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The Diagnosis of a Gearbox Transmission System Using Electrical Control Parameters

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***Abstract*—Most of the techniques used to monitor and diagnose faults from machines are usually based on additional measurements which require high setup costs and installation difficulties. This paper focuses on developing a new sensorless method to monitor and diagnose different faults of a gearbox transmission system based on the parameters acquired from control systems. The control data, which are available in most of machines, including armature current, load set point, speed demand, motor current, torque feedback and speed feedback have been explored based on a gearbox test system. A non linear regression model is adopted to correlate the datasets to obtain residuals from the observed and the predicted control parameters. Subsequently a model based method is implemented to detect common faults such as lower oil levels and shaft misalignment in the gearbox system. The results confirm that it is possible to use existing control parameters for monitoring such faults.**

Keywords- Condition monitoring, Diagnosis, Gearbox transmission system, Control system parameters, Model based fault detection method.

I. INTRODUCTION

To develop more cost effective ways for early detection of faults in a gearbox transmission system, many methods have been investigated in data acquisition, signal processing and faults classification. In general, these methods can be considered to be based on vibration [1, 2], airborne sound [3], temperature/thermal image [4, 5, 6], motor current [7, 8, 9], acoustic emission and oil analysis [1, 6]. Unfortunately, none of these methods can be fully utilized by users because of low reliability and accuracy. Nevertheless, they all need additional costs and effort for setting up and maintaining the measurement equipment [10].

This study tries to explore a novel scheme for monitoring machines by utilizing control parameters from embedded sensors and available in most industrial applications. Thus the scheme does not require external sensors and accompanied sensor installation and this makes it easy and economical to be implemented in industrial environments.

Whether it drives a pump, a compressor or any other machinery, a gearbox transmission system is usually driven by an electrical motor with a control system which regulates operating characteristics to meet the requirement of the application. Many parameters have to be measured as inputs and outputs of the control system to fulfill various control tasks. By accessing these parameters it is possible to gain in parallel a rich set of information for processing healthy monitoring and fault diagnosis.

In addition, control parameters based monitoring can also be implemented away from the monitored machines for remote monitoring. As it is unnecessary to reach the machine being diagnosed to fix mechanical sensors for gathering data, it is particularly useful in places where usual methods are inappropriate such as deep wells in the oil industry. In this way it overcomes the problems with sensor poison or contamination and sensitivity changes due to prolonged exposure to certain harmful materials [11]. Therefore, this technique benefits from not using mechanical sensors because:

- Sensors often operate in a noisy environment and may be adversely affected by it;
- The different sources may interfere;
- Transducers may not fit easily into the space available;
- The instrumentation and transducers will usually require special arrangements and special handling;
- Data collected will, to a certain extent, be dependent on the position of the transducer.

The main objective of this paper is to evaluate this scheme based on a multi-stage gearbox transmission system. The test rig has a number of operating parameters that can be accessed. By analyzing these parameters a non linear regression model is developed to describe the interconnections between the parameters and to implement a model based detection strategy. Then the model based method is used to detect a number of common faults induced into the test rig.

II. MODEL BASED FAULT DETECTION

A. *Fault Diagnosis Methods*

Due to the increasing demand on maintenance, safety, economics and reliability, the use of fault detection and diagnosis systems have become important practice in the industry and hence related techniques have been studied extensively and many fault diagnosis methods have been developed in recent years. As shown in Fig. 1, they can be reviewed by two main schemes: model-based and data

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driven methods [12]. Both the model-based and data driven methods are based on the prior process knowledge and can be further classified into two general categories: quantitative and qualitative methods.

For a model-based scheme, either qualitative or quantitative can be considered as model based a priori knowledge. The model is generally developed based on some fundamental understanding of the physics of the process. This can be expressed in terms of mathematical functional relationships between the inputs and outputs of the system in quantitative models. On the contrary, these relationships in qualitative model equations are expressed in terms of qualitative functions centered on different units in a process.

Both models require data for estimating model parameters and both the methods are based on process data extracting some form of a model to perform fault diagnosis.

