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A General Regression Neural Network Model for Gearbox Fault Detection using Motor Operating Parameters

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Abstract. **Condition monitoring of a gearbox is a very important activity because of the importance of gearboxes in power transmission in many industrial processes. Thus there has always been a constant pressure to improve measuring techniques and analytical tools for early detection of faults in gearboxes. This study forces on developing gearbox monitoring methods based on operating parameters which are available in machine control processes rather than using additional measurements such as vibration and acoustics used in many studies. To utilise these parameters for gearbox monitoring, this paper examines a model based approach in which a data model has been developed using a General Regression Neural Network (GRNN) to captures the nonlinear connections between the electrical current of driving motor and control parameters such as load settings and temperatures based on a two stage helical gearbox power transmission system. Using the model a direct comparison can be made between the measured and predicted values to find abnormal gearbox conditions of different gear tooth breakages based on a threshold setup in developing the model.**

Keywords: Condition Monitoring, Gearbox, Static dataset, Fault detection, General Regression Neural Network.

I. INTRODUCTION

Condition monitoring (CM) is a technique for acquiring different datasets and analyzing them to assess the health and condition of equipment. Thus potential problems can be detected and diagnosed at an early stage in their development, providing the opportunity to take suitable recovery measures before they become so severe as to cause machine breakdown. To obtain accurate results CM collects large amounts of data with wide diversity including operating parameters, high density dynamic signals and special event datasets to produce historical trends which are presented to engineers and stored in databases. This gives rise to the problem that the volume of data is very large and the relationship between measurements is very complicated. Consequently, the CM data is not always understood properly [1] and the extraction of useful and meaningful information from the data is extremely challenging. In addition, because machine and sensor technologies are growing in complexity, combined with the recent progress in information technology (IT), data acquisition systems (DQS) can produce an overwhelming amount of data which is continuously increasing and contains features representing hundreds of attributes.

Among the different methods for condition monitoring of rotating machinery, artificial neural networks (ANN), in the recent decades have become an outstanding method exploiting their non-linear pattern classification properties, offering advantages for automatic detection and identification of gearbox failure conditions, whereas they do not require an in-depth knowledge of the behaviour of the system.

Vibration signals which have been widely used in the condition monitoring and fault diagnosis systems of rotating machinery [2-4] can be exploited as the detection medium in this case due to straightforwardness of menstruation and the rich contents of the signal incorporating system-critical information. However for fault detection and identification matters, the frequency ranges of the vibration signals are often wide; and according to the Shannon's sampling theorem, a high sampling rate is required, and consequently, large-sized samples are needed for the bearing fault detection purposes. Therefore due to existence of superfluous data and their large dimensionality, there is a requirement to pre-processing to extract an appropriate and economised feature vector which is essentially used to train a well-educated ANN.

In the literature, there are many signal processing tools for data analysis and diagnostic feature development. These include time domain averaging, power spectrum, cepestrum, demodulation, adaptive noise cancellation, time-series analysis, high-order statistics, time–frequency distribution, wavelet, etc., [5-7] and show good results in detecting gearbox faults. However, these techniques often need an additional vibration measurement system, which leads to high cost of the monitoring system.

This paper examines the performance of a model based condition monitoring approach by using just operating parameters for fault detection in a two stage gearbox. It has the potential to achieve cost effective monitoring system because the operating parameters are available in many systems. A model for current prediction is developed using a GRNN, which captures the complicated connections between measured variables and allows a direct comparison between the measured and predicted values to achieve gearbox fault detection.

II. MODEL-BASED CONDITION MONITORING

The aim of model-based fault detection and diagnosis is to create a model based on known and accepted mathematical and scientific principles verified and fine-tuned by past experience to generate accurate predictions of faults and defects likely to occur in target systems. Such models may be quantitative, qualitative or a combined system model. The model-based method is often referred to as an analytical method and has the enormous advantage that it is much less costly than constructing a real-life system for testing (possibly to destruction). Typically, the model of the target system is a continuous-variable dynamic system, with input(s) *u(k)* and output(s) *y(k)* in the presence of an unknown fault [8].

