PLS), Canonical variates analysis (CVA), etc), (4) Artificial Neural Networks (Multi-layers perceptron, Probabilistic neural networks, Learning vector quantization, Adaptive Resonance Theory Network, Kohonen self-organizing neural network, C++ Neural Networks, Probabilistic neural networks, Wavelet neural networks, Supervised back propagation neural networks etc.), (6) Optimization algorithms - Genetic algorithms, Ant colony optimization, Swarm particle optimization, Cross-entropy method, Evolution strategies, Extremal optimization, Gaussian adaptation, Stochastic optimization, etc., (7) Fuzzy logic, Fuzzy rule-based systems and neuro-fuzzy systems (ANFIS), fuzzy neural networks and Extended Neuro-fuzzy (ENF) scheme (8) Rule-based reasoning, Case-based reasoning and Model-based reasoning, (9) Decision trees, (10) Graphical models (Bayesian networks, hidden Markov models) (11) Support Vector Machines - Least Squares SVM, (12) Blind Source Separation Techniques, etc. (Rao (2005, 2010).

8. A brief background to Artificial Neural Networks (ANNs)

Neural networks (NN), a major component of neurocomputing, were first explored by Rosenblatt (1959) and Widrow (1960). NN are computational structures that can be trained to learn patterns from examples. By using a training set that samples the relation between inputs and outputs, and a learning method, for example a back propagation type of algorithm introduced by Werbos (1974), neurocomputing (and in particular neural networks) give us supervised learning algorithms that perform fine-granule local optimization. A comprehensive current review of neuro-computing can be found in Fiesler and Beale (1997).

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way the human brain processes information. A great deal of literature is available explaining the basic construction and similarities to biological neurons. The discussion here is limited to a basic introduction of several components involved in the ANN implementation. The network architecture or topology, comprising: number of nodes in hidden layers, network connections, initial weight assignments, and activation functions, plays a very important role in the performance of the ANN, and usually depends on the problem at hand. Figure 2 shows a simple ANN and its constituents. In most cases, setting the correct topology is a heuristic procedure. Whereas the number of input and output layer nodes is generally suggested by the dimensions of the input and the output spaces, determining the network complexity is yet again very important. Too many parameters lead to poor generalization (over fitting), and too few parameters result in inadequate learning (under fitting) (Duda et al. 2001). Some aspects of ANNs are: Input Layer: Size depends on Problem Dimensionality; Hidden Layer: A design parameter; must decide on number of layers and size for each layer. Creates a nonlinear generalized decision boundary; Output Layer: Size depends on number of classification categories; Bias: Further generalizes the decision boundary; Net Activation: Weighted sum of the input values at respective hidden nodes; Activation Function: Decides how to correlate the input to the output,
incorporating the most suitable non-linearity; 

**Network Learning**: Training an untrained network. Several training methods are available; 

**Stopping Criterion**: Indicates when to stop the training process; e.g., when a threshold MSE is reached or maximum number of epochs used. (Saxena and Saad (2005).

![Figure 2 showing input, hidden and output layer, along with the weights.](image)

Every ANN consists of at least one hidden layer in addition to the input and the output layers. The number of hidden units governs the expressive power of the net and thus the complexity of the decision boundary. For well-separated classes fewer units are required and for highly interspersed data more units are needed. The number of synaptic weights is based on the number of hidden units. It represents the degrees of freedom of the network. Hence, we should have fewer weights than the number of training points. As a rule of thumb, the number of hidden units is chosen as $n/10$, where $n$ is the number of training points (Duda et al. 2001, Lawrence et al. 1997). But this may not always hold true and a better tuning might be required depending on the problem.

Unlike the classical digital-processing techniques used by most computers, ANNs possess the ability to: a) Perform parallel processing of data, b) Cope with noisy data, c) Cope with system faults and d) Adapt to different circumstances and e) Graceful degradation of performance.