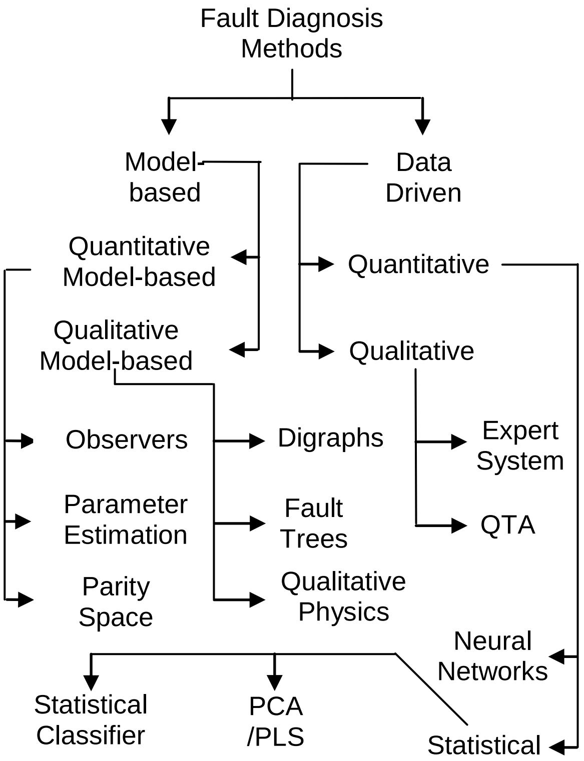

Figure 1. Fault diagnosis methods [12]

B. Model Based Fault Detection

One of the most powerful and very popular methods is model-based fault detection and diagnosis. It uses a mathematical model to measure any error signal from the system measurement and has two main steps. The first step generates differences between the actual and expected behavior. These differences which are known also as residuals are ‘artificial signals’ reflecting the possible faults of the system. The second step chooses a decision rule for detection and diagnosis.

The major advantage of this scheme is that it can be used under variable operating conditions because the model output can eliminate the influences due to changes in operating conditions. In addition, once the model is implemented with light demand in computational resources it is very suitable for real-time condition monitoring. Therefore, the focus of this study will be on developing a quantitative model-based scheme to utilize control parameters for monitoring a gear transmission system. This will allow the direct integration of the method into the control process in the future.

C. Model Selection

There are a wide variety of quantitative model types that can be considered for fault diagnosis. Some of the quantitative model types are first-principles models, polynomial curve fit, artificial neural networks, frequency response models and others. The first-principles models have been unpopular in fault diagnosis studies owing to the computational complexity in utilizing these models in real-time fault diagnostic systems and the complexity in developing these models. An important class of models which have been greatly investigated in fault diagnosis studies is the input/output or state space models. Thus the focus of this study is on these types of models to explore the gear transmission process.

In this paper, a nonlinear regression model is used to detect different faults of the gearbox transmission system. One of the main advantages in using a nonlinear regression model is the broad range of functions that can fit with good generalization performance. Many scientific or physical processes are inherently nonlinear; as a result, to attempt a linear fit of such a model would automatically cause poor results.

Moreover, it can benefit from the well developed theory for computing confidence, prediction and calibration intervals. It is well known that quite often the probabilistic interpretation of the intervals are only approximately correct, but these intervals still work very well in practice. Nonlinear regression shares the characteristic with linear regression of having very efficient use of the data. That is to say, nonlinear regression can provide good estimations of the unknown parameters in the model using relatively small data sets.

III. GEARBOX TEST RIG

A. Gearbox Test Bench

The test rig used in the experiment is illustrated in Fig.2. It consists of an induction motor, a two stage helical reduction gearbox with contact ratio 1.45 for the 1st stage and 1.469 for the 2nd stage, a DC generator which acts as a load device in the system. The AC induction motor is a four-pole, 3-phase induction motor and produces 11kW at 1465 rpm which matches the capacity of a 10kW gearbox. This specification and layout system share many features from industrial applications such as pumps, fans and compressors.

