Neural Network-Based Gear Failure Prediction in a Brushless DC Actuation System

Yan Chen[1], Christina Lucas[2], Jay Lee[2] and Michael Buehner[3]

[1,2]*School of Dynamic Systems, University of Cincinnati, USA*

chen2yn@mail.uc.edu
lucasci@mail.uc.edu
jay.lee@uc.edu

[3] *Control System, Woodward Inc. Fort Collins, USA*

Michael.Buehner@woodward.com

ABSTRACT

Due to its inherent efficiency and reliability, brushless DC (BLDC) driven actuation systems are widely used in a variety of industries such as aerospace, electric transportation and industrial positioning. However, it is inevitable that various types of faults can develop in the actuator either from the BLDC motor or geared positioning systems. This paper, focusing on actuator load positioning system failures, proposes a data-driven based failure prediction method. Run-to-failure data is first collected from test-beds of specific BLDC actuation systems and then critical features representing system performance are extracted. There are also dynamic behavioral tests used, which are designed to provide discrete measurements reflecting system health conditions. Ultimately, based on optimized mapping between the two groups of information, a general neural network model is developed to establish a nonlinear trajectory model for failure progression. The model also allows for prediction of gear failure without the interruption of performing dynamic behavioral tests during continuous working condition. This approach provides for real time monitoring of system behavior as well as possibility of the predicting the Remaining Useful Life (RUL) of the actuation system. Although many efforts have been done to predict gear wear based on vibration signal, the proposed method is formulated within a "sensor-less" environment and makes full use of existing on-board sensing information, which provides the possibility of a closed-loop control system for life management.

1. INTRODUCTION

Geared Brushless Direct Current Motor (BLDC) Electric actuators are common devices used for mechanical displacement, positioning or precision motion control. They are widely used in industry applications such as aircraft, natural gas and diesel engines, etc. These types of actuators usually consist of a BLDC motor, gearbox (referred as load system), and control board. Internal Faults in BLDC motors have been extensively investigated, such as stator, inverter, and rotor failures [1]. Besides motor related faults, the gearbox is another critical source of faults. Most of the gearbox condition based monitoring is focused on vibration analysis, which requires high-resolution accelerometers for diagnosis and performance prediction. However, in most industry applications, actuators are operated in a hostile environment, and even simple sensors installed would have to satisfy the strict requirements of compactness, lightness and reliability without sacrificing precision. Considering the cost and vulnerability of accelerometers, it was desired for the case study discussed to explore the feasibility of using only the existing feedback sensor technology of the actuator system for diagnosis and performance prediction. From the aspects of electric engineering, only a few efforts have researched the possibility of only utilizing the motor current and voltage information for identifying load system faults for an actuator such as: shaft imbalance, bearing and gear teeth wear out [2]. As such, there exist limited Condition Based Monitoring (CBM) efforts using the motor as a tool to identify external load gear system problems, not mention to predict gear failure. Traditionally, the actuator life is estimated statistically and conservative end life intervals are usually used based on offline accelerated life tests and empirical experiments. However, degradation of an on-duty actuator is a dynamic process and it is also affected by unanticipated variation during operation. Considering the limitations of current actuator system prognostics on sensing and inflexible end life, this study attempts to estimate gear failure degradation process of an actuator using only output position and motor stator current signals and predict its progress ahead.

The study in [2-5] mainly introduced and further reviewed both CBM or model based motor fault detection, identification and diagnosis methods. Many faults from both internal motor and external load system are studied in terms of their complex signatures in different signals and their combination. The problem of distinguishing between faults with the same fault signatures is also addressed. Researchers in [6] proposed a data-driven methodology for the remaining useful life prediction of a jet engine actuator system. The method utilizes the control system including hydraulic pressure, current and position to create a classification model, which can identify actuators state of health. For prognostic analysis, targeted at valve health, Kalman filter is used as a tracking or trending algorithm to model the failure progression. The valve health is estimated as a hidden state. Researchers in [7] propose a method to predict the failure state of starter motor gear engagement using Hidden Markov Models (HMMs). They use time–frequency features extracted from the motor current and methods for computing the parameters from limited data are presented.

