The application of current variance to DC motor prognosis

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***Abstract*— DC Motors are ubiquitous throughout many industries and consumer products. Today's vehicles have upwards of x controlling windows, mirrors seats and headlights and steering. With electric vehicles this is extending to the drive itself. In this paper, we propose an approach for fault detection and motor prognosis. An assessment of the faults and/or wear of a DC motors (brushtype or brushless, permanent magnet or wound excitation) can be made by monitoring the mean and variance of the motor current at a given voltage. This approach has the benefit of low computational overheads. An on-line estimate of the variance can also be obtained without the need for batch sampling. It is demonstrated how this approach can be used to determine the health status of a motor. Finally, we use the approach to predict the remaining useful life of a motor.**

Keywords: DC Motor, prognosis

I. INTRODUCTION

DC Motors provide the driving force for many of today's consumer products. They are used in automobiles for controlling windows, windscreen wipers and increasingly electric power assisted steering. The failure modes can be both mechanical and electrical. Typical faults are both mechanical and electrical such as bearing failure; brush and commutator wear and loss of magnetic flux. In many situations motor repair is not seen as cost effective and the replaceable item is the motor itself. Several techniques have been developed to determine these faults such as Fourier and wavelet transforms [Moseler and Isermann 1998, Zanardelli & Strangas 2003] however these rely on fast sampling rates and complex signal processing techniques

[Nandi 1999] provides a review of condition monitoring and fault diagnosis approaches for electrical machines.

Motor Current Signature analysis (MCSA) is a widely used too for condition monitoring of electrical machines. It has been applied to the detection of a number of different faults in the bearings, stator, and eccentricies of induction motors. The technique is a frequency response method that can isolate the fault to the specific cause.

Motor faults, for instance winding short- or open- circuit, magnet(s) demagnetization, brush / commutator wear, mechanical rotor eccentricities (bent rotor or damaged bearings), will affect the performance and life of a motor. However, in many situations it is only necessary to determine the fault to the line replaceable unit and is not necessary to root cause the fault to the level of the specific fault. In this paper we introduce a technique for determining faults in DC motors based on statistical properties of the current waveform. We also show how this technique can be used as a prognostic to determine the motor state of health and the remaining useful life of the component.

The paper is organized as follows. In Section II several of the fault modes of a DC motor and described and the effect on the current waveform is shown. Section III describes how the current variance can be calculated on-line and used to determine the fault severity. Section IV presents some accelerated aging tests and how we can use this information to determine a prognosis of the RUL of a DC Motor. Finally, the paper concludes with a summary in section VI.

II. MOTOR FAULTS

Figure 1 shows an example of uneven brush wear of a motor. Figure 2 shows a normally flat commutator has been worn down. This motor damage may be because of manufacturing quality, high operating voltage or other factors and may not be immediately apparent in the motors performance.

Figure 1. Example of Brush Wear on a DC Motor

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Figure 2. Example of Commutator Wear on a DC Motor