Digital computers process data serially in real-time, but the downside is that they have to prioritise tasks. However, ANNs process data asynchronously in real-time, which means they can cope with multiple simultaneous inputs without affecting the quality of the output. These have a remarkable ability to derive meaningful patterns and trends from complicated or imprecise data that are too complex to be noticed by humans or other computer techniques.

ANNs are employed to monitor both the steady state and the transient behaviour of dynamic systems and subsystems. This has the added advantage when, one is resorting to blending of data from various disciplines viz. performance, vibration, lubrication, etc. The integrated monitoring approach helps in enhancing the diagnostic visibility, reliability and also drastically reducing the false alarms. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze. This expert can then be used to provide projections given new situations of interest and answer "what if" questions. Other advantages include: Adaptive learning, Self-Organization, Real Time Operation and Fault Tolerance via Redundant Information Coding. Neural networks learn by examples. They cannot be programmed to perform a specific task. The examples must be selected carefully otherwise useful time is wasted or even worse the network might be functioning incorrectly.

(http://proceedings.informingscience.org/InSITE2009/InSITE09p083-095Awodele542.pdf)
ANNs are extensively used in all branches of engineering. This is extensively covered in the International Proceedings of Condition Monitoring and Diagnostic Engineering Management (COMADEM) Congresses and in the International Journal of COMADEM. Readers are referred to the website: www.comadem.com and papers/Proceedings published by Sorsa, Koivo, and Koivisto (1991), Palmer-Brown, Meireles, Almeida and Simões (2003), Ripa and Frangu (2004), Draganova, Pimenidis and Mouratidia (2009) and Wen Yu, Haibo He and Nian Zhang (2009).

9. Application of ANNs in Failure Diagnosis and Prognosis of Rolling – Element Bearings

Neural Networks are able to learn from experience, adapt to changing condition, recognise patterns and form associations. Their application in the field of ball bearings was performed by Li and Wu (1989) who used a Perceptron network to analyse experimental data from ball bearings: they were able to recognise artificial faults produced on a roller or on the outer raceway with a percentage of error smaller than that obtained by classical methodologies.

Perceptron topology of networks was used also by Kim et al. (1991) to identify the cause of malfunction between three different sources: shaft misalignment, gear and bearing failures.

In Liu and Mengel (1992), perceptrons were capable of distinguishing between six different cases of ball bearing states by observing the variations of the peak amplitude in the frequency domain, the peak RMS and the power spectrum. See reference Chiou, Y.S., Tavakoli, M.S. and Liang, S. (1992).

In 1993, Alguindigue, Loskiewicz-Buczak, and Uhrig, employed ANNs in monitoring and diagnosing rolling element bearings using artificial neural network. Vibration data was used to detect features that reflect the operational state of the rolling element bearings. The analysis led to the identification of potential failures and their causes which made it possible to perform efficient preventive maintenance. Neural network technology was selected because it operated in real-time mode and handled distorted and noisy data. This technique enhanced traditional vibration analysis and provided a means of automating the monitoring and diagnosing REBs efficiently.

In 1994, Baillie and Mathew undertook an investigation into diagnosing rolling element bearing faults with Artificial Neural Networks. They implemented vibration condition monitoring to detect and diagnose faults in rolling element bearings, as often faults can be identified by their characteristic patterns of vibration. By employing artificial neural networks they demonstrated to provide an effective new method for fault diagnosis in rotating machinery in terms of cost and reliability. They introduced the popular new pattern classification tool of neural networks, and examined to show they have been successfully implemented to diagnose faults in bearings. See reference Haddad, Chatterji, and Ogunfunmi (1994).

In 1995, Aiordachioae, Teodorescu and Puscasu presented the ability of a Kohonen network to classify 4 types of bearing faults and their combinations. These were: outer bearing race defect, inner bearing race defect, ball defect and train defect. The source of information was the vibration transducer. At each sampling moment, a narrow horizon Fourier analysis provided the spectral components, which were fed as inputs of the network. This one recognized the bearing vibration signatures. The training was supervised, requiring short time.

