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Review of Fault Classification in Gearbox Based on Neural Network

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Abstract

The present work focuses on classifying different gearbox faults based on neural networks. Efforts are made to include all the faults and classifiers based on the neural network of transmission systems reported in the literature. Fault classification is essential for reliable and quick protective digital protection. Hence, a suitable review is needed. So, the work concentrates on the different faults in the gearbox and available neural network-based approaches reported in the field.

Keywords: *Faults, Fault Classification, Transmission System, Neural Network*

Introduction

The gearbox is a essential part of the transmission system and transfers motion and power. The gearbox found its application in various sectors like industrial, military and wind turbine etc.[1]. Any failure in system elements causes the system to shut down. A gearbox failure results in downtime, costly repair and living causalities[2–4]. So, it is essential to detect these faults at an early stage. Many studies have been reported in the direction of the failure of different machine elements like bearing and Gear [5,6,15–24,7,25–34,8,35–44,9,45–54,10,55–62,11–14]. Many techniques are used to design the experiments and collect the data, like Taguchi[63,64,73–77,65–72] and so on. Different techniques like vibration[78], acoustic, wear monitoring, noise signature, and temperature analysis can diagnose gearbox faults [79]. As mentioned above, vibration is used widely due to its cost-effectiveness and easy information processing [80]. The vibration signature starts changing as the faults develop in the system[4,81]. The vibration data is preprocessed to get the feature vector to train the model. In literature, many signal processing techniques are available to extract helpful information from the vibration signal. The signal processing techniques are classified into time, frequency, and time-frequency domains [82]. The signal is demodulated, noise is reduced, and valuable information is kept using the signal processing techniques. A survey of these techniques is found in the literature [79,83,84]. NASA uses the wear debris-based technique to develop a complete framework for gearbox diagnosis [85].

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In literature, many algorithms are used to detect and diagnose the faults in gearboxes[86]; these are the support vector machine and neural networks. To reduce the dimensions of the failure feature vector, the technology of principal component analysis[87,88] is adopted to transform the original failure feature vector into a smaller set of variables. In literature, artificial neural networks combined with the empirical mode decomposition, fuzzy logic and support vector classification family attracted most of the attention as these results are good compared to other available methods[89]. Deep learning also succeeded in classification as it owns deeper representations for faulty features. Neural networks based on deep learning are also in practice.

This paper is structured on the different faults of the Gear and the use of different neural network-based techniques to classify the faults.

2. Failure modes of the gearbox and diagnostics

2.1 Failure modes and diagnosis

Due to its complex tribological interaction, Gear has to degrade over time. Gear failure is the function of tooth geometry, kinematics, forces, material, lubrication, and environmental characteristics. The gear tooth failure is classified based on strength and non-strength basis. The failure may occur gradually or sudden. The AGMA F14 [90]standard classifies failure into seven categories and 36 failures. In literature main focus is on the crack, pitting, flank wear and root fracture of the gears. Failure is defined as the termination of the ability of the element to perform the desired function. Failure is associated with the desired function. The failure mode describes different ways of an item's failure. The failure may be random or systematic. A failure result in the loss of production or services and safety. The failure may be detected or undetected. The failures may be design-related faults or operational errors. Detection is both localized and distributed.

Maintenance is a complex set of operations that compromise the diagnosis, scheduling, budgeting, and execution of decisions. The execution of the gearbox maintenance is a combination of planning, budgeting, and material and a group of personnel and organizations. The condition-based maintenance is a request-based upkeeping of machine availability. Timely actions are dependent upon the early detection of the damage. The damage detection process is divided into the following steps:

Step 1: Data collection

The data is measured with the help of the proper sensor like vibration, acoustic, wear debris etc. For example, the vibration sensor is mounted on the gear casing or bearing positions to measure the acceleration data of the gearbox.