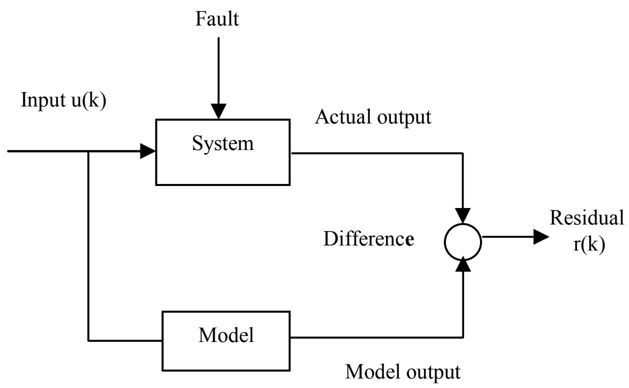


Figure 1: Model based fault detection

The model based fault detection method can easily find the fault in a system as shown in Figure 1. Residual *r(k)* in the figure is the difference between the outputs of the model and the actual system. The aim of the model is to generate a residual which can be used to indicate whether a fault is present and to identify that fault. However, the model can also be used "in reverse" information representing the behaviour of the system can be input to the model which produces an output that predicts what change in system components and/or features have taken place to produce that behaviour. The model can then predict likely causes of the change and even suggest other symptoms to search for to aid diagnosis.

A frequency division duplex (FDD) system includes three stages (procedures) with different functions: system modelling, residual generation and fault diagnosis. Firstly, a precise mathematical model is required to accurately predict system performance as model-based methods require such a model of the supervised process [11]. For most systems, such models are often very difficult to obtain. The robustness of the FDD system is often achieved by designing algorithms where the effects of model uncertainties and un-modelled dynamic disturbances on residuals are minimised and sensitivity to faults is maximised [9, 10]. Secondly, a set of residuals is generated to represent the deviation between actual and nominal features. Finally, the residuals are evaluated to relate to certain faults and to locate the fault if it is present. The model implementation and residual generation compose the model-based fault detection system.

III. GENERAL REGRESSION NEURAL NETWORKS

Artificial intelligence and neural nets are widely used for fault detection and diagnostic. General Regression Neural Networks (GRNN) is one of the type neural networks that can be used for fault detection and diagnostic. (GRNN) works as a multi-layer feed-forward network. It is the most common network today [12]. Due to their powerful nonlinear function approximation and adaptive learning capabilities, neural networks have drawn great attention in the arena of fault diagnosis [13]. GRNN is based on localized basis function NN which uses the probability density functions. The term general regressions imply that the regression surface is not restricted to be linear. In many previous applications of the GRNN, the sigma (sigma) which is referred to as the smoothing factor in the GRNN algorithm is usually fixed and thus not applicable in a dynamic environment [14].

The main task for regression is getting relations between input variables X and output variables Y based on data including representative set of elements for analysed field. If **X** is vector containing known inputs, it is possible to define the following scalar function

$$D_i^{\,2} = (\boldsymbol{X} - X_i)^T (\boldsymbol{X} - X_i) \tag{1}$$

This parameter provides the information about difference between two vectors. The estimate of output vector **Y** can be calculated by using this factor by:

$$\hat{Y}(\boldsymbol{X}) = \frac{\sum_{i=1}^{n} Y_i \exp\left(-\frac{D_i^{\,2}}{2\sigma^2}\right)}{\sum_{i=1}^{n} \exp\left(-\frac{D_i^{\,2}}{2\sigma^2}\right)} \tag{2}$$

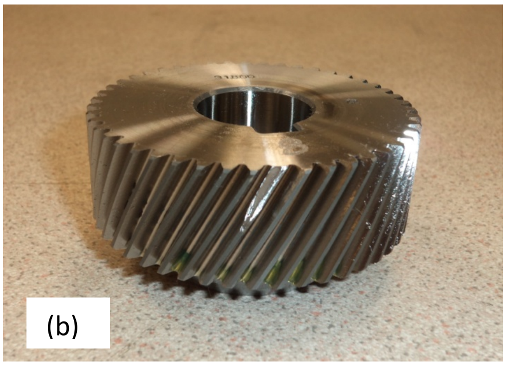
The major algorithm of the GRNN model is expressed by Equations (1) and (2). The estimate $\hat{Y}(X)$ is a weighted average of all the observed samples, Y_i, where each sample is weighted in an exponential manner according to the Euclidean distance, D_i, from each X_i. This appropriate weighting is explained by the inversely proportional relationship between the expression $\exp\left(-\frac{D_i^{\,2}}{2\sigma^2}\right)$ and D_i.

That is, as D_i increases, $\exp\left(-\frac{D_i^{\,2}}{2\sigma^2}\right)$ decreases and vice-versa. An optimal value for the smoothing parameter, σ- is the width of sample probability for each sample X_i, Y_i. Larger values of σ improve smoothness of the regression surface. It must be greater than 0 and can usually range from .01 to 1 with good results [15].