Wang and McFadden (1996) applied Backpropagation networks on the data created by a mathematical model of the vibration signal of ball bearings (McFadden and Smith 1984, 1985). They were able to simulate different operating conditions of the machine and the presence of damage on the rolling elements or the inner and outer races. In the present work Neural Networks were applied on experimental data - extracted from the casing of the ball bearing of a test machine in operating
condition - to localise eventual pitting damages on the bearing surfaces. A wide study was necessary to eliminate the noise effects, caused by the belt transmission: RMS, skewness, kurtosis and a series of parameters selected by the frequency spectrum, were used as network inputs for the analysis of vibration signals, acquired in the presence of artificial surface bearing defects. Different functions from MATLAB Neural Network toolbox were tested in order to identify the best architecture for this kind of pattern recognition. See reference Baillie (1996).

In 1997, Subrahmanyam and Sujatha employed neural networks for the diagnosis of localized defects in ball bearings using both MLP and self-organizing network (ART2) to recognize two main faults. The process information, provided by piezo-electric accelerometers, was subject of the Fourier analysis, which computed the spectrum components. These were then compressed in 8 significant descriptors, fed as inputs of the network. The meaning of the output, normalized between 0.1 and 0.9, was that of a scalar description of the possible defects of the bearing. The value 0.1 corresponded to a normal bearing, 0.6 to a ball defect and 0.9 to an outer race defect. The MLP was trained in a supervised procedure, whereas the ART network performed a clustering process. Both networks performed a 100% reliable recognition of the defect bearings (on the presented data sets). MLP distinguished the possible states of the defect bearings, for diagnose purposes, with a rate of success of 95%. The ART2 network was less accurate in recognizing different defects, but it was 100 times faster in training.

In 1998, Gouliani, Rubini and Maggiore of the University of Bologna, investigated the ball bearing diagnostics using neural networks. Ball bearings can be affected by several damage typologies. Surface flaws on inner and outer races or on rolling elements are the main causes of failure. The passing of a rolling element upon a localised defect generates a wide band impulse: during machine running, this particular phenomenon repeats itself at the fault characteristic frequencies, which depend on the bearing geometry. The authors showed the results obtained by the application of functions from MATLAB Neural Network toolbox to experimental data extracted from the casing of the ball bearing of a test machine in operating condition. The analysed bearings were affected by the above mentioned damages, artificially created by electric erosion. A comparison between the results obtained by the application of different network architectures is reported. See References: Lu, Q. and D. Li. (1998); Li, B., G. Goddu, M. Chow (1998).

In 1999, Gao and Randall investigated the detection of bearing faults in helicopter gearboxes employing Spectral analysis, Cepstral analysis, Envelope analysis and ANNs. See reference Jack, L.B., A. K. Nandi, A. C. McCormick (1999).

In 2000, Y Shao and K Nezu proposed a new concept referred to as progression-based prediction of remaining life (PPRL) to solve the problem of accurately predicting the remaining bearing life. The basic concept behind PPRL was to apply different prediction methods to different bearing running stages. A new prediction procedure which predicts precisely the remaining bearing life was developed on the basis of variables characterizing the state of a deterioration mechanism which are determined from on-line measurements and the application of PPRL via a compound model of neural computation. The procedure consisted of on-line modelling of the bearing running state via neural networks and logic rules which not only solved the boundary problem of remaining life but also automatically adapt to changes in environmental factors. In addition, multi-step prediction was possible. The proposed technique enhanced the traditional prediction methods of remaining bearing life. See reference by Miettinen (2000).

