COMPARISON BETWEEN ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM AND GENERAL REGRESSION NEURAL NETWORKS FOR GEARBOX FAULT DETECTION USING MOTOR OPERATING PARAMETERS

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ABSTRACT

Condition monitoring of a gearbox is a crucial activity due to its importance in power transmission for many industrial applications. Thus, there has always been a constant pressure to improve measuring techniques and analytical tools for early detection of faults in gearboxes. This study focuses on developing gearbox monitoring methods using the operating parameters obtained from machine control processes rather than the traditional measures such as vibration and acoustics. To monitor the gearbox conditions, an adaptive neuro-fuzzy inference system (ANFIS) is used to capture the nonlinear connections between the electrical motor current and control parameters such as load settings and temperatures. The predicted values generated by the ANFIS model are then compared with the measured values to indicate the abnormal condition in gearbox. Furthermore, a comparative study of the results this technique and the general regression neural networks (GRNN) is also carried out. The comparison results show that the ANFIS model performs more accurately than the other model in gearbox condition monitoring and fault detection.

Keywords: Gearbox fault detection, static data, adaptive neuro fuzzy inference system, neural networks.

1. INTRODUCTION

Condition monitoring (CM) is a technique for acquiring different datasets and analyzing them to assess the health and condition of equipment. In so doing, 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 in association with the recent progress in information technology, data acquisition systems can produce an overwhelming amount of data which is continuously increasing and contains features representing hundreds of attributes.

Vibration is a widely used signal in the condition monitoring and fault diagnosis systems of rotating machinery [2-4]. To process vibration signal, several signal processing tools have been proposed. 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. Alternatively, static data being another signal can be used for detecting and diagnosing the faults in gearboxes. It contains mainly measurements from the controller, which are used to demonstrate the performance characteristics of the system. Additionally, this type of data can give a quick indication of system health. The static data, which are available in most machines, include armature current, load set, speed feedback, torque feedback, motor current, speed demand and have been explored based on a gearbox test system.

Among the different methods for condition monitoring of rotating machinery, artificial neural networks (ANN), which have become an outstanding method exploiting their non-linear pattern classification properties in the recent decades, have been 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. Fuzzy logic is combined with ANN to utilize the learning abilities of neural networks with human knowledge representation abilities of fuzzy systems. Adaptive neuro-fuzzy inference system (ANFIS) is one of these kinds of combinations, which is an integration of a fuzzy inference system with a back-propagation algorithm [8-9]. In recent years, many investigations have been performed to apply the ANFIS system for modelling of the engineering processes [10-12]. General regression neural networks GRNN was proposed by Donald Specht [13]. It uses a non-iterative process and hence a fast learning capability. In addition, it requires only a few training samples and is very flexible for adding new information with very little retraining work. For these benefits, many condition monitoring applications applied GRNN to classify different fault cases. For example, GRNN is used to diagnose different engine faults based on features extracted wavelet packet transform analyses of acoustic signals, showing GRNN is effective in classifying the faults induced to the test engine [14]. In addition, GRNN detects rotor faults of induction motor load, showing good results for rotor fault classification [15].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 produce a cost effective monitoring system because the operating parameters are available in many systems. A model for current prediction is developed using an ANFIS and GRNN to capture the nonlinear connections between the electrical motor current and control parameters such as load settings and temperatures. The predicted values generated by ANFIS and GRNN models are then compared with the measured values to indicate the abnormal condition in gearbox. The result obtained from the ANFIS technique was compared with the GRNN result.

2. METHODOLOGY

2.1 General Regression Neural Networks

General Regression Neural Networks (GRNN) is one of the types of neural networks that can be used for fault detection and diagnostics. GRNN works as a multi-layer feed-forward network which is the most common network today [16]. Due to their powerful nonlinear function approximation and adaptive learning capabilities, neural networks have drawn great attention in the arena of fault diagnosis [17]. GRNN is based on localized basis function NN which uses the probability density functions. The term general regressions implies that the regression surface is not restricted to being linear. In many previous applications of the GRNN, the sigma (σ), which is referred to as the smoothing factor in the GRNN algorithm, is usually fixed and thus not applicable in a dynamic environment [13]. Figure 1 is a schematic of the GRNN architecture with four layers: an input layer, a hidden layer (pattern layer), a summation layer, and an output layer.