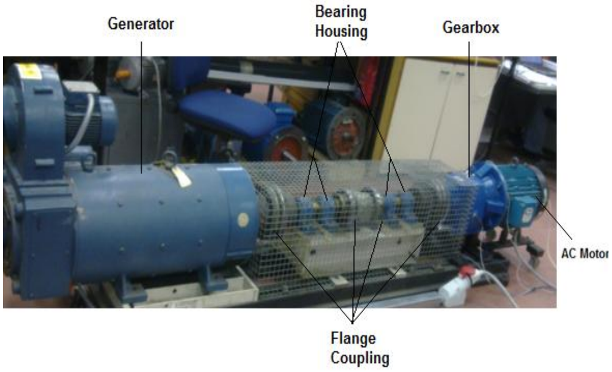

Figure 2. Gearbox test rig

B. *Control System*

Although the test rig described above is not very complex, it still needs a control box for the following reasons. Firstly, a repeatable, deterministic series of tests is to be undertaken on the rig to keep the motor speed and load profile identical through each test run. Secondly, different faults are to be introduced into the electrical or mechanical system at the same time as keeping the test condition parameters exactly the same from one run to another. Thirdly, any fault information is expected to be traceable in the test rig control system. Therefore, some modifications have been made to provide reliability and repeatability of test criteria required and to satisfy the exact test conditions required [13].

1) *Equipment used to automate the test rig*

Programmable logic controller (PLC)

A Siemens S7-222 PLC is widely used for machine and process control. It is the most suitable for automating the test rig and therefore is selected to control the test rig.

Input modules - Input modules have the ability to take various types of inputs, from digital (24VDC, 110/240VAC), to analogue (0-10VDC, 4-20 mA). Since the input signals are high-voltage, the modules protect the processor by isolating the high-voltage input signals from the low-voltage used by the processor.

Output modules - The function of the output modules is to make the output signal from the PLC in a form that can be used to control equipment.

Operator touch-screen - Siemens manufacture a touch-screen that is designed to communicate with the S7-222 PLC over the PPI network. The screen is programmed by Siemens WinCC Flexible Micro 2008 software. By using this software the user can easily program a number of operator screens that can contain input/output values, pushbuttons, text lists, graphics, and trending displays. All of the values used by the screen are programmed and referenced to the internal parameters in the PLC.

2) *Test rig modifications – closed-loop operation*

An encoder ‘Technology Box’ SSD Drives would be installed to the existing inverter for upgrading the 690+ Vector drive to a closed-loop operation. As part of this upgrade, an encoder would be fitted to the motor for speed feedback purposes and linked to the inverter drive. Closed-loop encoder control lets the motor torque and speed be more finely controlled with speed holding of typically +/-0.1%. Fitting of the encoder signal box is straightforward and is simply fitted into the front of the motor drive.

C. *Control Parameter Characteristicss*

The control system contains rich information for condition monitoring. In other words, there are many parameters which can be obtained from the control system. Parameters obtained from the control system so far are the demand and feedback of (torque, speed and current). In addition, an additional temperature measurement is added to the system for more accurate detection. These parameters are used for detecting gearbox conditions under low oil level and shaft misalignment. Fig. 3 shows a typical data set for all parameters. It can be seen that load related parameters have an increasing trend. Especially, the temperature has a slow change rate. This means that any faults that cause load variation may be detected by these parameters.

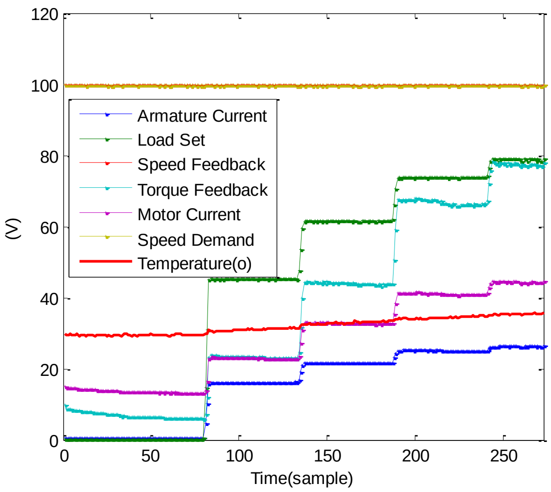

Figure 3. A typical data set obtained from control system

D. *Faults Simulation*

The faults that have been examined in this work are gearbox low oil level and shaft misalignment. All data has been collected for the two types of faults under the same test conditions which are at full speed and five different load steps: 0%, 44%, 60%, 72%, and 77%.