In 2001, Samanta and Al-Balushi presented a procedure for fault diagnosis of rolling element bearings through artificial neural network (ANN). The characteristic features of time-domain vibration signals of the rotating machinery with normal and defective bearings have been used as inputs to the ANN.
consisting of input, hidden and output layers. The features were obtained from direct processing of the signal segments using very simple preprocessing. The input layer consisted of five nodes, one each for root mean square, variance, skewness, kurtosis and normalised sixth central moment of the time-domain vibration signals. The inputs were normalised in the range of 0.0 and 1.0 except for the skewness which was normalised between −1.0 and 1.0. The output layer consisted of two binary nodes indicating the status of the machine—normal or defective bearings. Two hidden layers with different number of neurons were used. The ANN was trained using backpropagation algorithm with a subset of the experimental data for known machine conditions. The ANN was tested using the remaining set of data. The effects of some preprocessing techniques like high-pass, band-pass filtration, envelope detection (demodulation) and wavelet transform of the vibration signals, prior to feature extraction, were also studied. The results showed the effectiveness of the ANN in diagnosing machine condition. The proposed procedure required only a few features extracted from the measured vibration data either directly or with simple preprocessing. The reduced number of inputs led to faster training requiring far less iterations making the procedure suitable for on-line condition monitoring and diagnostics of machines. See reference by Vyas and Satishkumra (2001).

In 2002, Peng Xu and Andrew K. Chan proposed a new design of a neural network based system to detect faulty bearings using acoustic signals in a noisy wayside environment. Statistical features were generated from discrete wavelet transform (DWT) coefficients, and a genetic algorithm was used to select the optimal features. The false negative rate for detecting a condemnable bearing was as low as 0.1% regardless of the speed, load condition, and bearing type. See reference Yang, D. M., A. F. Stronach, P. and MacConnell (2002).

In 2003, Samanta and Al-Balushi presented a procedure for fault diagnosis of rolling element bearings through artificial neural network (ANN). The characteristic features of time-domain vibration signals of the rotating machinery with normal and defective bearings have been used as inputs to the ANN consisting of input, hidden and output layers. The features were obtained from direct processing of the signal segments using very simple preprocessing. The input layer consists of five nodes, one each for root mean square, variance, skewness, kurtosis and normalised sixth central moment of the time-domain vibration signals. The inputs were normalised in the range of 0.0 and 1.0 except for the skewness which is normalised between −1.0 and 1.0. The output layer consists of two binary nodes indicating the status of the machine—normal or defective bearings. Two hidden layers with different number of neurons have been used. The ANN was trained using backpropagation algorithm with a subset of the experimental data for known machine conditions. The ANN was tested using the remaining set of data. The effects of some preprocessing techniques like high-pass, band-pass filtration, envelope detection (demodulation) and wavelet transform of the vibration signals, prior to feature extraction, were also studied. The results showed the effectiveness of the ANN in diagnosis of the machine condition. The proposed procedure requires only a few features extracted from the measured vibration data either directly or with simple pre-processing. The reduced number of inputs leads to faster training requiring far less iterations making the procedure suitable for on-line condition monitoring and diagnostics of machines. (repetition) See reference Samanta., Al-Balushi, and Al-Araimi, (2003).

In 2004, Gebraeel, Lawley, Liu, Parmeshwaran and Taplak, Uzmay, and Yildirim in 2006 used to detect faults in bearings and predicted the residual life from vibration – based degradation signals. See references by Ling Wang and Hope (2004), Gebraeel and Lawley (2004), Li, Mecheske and Li (2004), Al-Araimi, Saeed A., Khamis R. Al-Balushi ; B. Samanta (2004), Eren, L., A. Karahoca, and M. J. Devaney (2004).