2.2 Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS architecture consists of five layers in which the first and the fourth layers are adaptive nodes while the remaining layers are fixed nodes. The adaptive nodes are associated with their respective parameters, get duly updated with each subsequent iterations while the fixed nodes are devoid of any parameters [18-20].This system contains two inputs namely x and y and one output f which is associated with the following rules:

Rule 1: If (x is A_1) and (y is B_1) then ($f_1 = p_1x + q_1y + r_1$)

Rule 2: If (x is A_2) and (y is B_2) then ($f_2 = p_2x + q_2y + r_2$)

where x and y are the inputs, A_i, B_i and f_i are fuzzy sets and systems output respectively. p_i, q_i and r_i are the design parameters that are determined during the training process. The ANFIS architecture to implement these two rules is shown in Fig. 2, in which a circle indicates a fixed node, whereas a square indicates an adaptive.

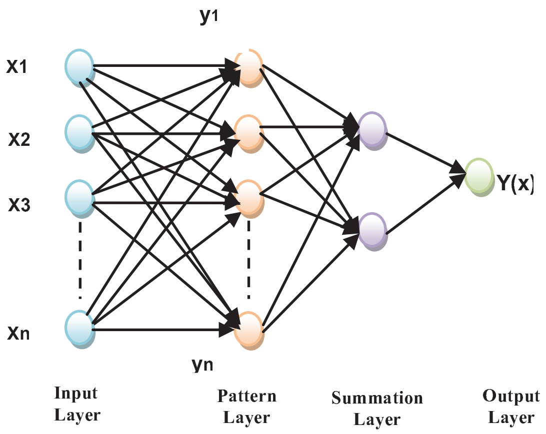

Figure 1: Architecture of GRNN

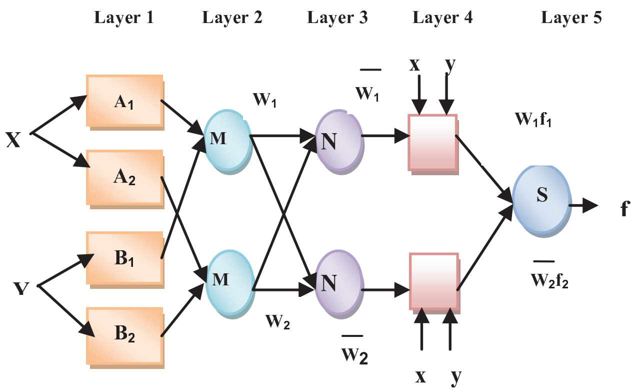

Figure 2 : Architecture of ANFIS

2.2.1 Learning Algorithm of ANFIS

As mentioned earlier, both the premise (non-linear) and consequent (linear) parameters of the ANFIS should be tuned, utilizing the so-called learning process, to optimally represent the factual mathematical relationship between the input space and output space. Normally, as a first step, an approximate fuzzy model is initiated by the system and then improved through an iterative adaptive learning process. Basically, ANFIS takes the initial fuzzy model and tunes it by means of a hybrid technique combining gradient descent back propagation and mean least-squares optimization algorithms. At each epoch, an error measure, usually defined as the sum of the squared difference between actual and desired output, is reduced. Training stops when either the predefined epoch number or error rate is obtained. There are two passes in the hybrid learning procedure for ANFIS. In the forward pass of the hybrid learning algorithm, functional signals go forward till layer 4 and the consequent parameters are identified by the least squares estimate. In the backward pass, the error rates propagate backwards and the premise parameters are updated by the gradient descent. [21]

3. GEAR FAULT SIMULATION AND DATA ACQUISITION

A tooth breakage is one of the common faults in gearboxes. Different levels of breakages on the pinion gear are examined in this part of the research. Two levels of fault severity: 25% and 50% of a tooth are removed from tow pinion gears.

The data were collected for the two gear sets: Gear07 and Gear08 using the same gearbox case. Gear07 and Gear08 were induced with 25% and 50% tooth breakage. As there was not a healthy gear for more tests, Gear07 with the smallest gear fault is 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 underlying principle. Figure 3 respectively shows eight data sets collected from eight independent tests based on Gear 07. 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 with a nonlinear behaviour, which indicates 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 in 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 the damping effect of lubrication decreasing with temperature. Nevertheless, the correlation also shows as nonlinear. 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.