Similarly, in this study, the real gear wear is not directly measured. A series of dynamic tests are conducted to evaluate gear condition with standard control signal. The failure progression modeling is formulated as a mapping issue between discrete failure "measurement" and real time observation. The position error waveform signatures quantify the failure and the real time observation are representative features of the system performance, which are extracted from state current and position error frequency signature. These features are processed to be more generic avoiding the influence of individual unit setup position. The neural network method is used to track the failure progression and perform the failure and remaining useful life prediction.

The organization of the paper is as follows. In section II, we first introduced experiment test-bed and then overview the proposed approach step-by-step. All of the extracted features are introduced in section IV as well as feature normalization methods. In section V, the failure quantification method is introduced. Finally, the General Neural Network method based failure progression method is introduced in section VI and RUL prediction is validated by two more testing units in section VII. This paper also introduces how to tackle mapping issues between discrete failure measurement and continuous feature variable.

2. ACTUATOR ACCELERATED TESTING

The test bed set up within Woodward Inc. to run three BLDC electric actuators to failure is seen in Fig. 1. The actuators are used in natural gas and diesel engines and are expected to achieve a life goal of 30,000 hours. For the test, springs were attached on the output shafts to intensify the working condition. This test bed had the first actuator, Unit 1, with on-board electronics, the second actuator, Unit 2, had of the electronics off-board and the third actuator, Unit 3, had similar configuration as the Unit 1 but with oil lubrication. Unit 1 was run to complete failure, while Unit 2 was terminated shortly after Unit 1, for it was needed for another project.

The following subsections describe the two types of tests that were conducted on the actuators: endurance testing and dynamic testing.

Figure 1. BLDC actuator test bed

2.1. Endurance test

In order to run the actuators to failure in a realistic window of time for data acquisition, endurance testing was performed in which the actuators were running constantly in a small range of full travel and five times faster at 10 Hz than normal conditions at 2 Hz. In normal conditions, the actuator would be shut down once per day, at this faster pace it was necessary to have the actuators automatically shut down every 5 hours. This shutdown allowed the spring to drive the actuator to a mechanical stop and also redistributed the grease on the gears. In order to keep dataset size to a minimum, only ten minutes of data were collected daily from the actuators at a 1 KHz sampling rate. The various types of data signals collected were almost identical on the units with the exception of no temperature reading from the actuator with off-board electronics.

2.2. Dynamic testing

In addition to the endurance test, dynamic tests were also performed on the actuators on a week-to-week basis. During the test, gear positioning system will run in full travel range under steady speed, which will allow inspection of all of gear teeth in motor pinion gear and frequent engaged teeth in drive train gears. The dynamic tests consisted of various signal inputs such as: steps, ramps, sweeps and steady state positions. Fig. 3 shows the raw transmission error, or difference between the shaft and motor positions, with the ramp input for all seven days the dynamic test was performed on Unit 1.

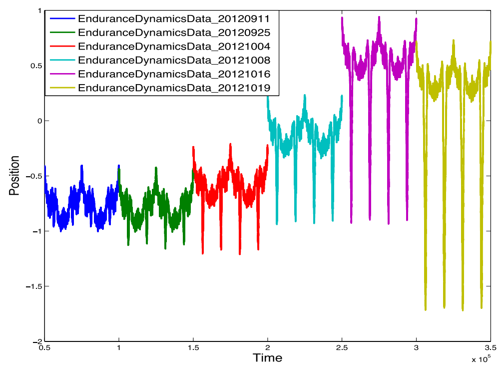

Figure 2. Raw transmission error for each dynamic test

3. Actuator Degradation and Remaining Useful Life Prediction

This research focuses on developing data-driven method for actuator remaining useful life prediction based on positioning gear failure progress modeling. On the one hand, the daily endurance data of position or current signals from on-board control system is used to extract performance-indicating features; Through frequency domain analysis, original signals can be translated to features that represent gear mesh t signatures. The input and output position signal are also analyzed together to quantify transmission error caused by nonlinear backlash over time. Since each unit has its own initial condition, Minimum Quantization Error (MQE) of Self-organizing map (SOM) method is used to convert all of critical feature into a single dimension health indicator by comparing them with consistent baseline normal condition from unit 2. On the other hand, weekly dynamic behavior test data provides quantitative information directly related to the gear wear. Based on the two groups of information, a simple General neural network based approach is used to develop baseline failure degradation model.

