Fault Diagnosis of a Single Ball Bearing System Based on Vibration Analysis Using Neural Network

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Abstract – The defects in the induction engine bearing are a significant cause of disastrous machinery failure. Detection and detection of flaws in coats is also very critical for safety. This paper focuses on the malfunction evaluation through the usage of wavelet extraction induction engine carrying localized defects. This research uses the research rig for the defective diagnostic of deep ball bearing NSK-6203 for the machinery fault simulator (MFS) examination. Vibration signals obtained from the different conditions of carrying-healthy bearing (HB), outer race defect (ORD), inner race defect (IRD). The elimination of mathematical characteristics from raw vibration metrics utilizing separate wavelet Daubechies coefficients. Finally, these mathematical characteristics are listed as an input to the technique for classification of defects in the artificial neural network (ANN). The outcome of the test indicates that ANN defines more correctly the default groups of rolling components for Db4 and has a higher diagnostic efficiency than for other Daubechy-classified waves.

Key Words: Artificial Neural Network, Daubechies Wavelets, Ball Bearing

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INTRODUCTION

Revolving coils are a big component of revolving equipment and are commonly used. The roller rolling fault may trigger a spinning system to break down and, in addition, the malfunction may have drastic implications. Thus, rolling bearings are most critically tracked and diagnosed for loss to ensure manufacturing quality and plant safety[1] [2]. The use of vibration signals in machinery diagnosis allows it efficient for the identification and discrimination of the type of malfunction, because the signals provide complex machine state information[3][4].

However, the meanings of the vibrational signals for fault diagnoses measured symptom parameters are unclear. Although faults in rolling coils are often artificially diagnosed using vibration signals' timing or frequency analysis, it does involve an accurate, quick automatic diagnostic process. The possible uses of neural networks (NN) in automatic detecting and computer fault diagnostics[5]-[8]. However, a classical neural network can not accurately represent unclear diagnostic difficulties and never converges when symptom parameters input into the first NN layer have similar values in numerous states [9].

For these purposes, this paper suggests a sequential fuzzy diagnostics approach to track the state of a rolling layer using the neural network and possibility principle in order to resolve these problems and increase the performance of fault diagnosis. A neural network with a partly linear neural network is developed, which enables automated assessments of the state of a bearing on the basis of the potential distribution of symptom parameters. For conditional diagnosis a bearing are also established the non-dimensional symptom parameters (NSP) in the time domain.

The identification index (DI) is used to detect the NSP 's sensitivity to detecting defects. The reliability of this approach is confirmed by realistic illustrations of fault diagnosis for rolling bearings in a centrifugal blade. The neural network is a model of knowledge processing focused on the way the details in the human nerve and animal nervous system are stored in the brain. In 1943, Warren McCulloch and Walter Pits manufactured the first artificial neuron model in the world[8]. Sadly, the technology has reduced its quest at that period. Neural Network 's behavior is the same as individual, in an explanation of learning. The Back Propagation Network is a tool for collecting multiple network weights. This approach has already been used to address neural network problems through supervised learning techniques. This method 's simple algorithm is for the definition of error feature to minimize error or network error.

DAUBECHIES WAVELET

The only distinction between these scaling signals and wavelets is how to measure the current averages and differences using scalar products with scaling and wavelet signal. The scaling signals and wavelets have much longer supports for the Daubechies wavelet transformations, i.e. they obtain averages and variance of just a few more values from the signal. However, this small improvement would significantly increase the potential of these latest transformations. They offer a range of effective resources to execute simple signals. These activities include encoding and noise reduction for audio and image signals, as well as improving and identifying images. The wavelet variable Daubechies has a huge potential in the local high gradient analysis of the problem. Daubechies wavelet has the following double-scale structure: The scale structure Φ(x) and wavelet function β(x):

$$\emptyset(x) = \sum_{i=0}^{N-1} P_i \emptyset(2x - i) \quad (1)$$

$$\beta(x) = \sum_{i=2-N}^{1} (-1)^i P_{1-i} \emptyset(2x - i) \quad (2)$$

Where, Pi = filter coefficients (i=0, 1, --------, N-1)

N = even integer

The scaling function Daubechies will exactly reflect any polynomial with an order no higher than N/2 – 1,

$$f(x) = \sum_{k=-\infty}^{\infty} C_k \emptyset(x - k) \quad (3)$$

BPNN MODEL DEVELOPMENT AND CLASSIFICATION ACCURACY

The prevailing parameters and the bearing mechanism was described with six BPNN versions. The input layer size and the secret layer size distinguish these versions. To evaluate the architecture of whole-neural network models, the choice of the number of secret neurons and layers is important[10]. Although the secret layer does not communicate explicitly with the outside, the effect would be influenced later by this layer. Thus it is important to stress the amount of neurons in the secret layer and to render the selection proper.