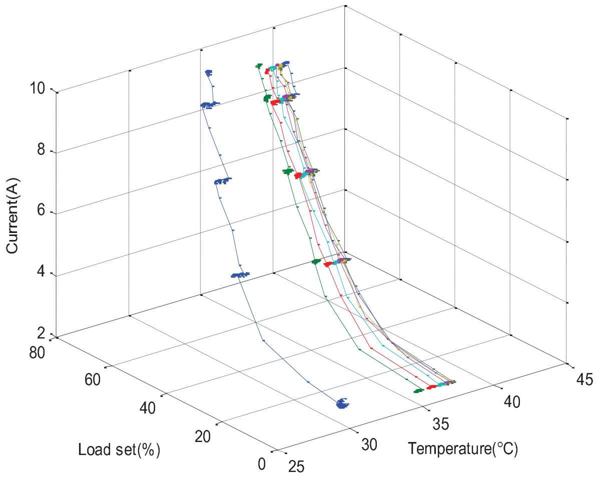

Figure 3: Data characteristics of current with temperature and load of gear in Gear 07

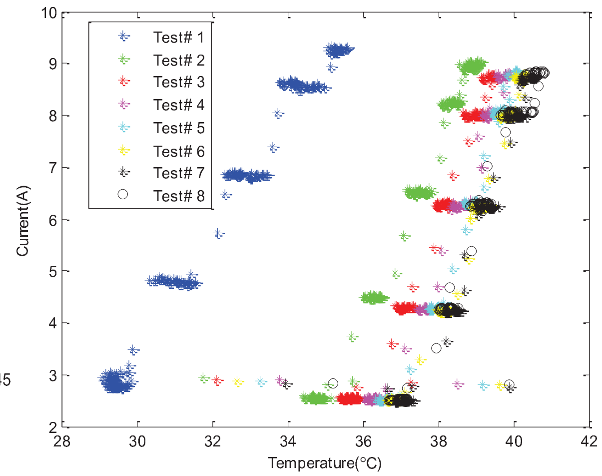

Figure 4: Data characteristics of current with temperature of gear in Gear 07

4. MODELS DEVELOPMENT

GRNN and ANFS models are developed using MATLAB software based on the baseline datasets from Gear 07. Each model has two inputs: temperature and load set points and one output: AC current. To train each model, the datasets from Gera07 are 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 model training and the other for model verification.

4.1 GRNN model development

After several tuning cycles, it is found that when GRNN spread parameter is 0.06, the network produces a balanced prediction in generalization 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 has only very small output if there is not 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.

4.1.1 Model evaluation and detection threshold

To confirm the model performance, the 2nd dataset is employed as the input and output of the model developed from the 1st 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 1st 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 is the number of sample, I_{mi} *is* the actual value determined from measurements, and I_{pi}. is the predicted value using the GRNN.

Figure 6 shows model verification results which are calculated using the model using the 2nd part of data from Gear 07. It can be seen that most of the errors are within the threshold and means that the model fits 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.