IV. GEAR FAULT SIMULATION

A tooth breakage is one of common faults in gearbox. Different levels of breakages on the pinion gear are examined in this part of research. Three levels of fault severity: 25%, 50% and 75% of a tooth are removed from three pinion gears respectively. Figure 2 illustrates the details of the faults for Gear 07 with 25% tooth breakage and Gear 08 with 50% tooth breakage. Although the defects look very large they not influence the transmission significantly because of high overlap ratio of the gear set.

Figure 2: (a) Gear No 7 with 25% tooth breakage (Baseline)



(b) Gear No 8 with 50% tooth breakage

V. GRNN MODEL DEVELOPMENT

GRNN was proposed by Donald Specht [14]. It uses non-iterative process and hence fast learning capability. In addition, it requires only a few training samples and very flexible to add new information with very small amount work of retraining. For these benefits, many condition monitoring applications applied GRNN to classify different fault cases. For example, GRNN is used to diagnosis different engine faults based on features extracted wavelet packet transform analyses of acoustic signals, showing GRNN is effective to classify the faults induced to the test engine[16]. In addition GRNN detectors of rotor faults of induction motor load, showing good results for rotor fault classification [17].

A. Data characteristics

The data were collected for the three gear sets: Gear07, Gear08 and Gear09 using a same gearbox case. Gear07, Gear08 and Gear09 were induced with 25%, 50% and 75% tooth breakage respectively. As there was not a healthy gear for more tests, Gear07 with the smallest gear fault are taken as the baseline for model development.

To evaluate the neural network, only three variables: AC current, load set points and gearbox temperate are explored for full understanding of the principle behind. Figure 3 shows eight data sets collected from eight independent tests respectively based on Gear07. It can be seen that each data set shows a gradual increase in the current with increase in load and temperature of the gearbox. The rate of current increase with load settings is very high and in a nonlinear behavior, which indicate a complicated correlation between the current and load setting and it is not easy to model it with a simple method.

In addition, the temperature also shows considerable influences on the current. As can be seen in Figure 3, a slight inverse influence on the current can be observed. However, the decrease rate becomes smaller at higher temperature, which again indicates a more complicated model is required to describe the connections between electrical current, load settings and temperature influences.

Figure 4 shows more details of the temperature influence. It can be seen that the current decreases with the increase in temperature at each load setting. It may be due to that the damping effect of lubrication decreases with temperature. Nevertheless, the correlation also shows a nonlinear way.

As this temperature influence is very clear, it will certainly impact the model development. Fault detection must include this influence for obtaining more accurate results.

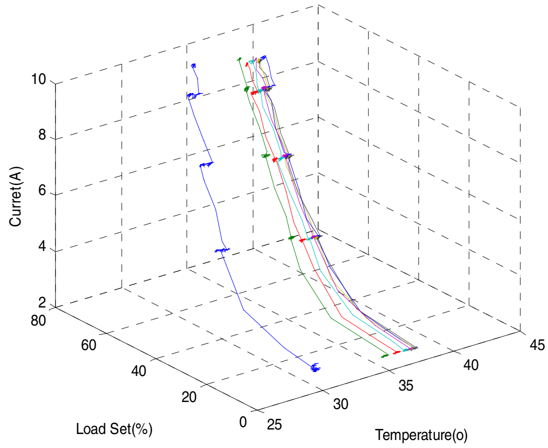


Figure 3: Data characteristics of current with temperature and load of gear in Gear07

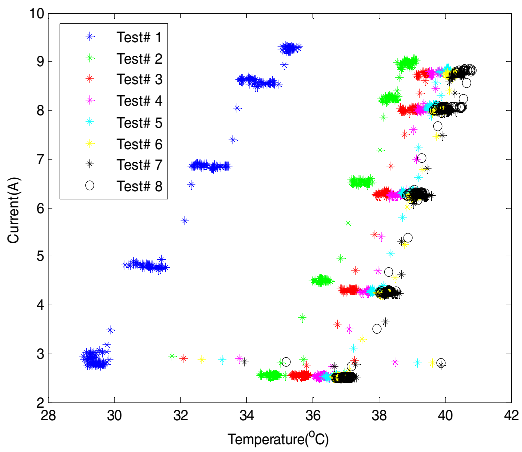


Figure 4: Data characteristics of current with temperature of gear in Gear07

B. Model development

To capture the relations between the three measurements and hence to perform the model based detection discussed in Section II, a GRNN model is developed using MATLAB software based on the baseline datasets from Gear07. The model has two inputs: temperature and load set points and one output: AC current.