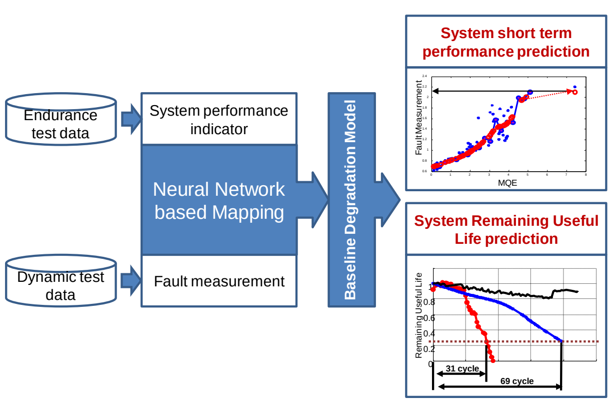

Figure 3. Method overview

As seen in Fig. 3. With baseline failure degradation model, system failure condition can be predicted without interrupting continuous work for dynamic tests; furthermore, after translating fault measurement to design actuator life information, the RUL prediction can be realized.

4. Feature Extraction

4.1. Transmission error

The transmission error (TE) of a gear, gear set, or of a complete gearbox is defined as the deviation between the theoretical angular position of the driven gear (output) and its actual position, when driving the input at a constant steady rotation. In this study, TE is defined as the deviation between gearbox driven motor position and the output gearbox shaft position. The absolute transmission error is also partially adjusted by the feedback control mechanism, because when the gearbox is degrading, the feedback position signal will try to compensate the loss by demanding more current.

$$TE = Shaft\ Position - Motor\ Position \qquad (2)$$

As able to clearly observe the position error caused over different rotational angles, the transmission error spectrum is calculated over time against position of motor shaft (as Fig. 4 shows). According to endurance tests, the motor is setup to run within one revolution (44 rad-38 rad), however the travel range has been changed twice at the end of actuator life. Before the changes, the transmission error variance at certain position of motor shows gradually increasing. This becomes a good indicator to actuator gear system performance. Therefore, average TE variance over motor drive range (in Fig. 5) is calculated as one of the critical features.

Instead of focusing on the absolute value of TE and motor or shaft position, the frequency domain features, which are directly related to motor and shaft rotation variations, are more concerned. Fig. 6 shows shaft position feature in frequency domain. Because the actuator is operated at 10hz and every stroke movement includes the forward and backward actions, the 20hz becomes signature frequency to indicate vibration increasing caused by friction and backlash. Apparently, Unit 1 has a more dramatic degradation pattern starting about one-third of the way into the test.

4.2. Frequency Response of gear system

Faults such as gear wear caused friction or nonlinear backlash in actuator positioning system can be considered as system instinct characteristic change. The variation of total backlash in the gear system will affect system frequency response characteristics. Therefore, in the study, the feature of power distributed at the low frequency range (around 20 hz) is extracted from the frequency response spectrum with input motor position and output shaft position to indicate system performance change as shown in Fig. 7.