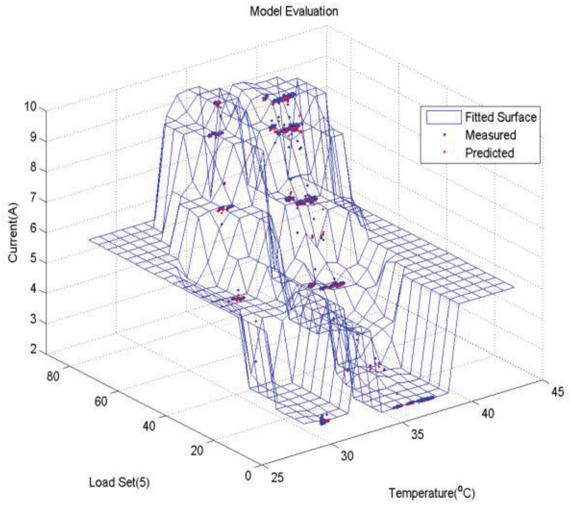

Figure 5: GRNN model inspection in the input space

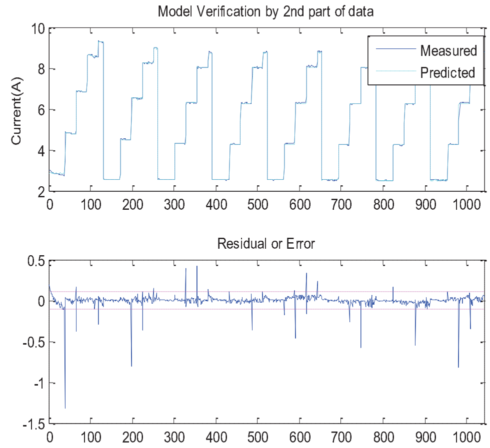

Figure 6: Model verification by 2nd part of data from Gear 07

4.2 ANFIS model development

For each input, a bell shape is chosen for each membership function (MF) and the number of MFs is 2. In order to evaluate the learning process, the convergence of root mean squared error (RMSE) is utilized. If the decreasing rate of the RMSE as well as the performance is not significant, the learning process can be terminated. Through the learning process, the parameters of MFs are automatically adjusted in order that the outputs of ANFIS model match the actual values in training data. In this study, after executing 300 epochs, all RMSEs of the outputs reach the convergent stage as shown in Figure 7. The initial shapes of MFs and their changes after learning are show in Figure 8. It can be seen that the MF parameters are significantly changed to match the outputs of model with the measured values in the training set. The result of the training process is presented in Figure 9. Obviously, the outputs of the ANFIS model are very identical with the measured values, which indicate that the ANFIS model has been well trained.