1) *Low oil level*

The lubrication oil of the gearbox is reduced to 50% of the gearbox oil level to simulate oil leakage problems. In general, a lower oil level will load lead more friction and hence more load to the system.

2) *Misalignment on gearbox output shaft*

Misalignment was created to the gearbox by inserting a shim of thickness 0.35 mm under the base of the gearbox of the mechanical load side as shown in Fig. 4. The same test procedures and conditions which had been applied for the first fault (gearbox low oil level) will be applied for this fault.

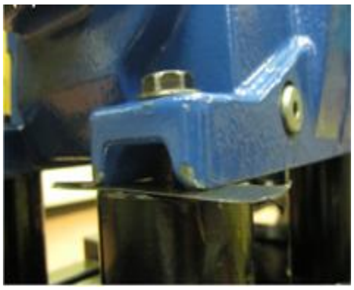

Figure 4. Gearbox misalignment

IV. NON-LINEAR REGRESSION MODEL BASED METHOD FOR FAULT DETECTION

All eight parameters from the system have been examined based on physical models such as the connection between electric power and mechanical power. It has been found that these conventional models are unable to include temperature influences. So by focusing on developing a model to describe the relation between load settings, temperature and output current, a multivariate nonlinear model is adopted and trained with baseline data. Subsequently the model and its residual characteristics are used to diagnose the faults simulated to the system.

A. Data Charactetristics

To evaluate the system behavior, three key parameters: AC current, gearbox temperature and load set point are selected to build a model to explore the input and output relationship at constant speed operation. Fig. 5 illustrates the connection of the three parameters of the data sets collected from three independent tests. It is clear that each data set shows nonlinearity in the current with increase in load set point and the temperature of the gearbox. However, the rate of current increase with load is much higher which indicates the output current has stronger connection to the load settings. These show a complicated relationship between the current and load setting.

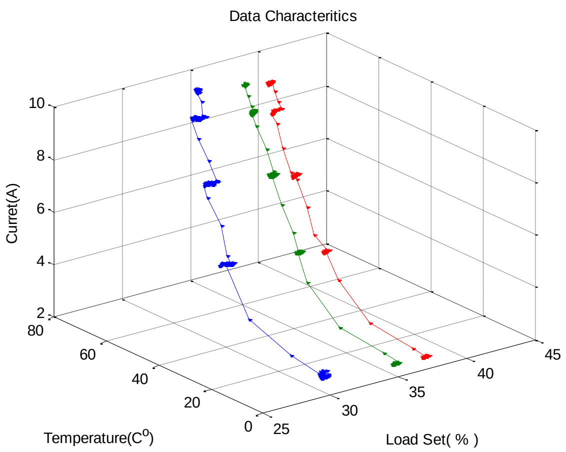

Figure 5. Data characteristics of current with temperature and load

In the mean time, the temperature also shows noticeable influences on the current. As can be seen in Fig. 5 and Fig. 6, a small inverse influence on the current can be observed under low load settings. Nevertheless, the decrease rate becomes smaller at high temperature where lubricant damping effect decreases with increasing in oil temperature. Once more this indicates a more complicated model is required to describe the relationship between current, load setting and temperature.