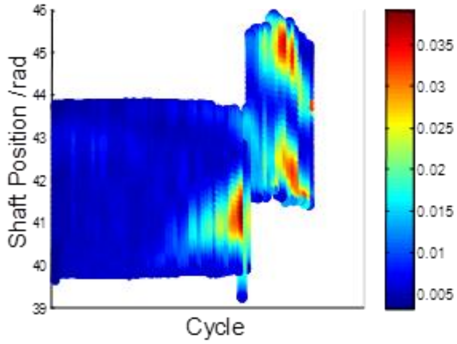

Figure 4. TE spectrum over motor position

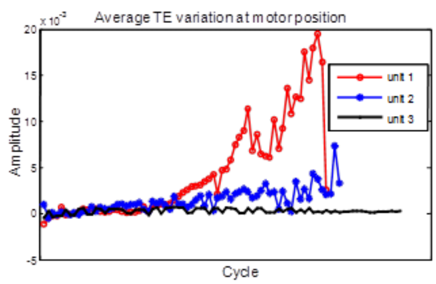

Figure 5 TE variation feature

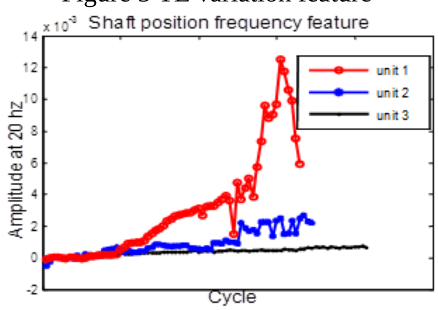

Figure 6. Position feature in frequency domain

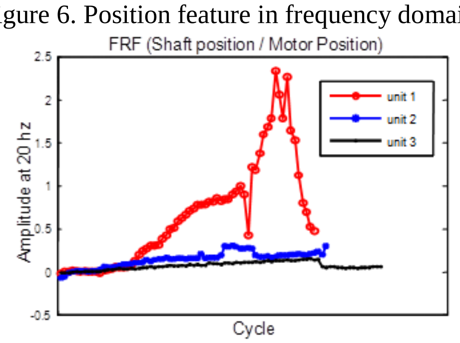

Figure 7. Frequency response at 20 hz

4.3. Current Signal Analysis

Stator current has been one of critical signals used in motor fault detection and diagnosis [4]. However, in particular, for the load system that usually consists of gearbox, coupling, and bearing supports, vibration based analysis is very popular and in fact, some electro-machine system systems are equipped with vibration sensors. Vibration sensors usually are delicate and expensive; however, they can detect early incipient failures. In this study, instead of using a vibration sensor, as suggested in [3], spectral analysis of stator current is utilized to spot faults from load system.

The faults from the load system mainly are induced by: worn and broken teeth on motor pinion gear, driving gear box, and the increase in friction caused by the diminishing lubricant [4, 8]. These faults will cause instability in load torque and result in pulsating components. As seen in (1), during steady speed operation, load torque has a nearly linear relationship with state current.

$$T_L \approx T_{em} = k_T I \tag{1}$$

Therefore, ideally, if the motor itself was considered under good condition, a stator current spectral analysis could indicate localized fault from gears in load system, particularly for the motor pinion and driving wheel gear.

In the dynamic testing, the ramp signal is fed into the system, which leads to steady motor rotation. The Welch Power density spectrum for the phase A stator current and its transformation in d-q coordination are shown in Fig. 8. The dynamic test is run at a 1 Hz frequency and the number of teeth on the motor pinion is 14, therefore the motor pinion gear mesh frequency can be seen around 14 Hz.

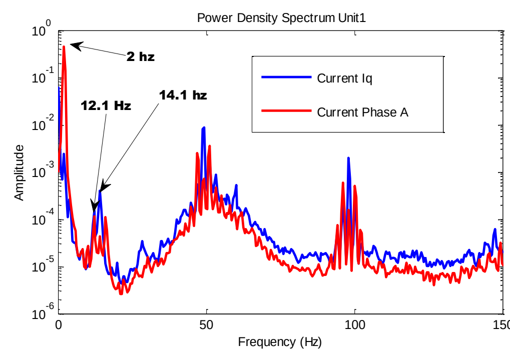

Figure 8. PDS of stator current

4.4. Feature Calibration and Normalization

In real utilization, every unit might be subjected to random emerging conditions. One of frequent condition changes comes from the demanding or input signal, material and supply power. During machining, produced parts might be slightly different because of variation in the input material. Actuators performance might also be changing due to drifting power supply and other thermal effects. As Fig. 8 shows, during endurance the test, Unit 2's current sensor suffers a high temperature meltdown. After replacing, the supply voltage has an increase, which caused an obvious change in the current signals. This variation has affected all of current related features.