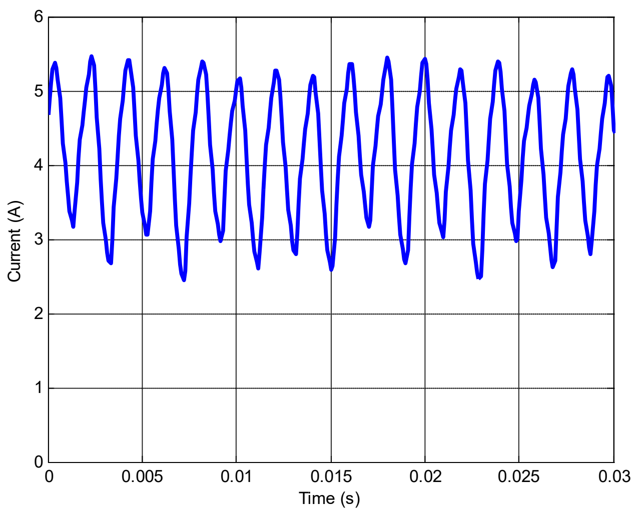

Figure 3. Current waveform for a healthy motor

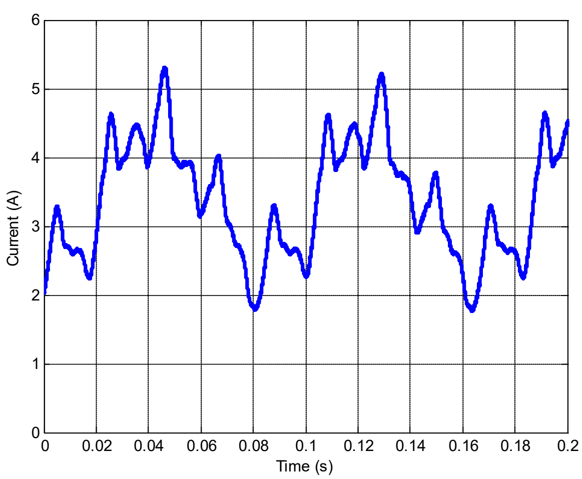

Figure 4. Current waveform for an aged DC Motor with brush and commutator wear.

If we compare the current profile of a healthy DC motor to that of one where we have worn brushes the waveforms look different. For a new motor (after bedding in) has a sinusoidal appearance as in Figure 3. The current is sinusoidal as the brushes change from one commutator segment to the next. For the worn motor, as shown in Figure 4, distortions appear as the contact between the brushes and the commutator is lost.

III. VARIANCE ESTIMATION

The current variance is a measure of the amount of variation of the current. Consider a waveform to describe the current given by, a sinusoid with a DC offset I_{DC} and zero mean, white noise η,

$$y = Asin(wt) + I_{DC} + \eta$$

The variance of y is given by $A^2/2$. Note that this is only a function of the amplitude of the sinusoid not the frequency. It is also invariant to the constant offset I_{DC} on the signal.

Figure 3 is better approximated by

$$y = I_{DC} + Asin(wt) + Esin(wt/8) + \eta$$

The eccentricity is captured by the $Esin(wt/8)$. In this case the variance is $A^2/2 + E^2/2$

If the eccentricity is 10% of the value of A then the variance is 1% affected. Gaussian white noise with st.dev 10% of A gives a variance of 2%

Variance has many benefits over other techniques such as wavelets and Fourier transforms, these include:

- Computational simplicity
- The variance is not a function of motor speed.
- The variance is affected by the amplitude and the shape of the waveform.
- St. deviation squared
- No requirements of fast sampling or complex signal processing tools (FFTs, Wavelets)
- It is a non-negative quantity so can applied directly be used as a performance function.

The basic definitions of variance can be found in any standard probability and statistics book [for instance Montgomery 1994]. The variance of the signal is given by

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2$$

where the mean is

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$$

Sampling this signal we can obtain an unbiased sample variance using

$$\sigma^2 = \frac{1}{n-1}\sum_{i=1}^{N}(x_i - \mu)^2$$

with a sample mean of

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$$

On-Line Variance Estimation

The estimate of the variance of the current signal can be obtained off-line by sampling the motor and calculating the (sample) variance for a batch of data. This can be repeated at regular intervals to determine how the variance changes.

Several approaches have been developed to obtain an estimate of the variance on-line moving [West 1979, Chan 1979].

Consider the definition of variance. For a random variable X, with expected value (mean) defined as $\mu = E[X]$,

$$Var(X) = E[(X-\mu)^2]$$

The variance is the expected value of the squared difference between the variable and its mean value. The mean or expected value can be approximate obtained online by a low-pass filter, so the above equation can be implemented as shown in figure 5.

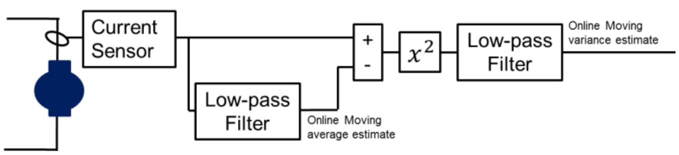

Figure 5. Online Variance Estimation of Current

Expanding the variance term gives

$$\begin{aligned} Var(X) &= E\left[(X-\mu)^2\right] \\ &= E\left[X^2 - 2\mu X + \mu^2\right] \\ &= E\left[X^2\right] - 2\mu E\left[X^2\right] + \mu^2 \\ &= E\left[X^2\right] - 2\mu^2 + \mu^2 \\ &= E\left[X^2\right] + \mu^2 \\ &= E\left[X^2\right] - (E[X])^2 \end{aligned}$$

The variance is equal to the mean of the square minus the square of the mean. This can be implemented in the same manor using low-pass filters as shown in Figure 6, but it less computationally efficient requiring an additional squared term.