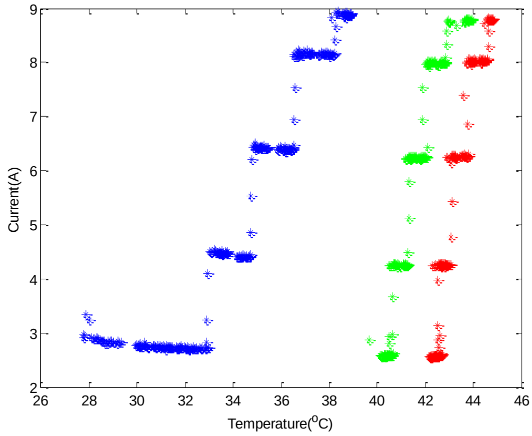

Figure 6. The correlation between AC current and gearbox temperature

B. Model Development

Based on data characteristics from the above data analysis, a multivariate nonlinear model is adopted in the form of equation (1). It has two inputs: load setting x_1 and temperature x_2, and one output: AC current y. In the model, the nonlinear term for temperature is not considered because temperature has a lower rate of influence on the current. In the meantime it has been validated during the process of model parameter optimization in which the residuals are compared for simple models and with low model residuals under different model structures. Finally, a model of (1) with five parameters β_i $(i = 1\ldots5)$ selected and its parameters are determined by using MATLAB software based on the first half of baseline datasets which has 2088 data samples from 5 independent tests.

$$y = \beta_1 + \beta_2 x_1 + \beta_3 x_2 + \beta_4 x_1 x_2 + \beta_5 x_1^2 \tag{1}$$

$$\beta_1 = -0.4956$$
$$\beta_2 = 1.2416$$
where $$\beta_3 = -0.0861$$
$$\beta_3 = -0.0285$$
$$\beta_4 = -0.5115$$

As shown in Fig. 6 the measured and predicted outputs for the 2nd half of the data are agreed. Moreover, a fitted surface produced over the entire input plane, is smooth in the region of interest, showing that the model fits the data well and has good generalizing capability for the region even where no training data are presented.

C. Model Evaluation based on Detection Threshold

From the nonlinear regression fitting procedure, a detection threshold D_{th} can be defined as the 95% confidence interval half-widths. For reliable detection, the 2nd half of the dataset is used to calculate the interval. Fig. 8 shows the model verification results which are calculated using the model using the 2nd part of the baseline data. In particular, the two dashed lines in Fig. 8(b) 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. In other words, it also indicates that the data reflecting the process is healthy.

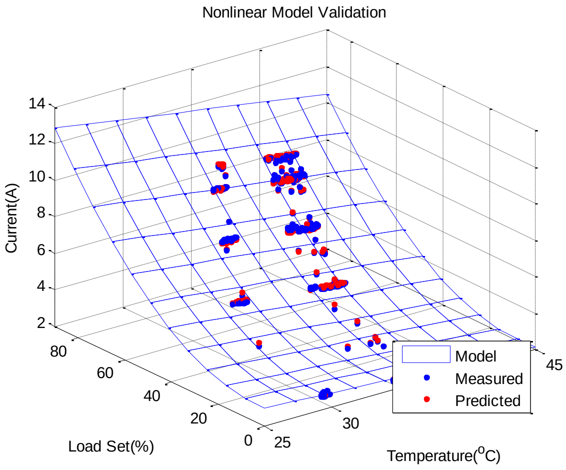

Figure 7. Non linear regression model inspection in the input space

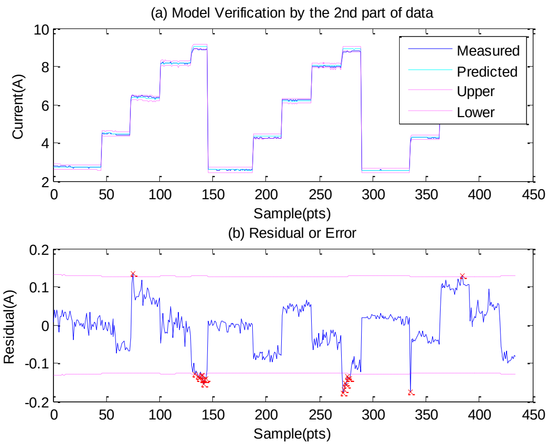

Figure 8. Model verification by the 2nd part of data

However, there are several data points exceeding the threshold. Careful examination shows that these data points, because of the outliers arisen from the load transient periods when temperature measurements have delayed responses to current increases. Simultaneously this may also indicate that the model is sensitive to small changes and is sufficiently accurate for implementing fault detection.