As to recover the trendability of the system degradation reserved in the significant current features, a linear feature calibration technique is used to adjust feature values after the voltage increase as shown in Figure 9

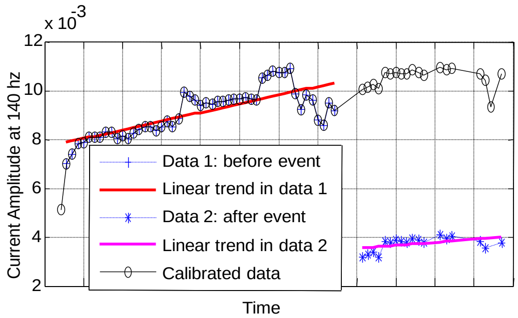

Figure 9. Current frequency feature and its calibration

Besides input variation, individual units will perform slightly different due to mechanical configuration variation or others. It is frequently observed that units start with different initial values; therefore the normalization step would be necessary to make different units compatible. Hence, every value in the feature matrix is normalized by comparing them with the starting baseline value of each feature as (3) shows.

$$f(x_{ij}) = \frac{\mathrm{f}(\mathrm{x_{ij}}) - \mathrm{M_j}}{\mathrm{M_j}} \tag{3}$$

In the equation, i is the instance index and j is feature index. $\mathrm{M_j}$ is the mean value of the first 5 samples in every feature.

5. FAILURE MEASUREMENT

During the dynamic test, with the ramp signal input to the system, motor is designed to run around 12 resolutions (from 3rad to 88rad) at steady speed. The output shaft finishes one stroke movement and is driven by geared load system that engaged with motor pinion. Since daily endurance tests always excise the system at a smaller range of one working cycle (one output shaft stroke), therefore, the frequent engaged motor pinion or driven train gear teeth are worn early and the same engagement position will have an apparent increase in transmission error compared with other position in dynamic test. As Fig.10 shows, at around 42 rad of every working cycle, compared with other position, the TE increases. In Fig. 10, the depth and time duration of the TE drop increases for each dynamic data set as depicted in the various colors. In Unit 2, because the calibration for the position was set opposite of Unit 1, the TE has an increased instead of decreased spike around the similar position. In this study, the depth of the drop in Unit 1 and the height of the spike in Unit 2 are used to qualify failure of the gear wear. From the Figure 10, it is obvious that Unit 1 has more severe degradation than Unit 2.

Compared with endurance tests that excise the actuator in a daily base and provide performance features, dynamic test is design to benchmark system failure. However, the dynamic tests are conducted less frequent than endurance tests, the size of samples of fault measurement are only 6, compared with around 60 samples from endurance test totally. The system performance and fault measurement mapping cannot be realized unless both the target and predictor variables have a compatible size of samples. Therefore, a curve fitting method is used to generate reasonable fault measurement for each performance sample. The fault measurement from initial dynamic test for Unit 2, before all of endurance tests, is taken as reference for all of Unit 2 fault measurements. The curve fitting result is shown in Fig. 11.