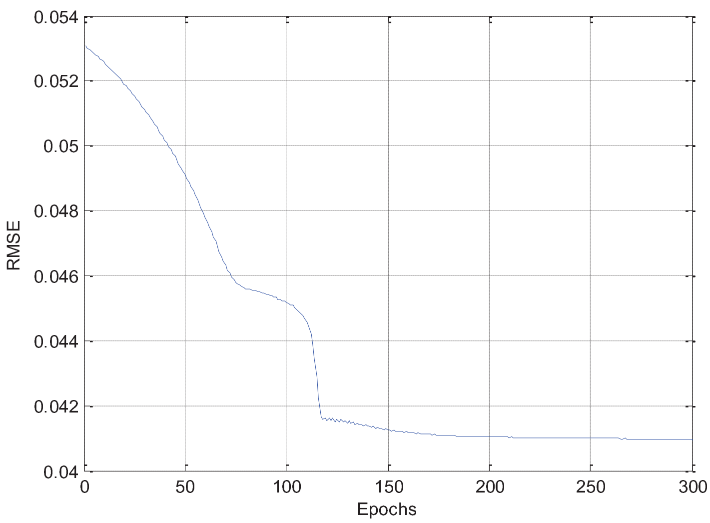

Figure 7: The network RMSE convergence curve

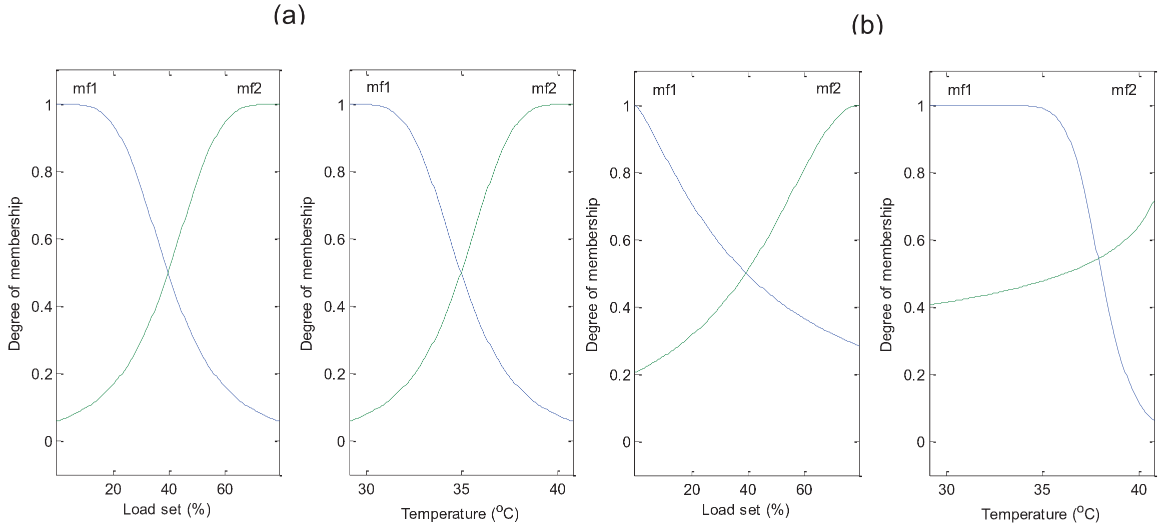

Figure 8: Bell shaped MFs a) Initial, b) Final

4.2.1 Model Evaluation and Detection Threshold

To confirm the model performance, the 2nd dataset is employed as the input and output of the model developed from the 1st set. To measure the quality of the model in fitting to the second data and to detect abnormalities from new datasets, the root mean square error (RMSE) is denoted as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(I_{mi} - I_{pi})^2} \tag{2}$$

where N is the number of samples, I_{mi} is the actual value

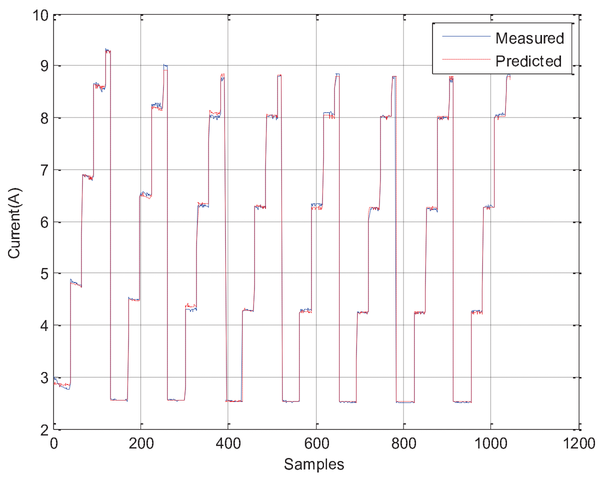

Figure 9: The training result

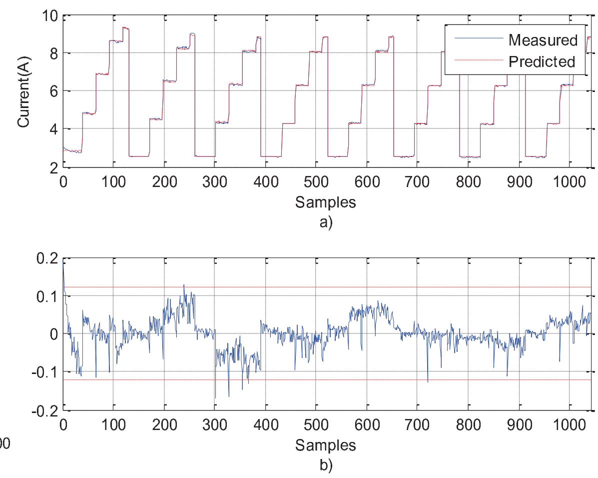

Figure 10: The testing result of ANFIS models a) Measured and predicted results,

Figure 10 shows model verification results which are calculated using the model using the 2nd part of data from Gear 07. In Figure 10(b), the two dashed lines are the upper and lower detection thresholds respectively.It can be seen that most of the errors obtained by a subtraction between predicted and measured values, are within the threshold, which indicates that the model fits the data with high accuracy. On the other hand, it also indicates that the data reflecting the process is healthy.
However, there are some data points exceeding the threshold. These data points are regarded as the outliers arising 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.

5. DETECTION RESULTS AND DISCUSSIONS

5.1 Fault Detection on Gear08 using GRNN

Figure 11 (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 are observed to have a large difference from the predicted one.
To examine the difference only the residual data is predicted in Figure 11(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.