In 2005, Satish and Sarma demonstrated a novel and cost-effective approach for diagnosis and prognosis of bearing faults in small and medium size induction motors. Even though, many
researchers dealt with the bearing fault diagnosis of induction motors by using traditional and soft computing approaches, the application of these techniques for predicting the remaining life time of electrical equipment was not seen much in the literature. Moreover, individual artificial intelligence (AI) techniques suffered from their own drawbacks, which were overcome by forming a hybrid approach combining the advantages of each technique. Hence, an attempt was made to combine neural networks and fuzzy logic and forming a fuzzy back propagation (fuzzy BP) network for identifying the present condition of the bearing and estimated the remaining useful time of the motor. The results obtained from fuzzy BP network were compared with the neural network, which showed that the hybrid approach was well suited for assessing the present condition of the bearing and the time available for the replacement of the bearing. See references by Saxena and Saad (2005), Liu, Ordukhani and Jani (2005).

In 2006, O¨ Nel, Burak Dalci and I˙brahim Senol investigated the application of induction motor stator current signature analysis (MCSA) using Park’s transform for the detection of rolling element bearing damages in three-phase induction motor. The authors first discussed bearing faults and Park’s transform, and then gave a brief overview of the radial basis function (RBF) neural networks algorithm. Finally, system information and the experimental results were presented. Data acquisition and Park’s transform algorithm were achieved by using LabVIEW and the neural network algorithm was achieved by using MATLAB programming language. Experimental results show that it is possible to detect bearing damage in induction motors using an ANN algorithm. See references by Castro, Sisamon and Prada (2006); Taplak, H., Uzmay, I. and Yildirim, Sahin (2006), Yu Y., Dejie Y., and Junsheng C. (2006).

In 2007, Ghafari presented an analytical study of a healthy rotor-bearing system to gain an understanding of the different categories of bearing vibration. In this study, a two degree of- freedom model was employed, where the contacts between the rolling elements and races were considered to be nonlinear springs. A neuro-fuzzy diagnosis system was then developed, where the strength of the aforementioned indices were integrated to provide a more robust assessment of a bearing’s health condition. A prognosis scheme, based on the Adaptive Neuro Fuzzy Inference System (ANFIS), in combination with a set of logical rules, was proposed for estimating the next state of a bearing’s condition. See references Mahamad, Saon, Abd Wahab, Yahya and Ghazali (2007) and Huang, Xi, Li, Liu, Hai Qiu and Jay Lee (2007).

In 2008, the investigation carried out by LI Yun-hong, ZHANG Yong-tao, PEI Wei-chi was based on the frequency domain characteristic of vibration signals of the ball bearings, the vibration signals were decomposed into different frequency bands through the method of wavelet packet analysis. Energy of various frequency bands acting as the fault feature vector was input into the Elman neural network to realize the mapping between the feature vector and the fault mode since the Elman neural network has strong fault tolerance and better dynamic capability. The emulator results verified the effectiveness of the proposed methods in motor bearing fault diagnosis. See references Sreejith, Verma and Srividya (2008), Khalid, Al-Raheem, Roy, Ramachandran, Harrison, and Grainger (2008), Ghaffari, Ismail and Golnaraghi (2008).

In 2009, Tran, Yang and Tan presented an approach to predict the operating conditions of machine based on classification and regression trees (CART) and adaptive neuro-fuzzy inference system (ANFIS) in association with direct prediction strategy for multi-step ahead prediction of time series techniques. In this study, the number of available observations and the number of predicted steps were initially determined by using false nearest neighbour method and auto mutual information technique, respectively. These values were subsequently utilized as inputs for prediction models to forecast the future values of the machines’ operating conditions. The performance of the proposed approach was then evaluated by using real trending data of low methane compressor. A comparative study of the
predicted results obtained from CART and ANFIS models was also carried out to appraise the prediction capability of these models. The results showed that the ANFIS prediction model can track the change in machine conditions and has the potential for using as a tool to machine fault prognosis. See references Zahari Taha and Khunsun Widiyati (2009) and Zhigang Tian (2009), Li, Bo, Mo-Yuen Chow, Yodyium Tipsuwan, and James C. Hung, Zhao, Fagang, Jin Chen, Lei Guo and Xinglin Li (2009).