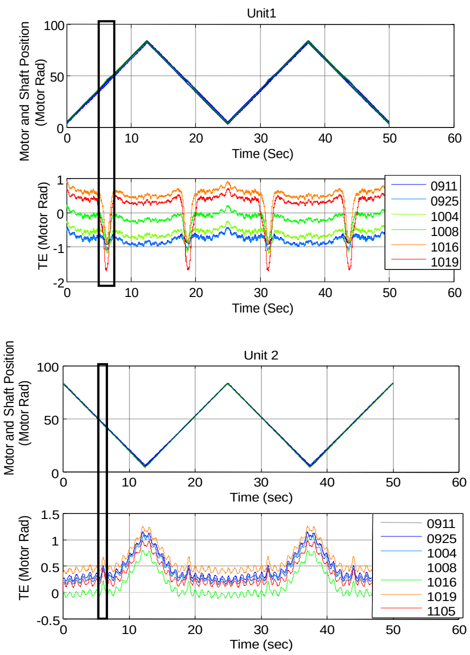

Figure 10. TE in dynamic test with ramp input

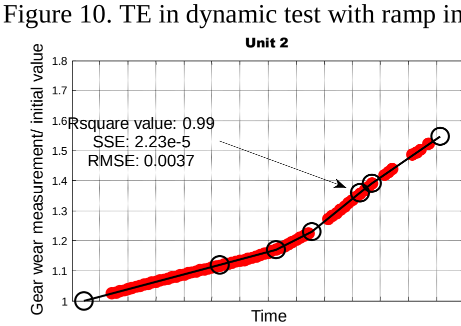

Figure 11. Curve fitting for gear wear

6. SYSTEM DEGRADATION MODELING AND PREDICTION

After evaluating features based on system knowledge and visualization of the trendability, four features, current frequency, shaft position in 20 hz, positioning frequency response and TE average variation over travel range, are extracted from endurance tests to formulate the data pattern of actuator system degradation. Consequently, the system degradation modeling issue becomes an optimized mapping issue between endurance test features (x_i) and failure measurement (y_i).

$$\min_f \sum_{t=1}^{T} L(f(\{x_1 x_2 \dots x_n\}_i), y_i) \quad (4)$$

In equation (4), $\{x_1 x_2 \dots x_n\}$ is performance features. Before the mapping, the features are first converted into Self-organizing map-minimum quantization error (MQE) values, that represent system performance health index.

6.1. Health index of actuator load system

Minimum Quantization Error (MQE) is a method of applying Self-organizing map (SOM) to measure system performance change by calculating the distance of current data with the normal baseline. The normal data are trained as the SOM map and the testing feature vector is compared with the weight vector of the all map units. The minimum distance between the new feature sample and the BMUs are used to quantify the health levels. Here, the baseline is selected from initial testing of unit 2. the MQE value of three unit test are calculated as shown in Fig. 12

SOM algorithm is a one layer neural network model. It also can be used to map high-dimensional data to a lower dimensional grid and convert the nonlinear relationship of the dataset into simple geometric distribution and then visualize it on a distance map [10]. During the map training iteration, the best matching units (BMU) are the neurons that have the closest distance to the input vectors.

$$MQE = \min ||D - w_{BMU}|| \quad (6)$$

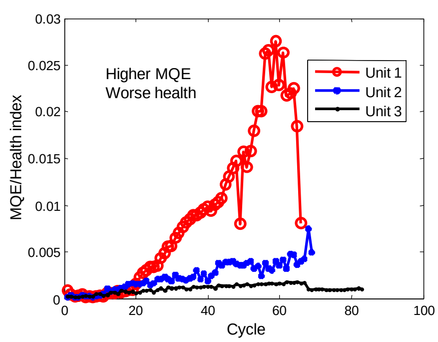

Figure 12. MQE value

Since only part of fault measurement samples are from the real dynamic test not curve fitting results, the original degradation modeling issue becomes a semi-supervised mapping optimization issue [9]. If it's assumed that Z is the subset of predictor variable samples in time series which contains the real measurement values:

$$\min_{f,Y} \sum_{t=1}^{T} L(f(mqe_i), y_i) + \lambda_z \sum_{t=z} L(f(x_i), z_i) \quad (5)$$

As mentioned in [9], there are two items added in the previous loss function (4). The first added item allows the points with real measurement value to have strong influence. The second item is to favor the progressing sequence of the Y measurement, adhering to prior knowledge; however, in this study, since the curve fitting results have shown promising goodness of fit, the influence of last term is ignored as equation (5) shows.