To train the GRNN model, the datasets from Gera07 is used as the baseline for model development. In total there are 2088 data samples from 8 tests of different runs. The 2088 data points are divided into two equal subsets of 1044 points: one for GRNN model training and the other for model verification.

After several tuning cycles, it is found that when GRNN spread parameter is 0.06, the network produces a balanced prediction in generalisation and accuracy for the first subset of data. As shown in Figure 5, the measured values are all on the model surface where the training data set is distributed. On the other hand, the model produces very small output for these which are not in the training set, which means that if there is deviation of the inputs the output will be small and the difference between measured output and predicted output will be large.

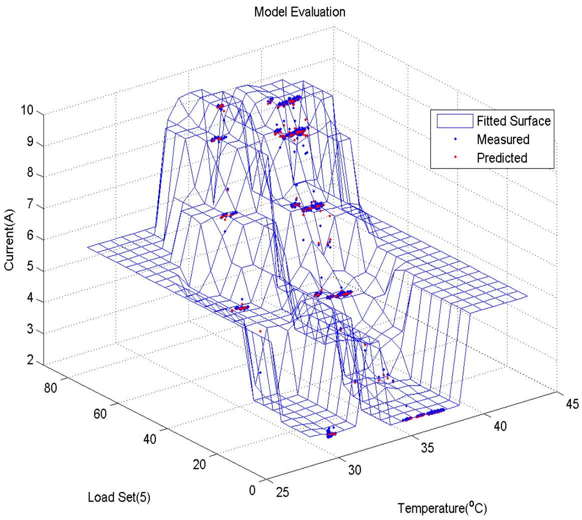


Figure 5: GRNN model inspection in the input space

C. *Model evaluation and detection threshold*

To confirm the model performance, the 2^{nd} dataset is employed as the input and output of the model developed from the 1^{st} set. To measure the quality of the model in fitting to the second data and to detect abnormalities from new datasets, a threshold is developed based on the 1^{st} dataset by comparison between the actual current and the predicted current. In particular, a threshold D_{th} is defined as 3 times of the root mean squared value between the real measurement and the model prediction:

$$D_{th} = 3\sqrt{\frac{1}{N}\sum_{i=1}^{N}(I_{mi} - I_{pi})^2} \qquad (1)$$

Where:
N = The number of sample.
I_{mi} = The actual value determined from measurements.
I_{pi} = the predicted value using the GRNN.

Figure 6 shows model verification results which are calculated using the model using the 2^{nd} part of data from Gear07. It can be seen that most of the errors are within the threshold and means that the model is fit the data very well.

On the other hand there are several data points exceeding the threshold. These data points are regarded as the outliers arisen from the load transient periods when the temperature measurements have delayed responses to current increases.

In general the model is sufficiently accurate for implementing fault detection for new data sets from other 2 gear sets.

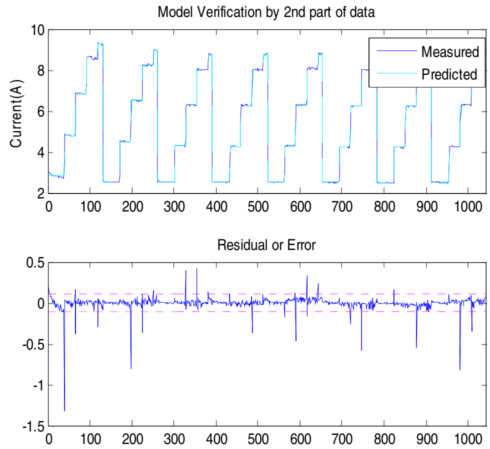


Figure 6: Model verification by 2nd part of data from Gear07

VI. Detection results and discussions

A. *Fault Detection on Gear08*

Figure 7(a) illustrates measured and predicted current for Gear 08 with 50% tooth breakage. It can be seen that the predicted current is very close to the measured one. However, many measurements have observed to have large difference from the predicted one.

To examine the difference only the residual data is predicted in Figure 7(b) and the details of the data points exceeding the threshold can be seen more clearly. Compared with Figure 6, many successive data points exceed the thresholds and indicate there is a fault in Gear08.