Step 2: Processing

The acquired data is processed to reduce the noise and other modulation components to detect the fault feature of the Gear. For example, the vibration signal is averaged about the shaft rotation by time-synchronous averaging (TSA). Different features are extracted and stored in the feature vector from this averaged data. Further, this feature vector is reduced in the dimension by principal component analysis (PCA).

Step 3: Classification of the fault.

The reduced vector of the feature is used to train the model by using SVM or NN. The unknown vector is then given as the input, and the trained model provides the diagnostic results.

2.2 Vibration-based failure indicator

Around 90% of faults are related to the unbalancing and misalignment of the rotating parts. Two main characteristics of vibration signals are frequency and amplitude. Table 1 summarizes the vibration-based fault indicator and various gear failure modes based on time, frequency and time-frequency modes. The performance of these indicators depends on the severity of the faults.

The indicators developed or chosen for the fault diagnosis should possess the following features:

a) Monotonicity - shows the trend over time
b) Robustness – tolerance to the outliers
c) Trendability/correlation – correlation with the other available indicators.

Table 1. Summary of fault indicator of various gear failure modes [79]

Type	Indicator	Fault identified
Time	RMS	Fault progression
	Kurtosis	Pitting
	Crest factor	Tooth fault localization
	Energy operator	Scuffing, severe pitting
	FM0	Distributed wear, tooth breakage
	NA4	Pitting
	NA4*	Progressing damage
	CCR	Pitting
	FM4	Crack, pitting
	M6A	Flank Wear
	Energy ratio	Uniform wear
Frequency	GMF harmonic amplitude	Wear
	Sideband amplitude	Pitting
	Sideband ratio	Pitting
	ALR	Crack, wear
	Cepstrum	All kinds of fault
	Spectral kurtosis	Pitting, crack
	Phase modulation	Crack
Time-frequency	NP4	All faults
	Wavelet	All faults
	EMD	All faults
	STFT	Early-stage faults
	WVD	Early-stage faults

3. Neural Network

The detection of localized and distributed defects is essential. The fault indicators are chosen to measure sure the deviation in the signature of the machinery's health. These selected fault indicators are further processed using classifier algorithms for classification based on the severity of the faults.

Preventive maintenance is used to delay the machinery shutdown. The available data is processed using data analytics and machine learning.

The fault classification techniques to classify different types of faults in the Gear, such as pitting, crack, wear etc., are classified based on the selected fault indicators. The classification approaches separate the different fault-based on some statistical criteria. For each type of failure, the evolution/ trend of a particular fault indicator may be different. Hence, so different techniques need to be applied for the classification. Table 2 summarizes the various classification approaches discussed.

Out of these techniques, Neural network-based techniques are discussed in the following text. The idea of a neural network mimics the biological nervous system. The artificial neural network (ANN) model is trained similarly to biological learning by experience. Various researchers train different types of ANN models for fault and severity classification.

Table 2. Fault classification models and used for the type of faults [79,91]

Classification Algorithm	Type of Gear	Type of fault	Fault indicator or process
Neural Network	Spur	Wear severity, tooth breakage	Wavelet
	Bevel	Crack, worn, tooth breakage	Wavelet, EMD
	Helical	Tooth breakage	Taguchi's
Fuzzy rule	Spur	Broken and worn gear tooth	Decision tree
Neuro-fuzzy	Spur	Crack	Wavelet, kurtosis, phase modulation
SVM	Spur	Pitting	Amplitude ratios of the frequency band (PCA), RMS, peak, kurtosis, average signal CC
	Planetary	Pitting	Frequency domain-based
	Compounded spur	Crack, missing tooth	% Energy of IMF of EMD
Random forest	Spur	Crack, pitting, wear, misaligned	Time-domain and frequency domain, time-frequency domain
Deep learning	Spur	Wear, pitting, crack, broken and chipped tooth	Time, frequency and time-frequency domain indicators

A neural network represents deep learning using artificial intelligence. An artificial neural network consists of various layers of interconnected artificial neurons powered by activation functions that help switch them on/off. Like traditional machine algorithms, neural nets learn specific values in the training phase. For each neuron, the inputs and random weights are compounded and a static bias value (unique to each neuron layer) is added; this is then transferred to a suitable activation function which determines the final output value. Backpropagation is used to modify the weights of the last neural network layer in order to minimise the loss function (input vs. output) after the output is created. Weights are numeric values multiplied by inputs. They are used to minimize the loss.