6.2. GRNN based degradation modeling

General regression neural network (GRNN) is used to map relationship between system performance health index and the off-board physical fault measurement. It also predicts system degradation. GRNN [11] is a one-pass memory-based neural network. It does not require an iterative training procedures like back propagation networks. It can be used for any regression problems without constrain on linearity. It approximates any arbitrary function between input and output vectors. As the training set size increases, the estimation error approaches zero [12]. A GRNN consists of an input layer, pattern layer, summation layer and output layer. During prediction, the predicted value y, according to a unknown input vector x, is:

$$y = \frac{\sum_{i=1}^{n} y_i exp - D(x, x_i)}{\sum_{i=1}^{n} exp - D(x, x_i)} \quad (6)$$

Based on (6), the optimization (5) is designed to find best spread of the radial basis function s, which is a parameter contained in D(x-xi), with least sum square error (SSE). It proved that when the spread equaled to 0.00031, the loss function of SSE value reached a global minimum.

Using this approach, an actuator degradation model can be established. Based on the model, given health value of MQE, the actuator degradation can also be predicted, for example, Fig. 13 shows prediction results for all unit 2 mqe value. in Fig. 14, the actual failure measurement of unit 2 from dynamic test is compared with predicted value. For unit 1 the first actual failure measurement already reaches 0.002. Based on the degradation model, unit 1's 28th cycle's mqe value is the one corresponding to the failure level.

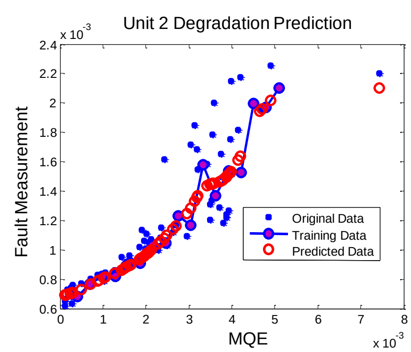

Figure 13 GRNN degradation model based on unit 2

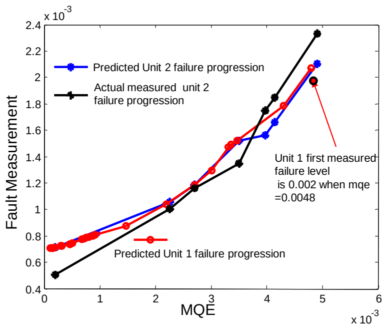

Figure 14 Degradation prediction for unit 1 and unit2

7. Remaining useful life Prediction

Among all of testing units, the unit 2 and unit 1 are finally disassembled after all of tests. Unit 2 proved to have 0.003 inch gear wear at motor pinion gear after 69 running cycle, which is 25% of remaining useful life left according to the product design. Unit 1 proved to fail much early than unit 2 and run further than accepted life term. At the end one tooth even fell. Unit 3, has special oil filter system and no failure symptom when the test is stopped. Therefore, all fault measurements of unit2 are linearly translated into remaining useful life as shown in Fig. 15. In the model only half of samples are used to train the model and the prediction MSE for all of samples is 0.009.

If assume the unit 2 as the baseline model as mentioned above, RUL of both unit 1 and unit 2 are predicted as Fig 16 shows. The prediction results are consistent with the real condition. Unit 1 is predicted to fail after 31 cycle. Unit 3 just consumed less than 20% of its life after 83 cycles