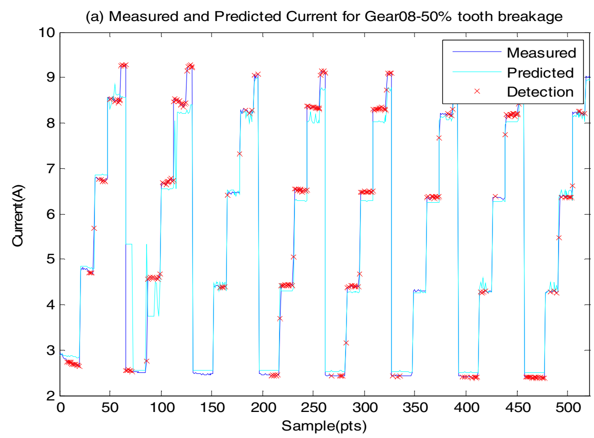
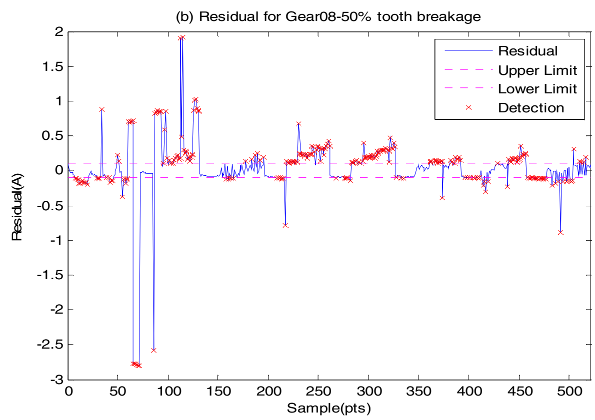


Figure 7:(a) Measured and predicted current for Gear08 under 50% tooth breakage



(b) Residual for Gear08 under 50% tooth breakage

B. *Fault Detection on Gear09*

Figure 8(a) illustrates measured and predicted current for Gear09 on which 75% tooth breakage was induced. It can be seen clearly that the predicted currents have large difference from the measured one. To examine the difference only the residual data is predicted in Figure 8(b) and the details of the data points exceeding the threshold can be seen more clearly. Compared with Figure 6, many successive data points exceed the thresholds, which indicate that there is a fault in Gear09.

Compared with Figure 7(b), the overall amplitudes of the errors are much higher and shows that this gear have a much severer fault than Gear08.

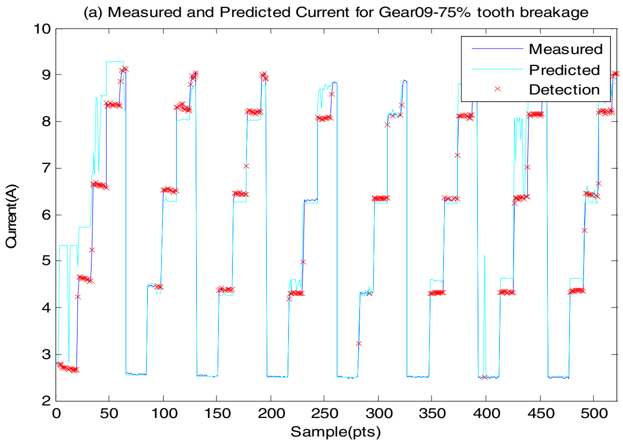
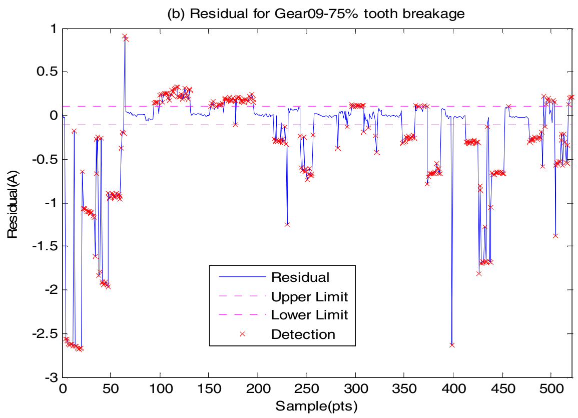


Figure 8: (a) Measured and predicted current for Gear09 under 75% tooth breakage



(b) Residual for Gear09 under75% tooth breakage

VII. Conclusion

A GRNN model based approach is presented in this paper to detect and diagnose different faults in a gearbox using motor operating dataset. The model developed using a baseline data captures the nonlinear connections between AC current, load setting and gearbox temperature. Test results show that the GRNN model based method is accurate estimators of the complex gearbox process and allows the generation of differences from baseline and between different gear faults. Therefore, it demonstrates the effectiveness of the proposed method for detecting and diagnosing tooth faults in a two stage gearbox just using motor operating parameters.

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