D. Model Based Fault Detection

1) Low oil level detection

Fig. 9(a) shows the model prediction against with measurement results. It can be seen that measured and predicted current are not close to each other, the measured current is below the threshold and the predicted is within the range of the threshold. The actual measurement is below the lower limit and draws less current because of the low oil level that cause less damping forces to the gear sets.

To perform detection, the residual data which is the difference between the predicted and measured results shown in Fig. 9(b) are used. It can be seen clearly that many data points go below the lower threshold, showing that it needs less power to drive the gearbox which is consistent with the analytic analysis of oil reduction effects in section 2. Therefore, this residual data increase in a negative way can be a good indicator for low oil levels.

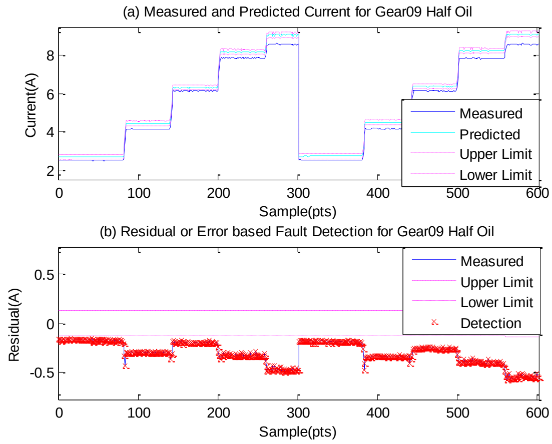

Figure 9. Residual Based Fault Detection at Low Oil Level

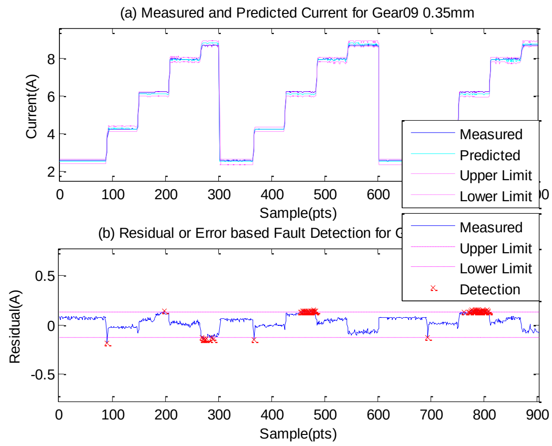

Figure 10. Residual based misalignment detection

2) Misalignment detection

Fig. 10(a) presents the comparison of AC current between measurement and model prediction. It can be seen that measured and predicted current are very close to each other and it is hard to see any significant difference. However, from the residuals in Fig. 10(b) it can be observed that there are a considerable number of measurements exceeding the upper limit of the threshold. This concludes that the misalignment will cause the residual exceeding the upper thresholds, showing that it needs more current to drive the gearbox due to the high torque oscillations from misalignment. The positive increases in residual can be an indication for detecting the misalignment and differentiating it from the low oil level which produces negative residuals.

V. CONCLUSIONS

This work confirms that it is possible to use existing control data for monitoring mechanical faults in gearbox transmission systems. Based on data characteristics and future integration requirements, a model-based approach is used for accurate and fast implementation over wider operating conditions. Because of the significance of temperature influences, a data driven nonlinear regression model has been used and evaluated to be able to describe accurately the complex connections between control parameters: load set points, gearbox temperature and electric current. In the meantime, a detection threshold is also obtained using the prediction confidence interval.

Using the model, a corresponding output can be produced for each measurement point to produce a residual for fault detection. The results show that two common faults: low oil levels and shaft misalignment can be detected and differentiated using the model-based methods, which show that the proposed method is sufficiently sensitive for mechanical faults detection and diagnosis.

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