The different types of Neural networks are as follows[89,92–94]:

- Perceptron
- Feed-forward neural network
- Multilayer perceptron
- Convolutional neural network
- Radial basis functional neural network
- Recurrent neural network
- Long short-term memory
- Sequence to sequence models
- Modular neural network

Perceptron

Neuronal networks include several smaller units that do specific calculations in order to identify characteristics or business information in the data. Weighted inputs may be entered into the system and applies the activation function to obtain the output as the final result. It is known as a threshold logic unit. It is a binary classifier. It can be implemented with logic gates like AND, OR, or NAND. It is helpful for linearly separable problems such as Boolean AND problem. It does not work on the non-linear problem.

Feed-forward neural networks

It is used where machine learning-based classification, face recognition, computer vision where target classes are challenging to classify, and speech algorithms have limitations. The simplest systems are forward-biased. And hidden layers may or may not be present in the model. The number of the layer depends on the complexity of the function. This does not have backward propagation. Weights are static. These are less complex, easy to design, fast and speedy, and highly responsive to noisy data. It cannot be used for deep learning.

Multiple perceptron

Work better for speech recognition, machine translation, and complex classification. Has multiple layer structure. The backpropagation is allowed to reduce the loss. Self-adjustment depends on the difference between predicted outputs Vs training inputs. It can be used for deep learning purposes. The only disadvantage is a slow speed.

Convolutional neural network

It is the three-dimensional arrangement of neurons. The first layer is called the convolutional layer. Each neurone in the convolutional layer processes information. A batch-wise input is allowed to speed up the process. The network understands the images into parts and can compute these operations multiple times to complete the full image processing. Processing involves the RGB correction and pixel change. It can be used for deep learning. It works bidirectional.

Radial basis function neural networks

It is multiple category input connected to followed by a layer of RBF neurons and an output layer with one node per category. Classification is performed by measuring the input's similarities to data points from the training set where each neuron stores a prototype when new data needs to be classified by measuring the Euclidean distance between input and its prototype.

Recurrent neural networks (RNN)

It is used to backpropagate to help in predicting the output layer. The first layer is feed-forward based and uses stored information of the last layer to input into the next layer and future. It is used for text processing, grammar check, and sequential inputs and depends on the historical data. It is not easy to train such an algorithm.

Long short-term memory network

It is an updated or improved version of RNN. The gates are used to store the information. It makes the information last longer than expected.

Sequence to sequence model

It consists of two RNNs; an encoder that processes the input and a decoder that processes the output. Both can be used in similar or different parameters. The input and output data vectors must be equal.

Modular neural network

It has multiple networks that function independently and perform sub-tasks. Network work independently during the computation process. It is fast in working due to independency.

The different types of faults in Gear are used to classify different kinds of faults in the Gear. The accuracy of the ANN model was tested with several neurons 2 to 30. The number of layers which shows the slightest deviation is selected for building the structure of ANN. The optimum network structure and number of nodes are difficult to determine[89,92–96].

4. Conclusions

The paper has presented a summary of the different failure modes, their diagnostic indicator and neural network-based classification and different types of neural networks. The ANN can classify the defects based on other faults diagnosis techniques like acoustic, wear debris, lubrication-related parameters, etc. In a few works of literature, the oil-based neural network classification is used[97]. But they are used for the unloaded condition. So, it is essential to study the effect of load. It is also suggested to use multiple algorithms to find the best algorithm for the particular type of fault.

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