The output neuron numbers are stable, this is for each model one neuron. The number of input neurons and secret neurons is different from each model. For the purpose of avoidance of change, the input-layer scale should not be too high to avoid the amount of neurons in a Neural Network model[11]. The six BPNN models used in our experiment are displayed in Table 2. If we can see, these models vary in the scale of the input layer that is 5 neurons and 1 neuron. Then the 5-input layer templates are distinct in the scale of the secret layer.

Three separate hidden layer sizes, one, three and ten hidden layer neurons, were used. The same goes with models of an input neuron.

REVIEW OF LITERATURE

Two forms of premature bearing defects have been studied by Gurumoorthy et al., (2013). A defect in a light-motor vehicle's rear axle ball and the other defect in a pilot ball bearing clutch exist. The original fault study concludes that the premature defect during remounting of the bearing or hub was most possibly triggered by an irregular impact power. The unintentional effect caused a part of the inner edge to be broken off, as well as creating dents in the course and balls.

Often indicated during mounting were the periodicities of the flaking sites that coincided with the pitch in the balls. A second form of loss ends with the collapse of the bearing. The dent that was created during handling of the dent possibly resulted in a cascade of results – harm to the caged, roll disability, rubbing up of the temperature and a deteriorating of the lubricant eventually culminating in utter seizing.

Upadhyay et. al., (2013) explain Rolling Contact Fatigue (RCF) is induced by cyclical stresses and by the processes correlated with rolling device rolling bearing loading failure. When spinning roller covers are subjected to friction or slipping oscillation, inaccurate brinelling happens. Due to the fake brinelling of the carrying field, the cavities generated on the carry raceway appear to inflict harm within a short time. It is often recommended that the existence of the bearing be extended.

The set, average value, standard deviations, kurtosis, vibration signal skewness and crest factor (2011) have been recorded by Kankar et. al., (2011), for use by vector machines in support of the surveyed attribute philtre for selecting prominent statistical features and classification. The machine learning method will aid automatic ball bearing error diagnosis.

Wang and Chen (2009) proposed to remove the element from the fault signal, which was heavily polluted by noise, and to reliably distinguish the types of faults centred on the wave of curtosis and the fault detection variations in the rolling element carrying portion. The kurtosis wave is described in the time area by using the vibration signal, and the Kullback-Leibler divergence with the kurtosis wave is also suggested.

S. Prabhakar et. al., (2002), for the diagnosis of single and multiple carrying faults, using discrete wavelet transformation.

N. Tandon (1994). Tandon. In order to examine vibration signals produced from localised coating defects, Antoniadis uses wavelet packet transform (WPT).

N. Saravanan et (2008) is concerned with vibration data collection of Morlet wavelet bevelet gearbox method and description of gear failures by vector help (SVM) and PSVM.

R. J. Antoni and S. Randall. Fault identification of the motor induction using SVM technique for the identification of split rotor bars was carried out by Chobsaard et. al., (2001). In the tests, a single, broken bar, two broken bars and three broken bars were explored without any loss.

G. Osypiw, and Luo, D., and M. Irle (2003) Hilbert 's conventional and wavelet transformations mixture is able to identify bearing errors, will indicate low efficiency in the detection of fault-based signatures, strengthened using 2 indicators one to pick the most effective comprehensive signature and a second to test process capabilities.

Q. In order to evaluate the position (on schedule) of defect-induced bursts in vibration signals, the study of singularity is carried out throughout all scales of the continuous wavelet transform, the amplitude of the modulus module max is adjusted and the defective vibration signature is highlighted and the bearing defect characteristics frequencies can easily be compared with f.