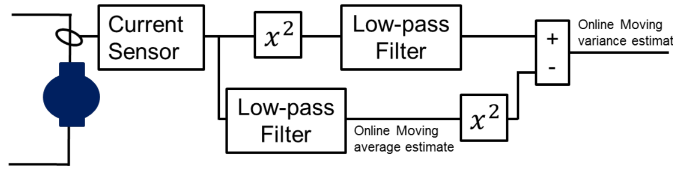

Figure 6. Online Variance Estimation of Current

In this paper we therefore considered the computationally simpler approach using low pass filters shown in Figure 5. First an exponentially weighted moving average is used to estimate the mean current value

$$\hat{I}_{mean}(t+1) = \lambda_1 \cdot \hat{I}_{mean}(t) + (1-\lambda_1) I^{Measured}(t)$$

The estimate of the mean is removed from the current signal. The result is then squared and used to calculate an exponentially weighted moving variance

$$\hat{I}_{Var}(t+1) = \lambda_2 \cdot \hat{I}_{Var}(t+1) + (1-\lambda_2)\left(I - \hat{I}_{mean}(t)\right)^2$$

The resulting approximate variance estimate can be tuned using the two parameters λ_1, λ_2. These are used to determine how fast changes in the variance can take places.

One important aspect is that the sampling rate should be a non-integer multiple of the motors speed, otherwise the waveform would always be sampled at the same positions in the current waveform.

IV. DIAGNOSIS & PROGNOSIS

An accelerated aging experiment was conducted for a DC motor. The variance of the current signal was measured at regular sample intervals for a DC motor. The motor was subjected to a constant voltage above the design specification of the motor to accelerate the aging process. Figure 6 shows the results obtained in blue. The first 100 samples are not shown since the motor was still in a bedding period. As can be seen the variance of the current remains low until around 900 samples when it starts to increase. The experiment was run for 2100 sample durations with no loss of performance of the motor observed.

The variance of the current can be used to diagnose the motor state of health by dividing the current ration into different regions. An estimate of the motors health can then be determined by observing which region the value of the current variance falls. Several values would need to be obtained because the variance estimate can be seen to fluctuate.

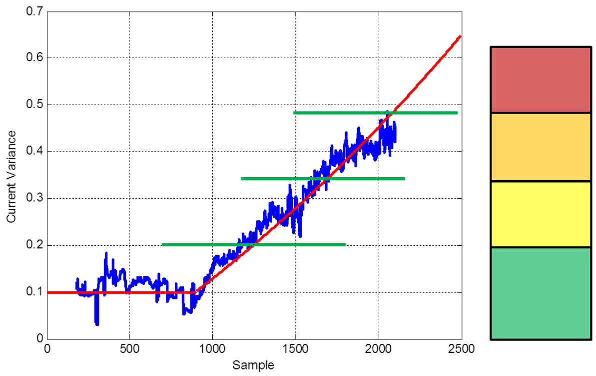

Figure 6. Current variance of DC Motors during accelerated aging tests

A method is developed below to formalize this. This method is generic in the sense it can be applied to any signal with any number of health states

First the region of the current variance is divided into different operating regions. For example with 5 regions we have

$$\text{region 1} \quad \hat{I}_{Var} < X_{\min}$$

$$\text{region 2} \quad X_{\min} \le \hat{I}_{Var} \le X_2$$

$$\text{region 3} \quad X_2 \le \hat{I}_{Var} \le X_3$$

$$\text{region 4} \quad X_3 \le \hat{I}_{Var} \le X_{\max}$$

$$\text{region 5} \quad \hat{I}_{Var} > X_{\max}$$

A discrete probability function is defined over these regions. The probability represents a health assessment estimate that the motor is operating in that region. For instance, a new motor will have the initial distribution set to [1,0,0,0,0] since the current variance will be in region 1.