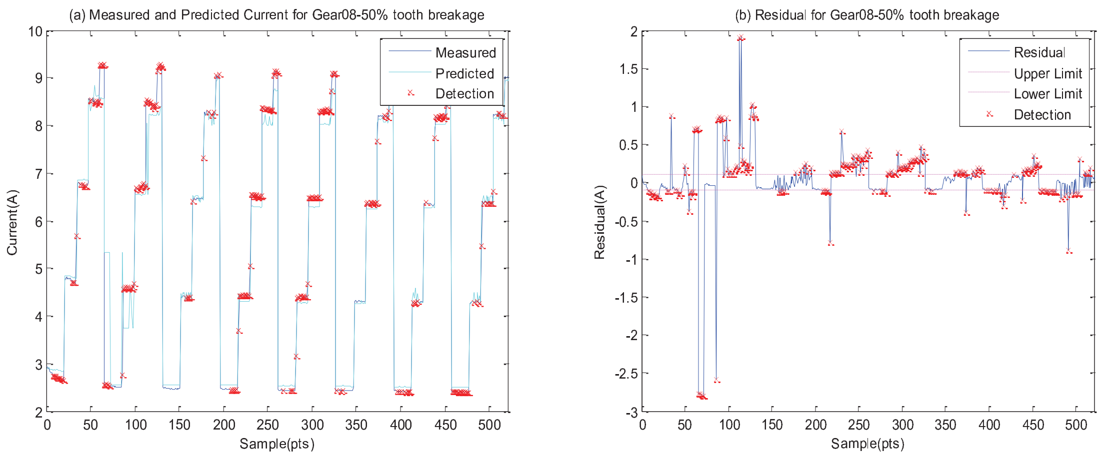

Figure 11: a) Measured and predicted current for Gear 08 – 50% tooth breakage, b) The residual

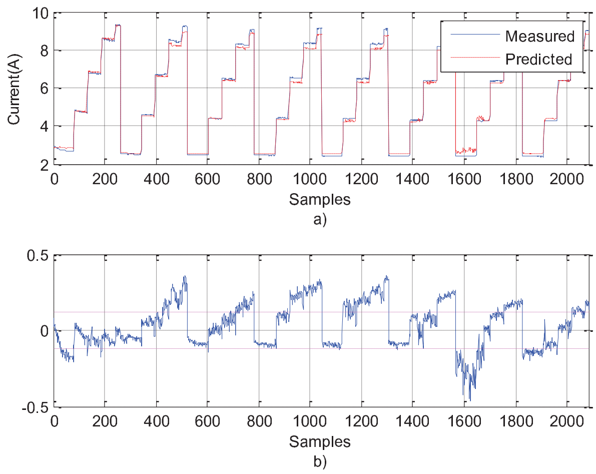

Figure 12: a) Measured and predicted current of the gear No. 08 – 50% tooth breakage, b) The residual

5.2 Fault Detection on Gear08 using ANFIS

Figure 12(a) illustrates the measured and predicted current for the gear No. 08 on which 50% tooth breakage was induced. It can be seen clearly that the predicted currents have a large difference from the measured ones. However, many measurements are observed to have large difference from the predicted one. To perform detection, the residual data which is the difference between the predicted and measured results presented in Figure 12(b) and the details of the data points exceeding the threshold can be seen more clearly. Compared with Figure 10, many successive data points exceed the thresholds and indicate there is a fault in the gear No. 08.

6. CONCLUSIONS

This paper confirms that it is possible to use static data which contains mainly measurements from the controller for monitoring mechanical faults in gearbox transmission systems. Based on data characteristics and future integration requirements, the ANFIS and GRNN approaches of gearbox fault detection and diagnosis have been presented for using the static dataset of motor operation. The models developed using a baseline data captures the nonlinear connections between AC current, load setting and gearbox temperature. Tests results show that the ANFIS model based method is an accurate estimator of the complex gearbox process and allows the generation of differences from baseline and between different gear faults. The accuracy of the ANFIS model was compared with the GRNN model. The comparison results reveal that the ANFIS model performs better than the ANN models. In additional, GRNN gives good performance results in every test case. Therefore, it demonstrates the effectiveness of the proposed methods for detecting and diagnosing tooth faults in a two stage gearbox just using motor operating parameters.

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