ARTIFICIAL NEURAL NETWORK

Artificial intelligence techniques, such as fugitive reasoning, the Artificial Neural Network (ANN), for the identification and analysis of faults have been used consistently and efficiently. ANNs consist of integrated processing units known as neurons, and throughout the learning period, they change their form. Non-linear categorized artificial neural networks have a parametrically constructed class of non-linear functions. Nonlinear functions are defined by summation and sigmoid composition. ANN is used for solving a number of template markers, predictors, optimizers and control issues. The back propagation method is used for training purposes, for which the weights of the ANN projections and effects are modified to reduce the error. ANN is an adaptive framework focused on knowledge streaming across the network that adjusts its structure. ANN executes a particular role during training by changing the interconnection weight and the mechanism until the error between the network output and the target output is below the default value, thus weight and bias are adjusted to reduce the error. Multi-layer feed forward multi-drive architectures have separate ANN propagation algorithms.

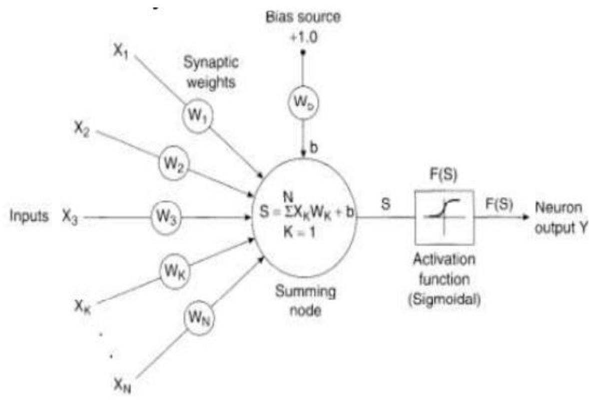

Fig.1. Model of a single non-linear neuron

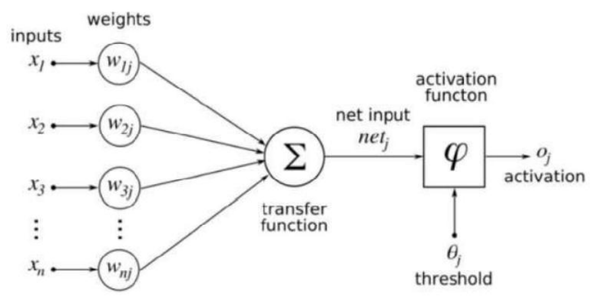

Fig.2. Artificial Neural Network (ANN)

One neuron is comprised of synapses, adder and induction. Bias is a neural network external parameter. Neuron model shown in Fig. 1. The following mathematical model may be interpreted.

$$y(k) = \emptyset\left(\sum_{i=1}^{p} W_{ki}X_I + W_{ko}\right) \qquad (4)$$

Input vector representing the p inputs and all weighted inputs are paired with the corresponding synaptic weights. A constant feedback threshold (bias) is used. The activation feature transforms the performance into a narrow output set.

DESIGNED METHOD FOR FAULT DETECTION BASED ON NEURAL NETWORK

This segment primarily aims at designing a neuronal network-based RNFC philter. Another neural network is then built to identify faults.

Intelligent RNFC filter design

The most popular approaches for the diagnosis of defects focused on the study of the vibration signal consisting of both good and defective materials.

However, it is unprofitable for fault detection to examine the stable aspect of the signal. The irrelevant portion is initially calculated using an artificial neural network dependent philter, and then the calculated portion from the key vibration signal sampled, to avoid the analysis of the non-striking fault section, that is, the stable portion. Figure displays the RNFC block diagram. And the following specifies all vector names:

v(n): Indicator of engine vibration. Y (n): approximate vibration signal insignificant element (non-bearing fault components).

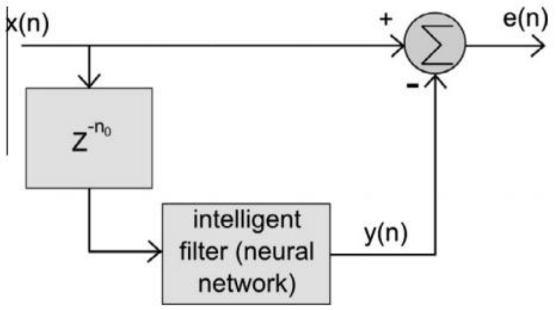

Fig. Removing non-bearing fault component (RNFC) filter.

CONCLUSION

BPN N is the best model chosen, because of the simplest configuration and capacity to do the network training in a lower CPU running period, BPNN model with one input neuron and one neuron in hider layer. Two or three bearings as an illustration for potential study may be used to develop this job. Another researcher can often use numerous strategies other than BPNN for artificial intelligence in seeking the dominant parameters.

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