In 2010, Jayaswal, Verma and Wadhwani provided a brief review of recent developments in the area of applications of ANN, Fuzzy Logic, and Wavelet Transform in fault diagnosis. The purpose of this work was to provide an approach for maintenance engineers for online fault diagnosis through the development of a machine condition-monitoring system. A detailed review of previous work carried out by several researchers and maintenance engineers in the area of machine-fault signature-analysis was performed. A hybrid expert system was developed using ANN, Fuzzy Logic and Wavelet Transform. A Knowledge Base (KB) was created with the help of fuzzy membership function. The triangular membership function was used for the generation of the knowledge base. The fuzzy-BP approach was used successfully by using LR-type fuzzy numbers of wavelet-packet decomposition features. The development of a hybrid system, with the use of LR-type fuzzy numbers, ANN, Wavelets decomposition, and fuzzy logic was found. Results showed that this approach can successfully diagnose the bearing condition and that accuracy was good compared with conventionally EBPNN-based fault diagnosis. The work presented a laboratory investigation carried out through an experimental set-up for the study of mechanical faults, mainly related to the rolling element bearings. The main contribution of the work has been the development of an expert system, which identifies the fault accurately online. The approaches can now be extended to the development of a fault diagnostics system for other mechanical faults such as gear fault, coupling fault, misalignment, looseness, and unbalance, etc. See references Martínez-Rego, Fontenla-Romero, Pérez-Sánchez and Alonso-Betanzos (2010), Kirchner, Southward and Ahmadian (2010), Li, Yu, Li and Meng (2010), Mahamad, Saon and Hiyama (2010), Bhavaraju, Kankar, Sharma and Harsha (2010), Guoqiang, Cai, Jia Limin, Yang Jianwei and Liu Haibo (2010), William, Kirchner, Southward, Steve; Ahmadian, Mehdi (2010),

In 2011, Vijay, Srinivasa Pai, Sriram and Rao conducted an investigation into radial-elements bearing Diagnostics by employing a Radial Basis Function Neural Network. They are a relatively new class of NNs which have the advantages of simplicity, ease of implementation, excellent learning and generalization abilities. Since Radial Basis Function (RBF) neural network architecture is not widely used for REB diagnostics the authors have used this architecture for fault diagnostics of REB using vibration signal features. Using a customized bearing test rig, experiments were carried out on a deep groove ball bearing namely 6205 under two different speeds and one load condition. The diagnostics was mainly concerned with classifying the bearing into two classes namely ‘Normal’ and ‘Used’. The performances of different learning strategies namely Fixed Centers (FC) selected at random, self-organized selection of centers using clustering algorithms – Fuzzy C Means (FCM), Density Weighted Fuzzy C Means (DWFCM) & Cluster Dependent Weighted Fuzzy C Means (CDWFCM) were compared. It was found that basic FCM and CDWFCM gave higher performance accuracy when compared to other strategies.

A number of patents exist in this field. For example: United States Patent 5566092 on Machine fault diagnostics system and method. This invention provides a machine fault diagnostic system to help ensure effective equipment maintenance. The major technique used for fault diagnostics is a fault diagnostic network (FDN) which is based on a modified ARTMAP neural network architecture. A hypothesis and test procedure based on fuzzy logic and physical bearing models is disclosed to operate with the FDN for detecting faults that cannot be recognized by the FDN and for analyzing complex machine conditions. The procedure described herein is able to provide accurate fault diagnosis for both one and multiple-fault conditions. Furthermore, a transputer-based parallel processing technique is used in which the FDN is implemented on a network of four T800-25 transputers.
10. **Challenging and innovative issues**

There are however, some challenging and innovative issues which need to be addressed. These are grouped under the following headings:

(a) Materials issues; Moyer (2001);
(b) Innovative Design issues (advanced oil-free compliant foil bearings, magnetic bearings); Andhare and Manik (2008),
(c) Education and Training issues; Rao, (1988);
(d) Environmental issues (electrical discharge failures, etc.); See Reference Prasad (2002), Zika, et al (2009),
(e) Energy related issues; Müller, Claus, Peter Schuster and Oliver Koch (2010),
(f) Remaining Useful Life prediction issues; Shao, and Nezu (2000), Essawy, (2001),
(g) Innovative Sensor/Multisensor/Data Management Technology issues; Braun & Datner (1979), Bently (1989), Billington (1997), Holm-Hansen (1999), Bylington and Garga (2001), Shirkhodaie, (2001), Juarez, Conkey, Perez, and Taylor (2002), Kovacs.; Peroulis; Sadeghi, (2007), Chen, Craig, Wood, Wang, Callan & Powrie (2008),
(h) Proactive maintenance/Asset management/Condition-based Maintenance issues; Jack, and Nandi (2001),
(i) Standardization issues. See references Mathew, J. (1997), Hitchcock, Leith. (2006), Various ISO Standards on Condition Monitoring and Diagnostics of Machines;
(j) Critical/unusual application issues. See references: Gerstenberger, and Poll (2001), Holm-Hansen (1999);
(k) Establishment of new criteria such as Overall Bearing Effectiveness criteria, etc.
(l) Application of innovative Signal processing/Artificial Intelligence techniques/Virtual Reality/Expert Systems/Fuzzy Logic; Ho, (1999), Jack, and Nandi (2001), Fan, Xianfeng, Ming Liang, Tet H Yeap and Bob Kind (2007), Feng, Yanhui (2008), Hajnayeb, Khadem and Moradi. (2008), Ganeshkumar, and Krishnaswamy (2009), Chen, Kan, and Pan Fu. (2009), Gao, Lixin, Zijing Yang, Ligang Cai, Huaqing Wang and Peng Chen (2011),
(m) Advanced Diagnostics/Prognostics; Widner, and Littmann, (eds.). (1976), Tandon, Nakra, (1992), Wen Yi, and Harrap (1993), Hownrd, Ian (1994), Liu, Shigonahalli and Iyer (1996), Li, (1999), Shiroishi, Li, Liang., Danyluk, and Kurfess, (1999), Li, Billington, Zhang, Kurfess, Danyluk, and Liang. (1999), Yang, Kurfess, Lian, and Danyluk, (1999), Ocal, and Loparo, (2001), Nikolaou and Antoniadis (2002), McInerny, and Dai. (2003), Hongyu Yang (2004), Sawalhi, and Randall (2005), Rao, Oraifige and Obeid. (2008), Sawalhi, and Randall (2007a and b; 2008a and b), Zhang, Geogoulas, Orchad, Saxena, Brown, Vachtsevanos and Liang.(2008), Wang, Dong, Qiang Miao, Xianfeng Fan and Hong-Zhong Huang. (2009).

Significant progress in some of these areas is being made as revealed in the Bibliography section of this paper. No doubt the quest to pursue better and improved rolling element bearing condition monitoring / fault diagnostic techniques will continue.

11. **Conclusion**

Rolling element bearings play a prominent role in today’s rotating machinery system. When a bearing fails, accurate, reliable and proactive diagnosis is the key to getting it back on-line quickly, efficiently and cost-effectively. It is vital that every aspect of bearing performance should be continuously monitored, diagnosed and prognosed using the latest available technology. ANNs are an added complement to the existing time-domain based technology. Judicious application of ANNs provides good success rate, improved accuracy, zero false alarms, fewer undetected faults, faster execution time. ANNs possess remarkable information processing characteristics such as nonlinearity, robustness, ability to learn and ability to handle imprecise and fuzzy/chaotic information. They are increasingly used as an effective, cost-effective and efficient automated ‘health’ indicator of modern
engineering/manufacturing systems. Of course, the accuracy and performance of ANNs depends upon the architecture, training set size, features selected and how efficiently data is managed. This paper presents a comprehensive glimpse of the applications of artificial neural networks (ANNs), in the last 25 years.

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