The probabilities are updated each iteration interval t:

If the current variance is in the range of the ith health state then

$$P^i(t+1) = P^i(t) + \alpha\big(1 - P^t(t+1)\big)$$

Otherwise $(k \neq i)$

$$P^k(t+1) = (1-\alpha)P^k(t+1)$$

Also the constraint

$$\sum P^{new} = \sum P^{old} = 1$$

Applying this system to the data in figure 6, with the regions given by $X_{min} = 0.2$, $X_2 = 0.35$, $X_3 = 0.5, X_{max} = 0.8$ and $\alpha = 0.1$. The results are shown in figure 7. As can be seen the system remains in Region 1 and then gradually transitions to higher regions as the motor degrades. The motor degradation as transitioned from Region 1 to Region 3 by the end of the test.

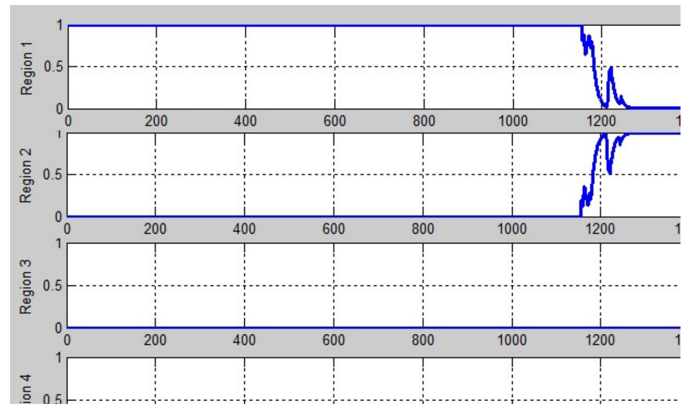

Figure 7 Health status regions for DC Motor

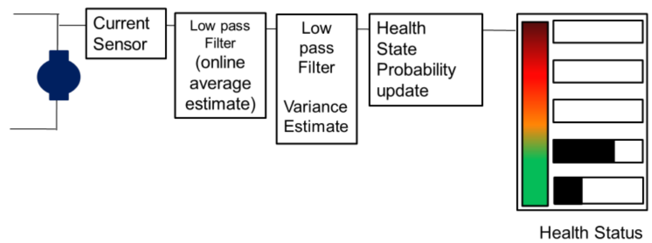

Figure 8. DC-Motor Fault Diagnosis & Prognosis Algorithm

While the above can be used as an indicator of the health of a DC Motor and can even be used to determine that the motor is near the end of its life it does not provide indication of the remaining useful life. This will be discussed in the next section.

V. REMAINING USEFUL LIFE

To estimate the remaining useful life from the accelerated aging test results we need a way of mapping from the accelerated aged data to that obtained on the actual motor whose life you are trying to estimate.

An approximate model is fitted to the accelerated aging data, shown in Figure 6. The data gives no indication of failure until around sample 900 where the variance grows. An exponential curve was fitted to the data from that point using standard regression techniques.

$$y = c - e^{k(X-900)}$$

Where X is the current sample. K was found to be 0.00374.

The aim is to use the model to determine the transition time from one region to another. We record the time when the motor transitions from region 1 to region 2 and from region 2 to region 3. We now know how long the motor was in region 2 for the actual motor and can ratio this against the test data. We can now extrapolate using the model to give an indication of how long it will take for the variance to get to a level that we consider to be the end of life.

VI. CONCLUSIONS

In this paper, it has been shown that by monitoring the mean and variance of the current, at a given voltage, an assessment of the electric machine's health (appearance and severity of faults & wear) can be made. The progression of the mean and variance features can also be fed into a health state estimator which can give an indication of remaining useful life.

This paper has shown:

1. Variance of current can be used as an indicator of the state of health of a DC Motor. It can also be used to as a prognosis and for remaining useful life of a dc motor.

2. A simple method to estimate (exponentially weighted moving) variance on-line using low pass filters.

3. A probabilistic method for determining the current health status of a motor that can be scaled to include as many different health regions as required.

4. An accelerated aging test for a dc motor

5. A method to use the accelerated aging tests and the health regions to determine the remaining useful life of a dc motor.

This single measure should not be used in isolation but combined with other indicators of motor health. Changes in variance of the current signal may be caused by external components connected the motor such as the gear box or to changes in the applied load. Parameter estimation can be used to determine changes in the motor resistance and back emf. This can also be done online and does not require high sampling rates. This approach has been patented [M.N. Howell et al 2015].

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