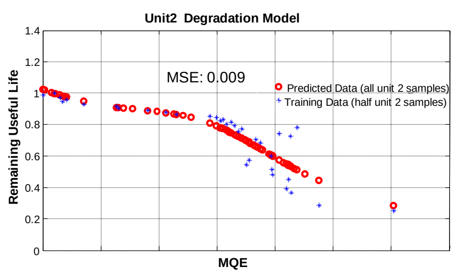

Figure 15. Unit2 Degradation prediction by RUL

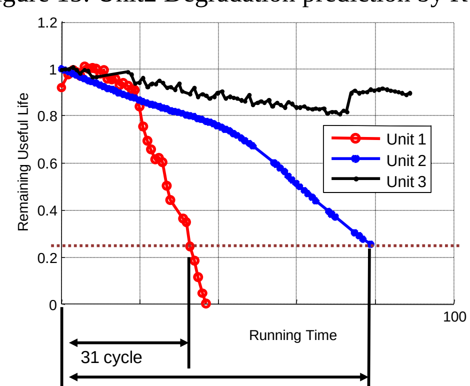

Figure 16. Unit1 and Unit 3 RUL prediction

8. Conclusion and Future work

The research discussed in this paper strives to predict gear failure and RUL in BLDC electric actuators using existing feedback sensors rather than adding cost with the inclusion of accelerometers. Through the implementation of a test bed within Woodward Inc., the proposed method is able to use run-to-failure endurance data to extract useful information from only current and position signals about the gear wear within the actuators.

A neural network based optimized mapping method is develop to model generic gear failure progression in the BLDC actuator system, which also lead to the prediction of gear failure before it reaches severe damage. The proposed method also made efforts to compensate for the semi-supervised mapping issue caused by "incomplete" discrete failure measurement samples compared to "complete" high sampling rate process observation features.

In this research, one actuator (Unit2) was used to develop the failure progression model and another two similar units were used to validate the method. Although each unit has different control mechanism and random operation variation, for similar gear failure issues, the proposed method is able to compensate the difference by extracting critical features to represent the failure progression, calibrating features based on every unit initial condition, and reducing feature dimension by MQE based method.

Using a general regression neural network, the paper successfully demonstrated the ability to predict the actuator gear failure progression and caused RUL. In the future, other regression modeling method will be benchmarked and this method will be improved for compatibility using run-to-failure endurance data from more actuators of the different type.

Acknowledgments

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References

Satish, R., et al., (2004). Diagnosis of potential rotor faults in brushless DC machines. in Power Electronics, Machines and Drives, Conf. Publ. No. 498.

Vachtsevanos, G., Lewis, F. L., Roemer, M., Hess, A., & Wu, B. (2006). *Intelligent fault diagnosis and prognosis for engineering system*. Hoboken, NJ: John Wiley & Sons, Inc

Rajagopalan, S., et al., (2006). Detection of rotor faults in brushless DC motors operating under nonstationary conditions. *Industry Applications, IEEE Transactions*. 42(6): p. 1464-1477.

Nandi, S. and H.A. Toliyat, (1999). Condition monitoring and fault diagnosis of electrical machines-a review. *Industry Applications Conference*, Thirty-Fourth IAS Annual Meeting. Conference Record of the 1999 IEEE.

Moseler, O., et al, (1999). Model-based fault diagnosis of an actuator system driven by the brushless DC motor. *American Control Conference*, 1999. Proceedings of the 1999.

Byington, C.S., M. Watson, and D. Edwards, (2004). Data-driven neural network methodology to remaining life predictions for aircraft actuator components. *Aerospace Conference*, 2004. Proceedings.

Zaidi, S.S.H., et al., (2011) Prognosis of Gear Failures in DC Starter Motors Using Hidden Markov Models. Industrial Electronics, *IEEE Transactions*, 58(5): p. 1695-1706.

Kliman, G. and J. Stein, (1992). Methods of motor current signature analysis. *Electric machines and power systems*, 20(5): p. 463-474.

Rahimi, A., B. Recht, and T. Darrell, (2007) Learning to transform time series with a few examples. Pattern Analysis and Machine Intelligence, *IEEE Transactions* on 2007, 29(10): p. 1759-1775.

Kohonen, T., (1990) The self-organizing map. *Proceedings of the IEEE*, 78(9): p. 1464-1480.

Specht, D.F., (1991). A general regression neural network. Neural Networks, *IEEE Transactions on, 1991*. 2(6): p. 568-576.

Cigizoglu, H.K. and M. Alp, (2006). Generalized regression neural network in modelling river sediment yield. *Advances in Engineering Software*, 37(2): p. 63-68.