A Study on the Characteristic of Stator Winding Degradation Process and Its Life Estimation of Induction Motors

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ABSTRACT

This paper presents an analysis on the characteristics of the stator winding degradation process. A diagnostic and prognostic parameter, which is derived using the sequence component approach, is proposed. It is estimated using only the measurements of voltages and currents, which are easily obtained, and hence, the method can be implemented in real-time applications. A test is designed for generating stator winding inter-turn fault and accelerating it. The characteristic of the degradation process based on the prognostic parameter is discussed. The collected data is modeled and the remaining useful life (RUL) is estimated.

1. INTRODUCTION

Condition monitoring of electrical machines has received considerable attention during the past few decades due to their importance in industries. They are subject to faults due to aging, severe operating conditions, and harsh environments. Industrial surveys have shown that stator winding accounts for a significant portion of failures in electrical machines, and can cause catastrophic damage to the electrical machines and the associated systems (Bonnett & Yung, 2008, Han & Song, 2003).

Condition-based maintenance requires the diagnosis process to not only detect fault, but also evaluate the severity of the fault condition. In addition, the development of advanced condition-based monitoring requires the incorporation of the degradation prediction and remaining useful life (RUL) estimation into an integrated health monitoring system. The estimation of severity information becomes the enabler for this development. Even though the fault detection for stator winding inter-turn fault has been matured, the techniques for its severity estimation remain limited.

The fraction of shorted turns is estimated using observer and parameter estimation techniques, as proposed in (Kallesoe et al., 2004) and (Bachir et al., 2006), respectively. However, they are tested for only small values of fault loop resistance. In (Nguyen et al., 2015), a closed-form solution for fault parameters based on the steady-state analysis of a faulty machine is proposed, but the estimation accuracy can be influenced by the inherent imbalance of voltage supplies. In (Nguyen et al., 2016), an approximate equality constraint on fault parameters has been applied to simplify the state-space model, so that only one unknown parameter is estimated, and the other parameter is determined using the constraint. In this paper, a quantity, combining the effects of both parameters, is proposed. It is calculated directly from the sequence components of stator voltages and currents, and requires no estimation step.

Data for degradation process can be collected using accelerated tests (Sharp, 2012, Erbay, 1999). In (Erbay, 1999), the motor is degraded using both thermal and electrical stresses. The thermal stress is achieved by introducing the imbalance in one of the phases. The electrical stress is created by on-off motor in cycles in order to generate high transient currents. In (Sharp, 2012), motors are degraded using thermal aging process, but not solely for stator winding fault. In this paper, a new test, specifically to the stator winding, is implemented. A portion of the winding is deliberately degraded. That is, some winding turns are scratched and shorted. After that, the motor is run until complete failure.

In general, the contribution of this paper is fourfold. Firstly, a diagnostic and prognostic parameter is proposed. Secondly, a test is designed for emulating stator winding inter-turn fault and accelerating its degradation process. Thirdly, an analysis of the characteristic of the degradation process based on the parameter and designed test is given. Lastly, it is data modeling and RUL estimation based on the calculated parameter.

This paper is organized as follows. Section 2 presents the sequence component model of a machine under fault and the diagnostic and prognostic parameter. Section 3 explains the accelerated test. Section 4 provides analysis on the characteristic of the degradation process and the model identification and RUL estimation. Section 4 concludes the paper.

2. PROGNOSTIC PARAMETER FOR STATOR WINDING INTER-TURN FAULT

2.1. Description of Stator Winding Inter-Turn Fault and Fault Parameters

Fig. 1 shows the stator winding of a star-connected three-phase induction machine under inter-turn fault in phase a. The fault is represented by two parameters, the fraction of shorted turns μ, and fault loop resistance r_f, described as

$$\mu = \frac{N_{as_f}}{N_{as}} \tag{1}$$

where N_{as_f} and N_{as} are the number of turns in the faulty portion as_f and the total winding as of the faulty phase winding, respectively, and rf is the insulation resistance of the stator winding fault loop portion.

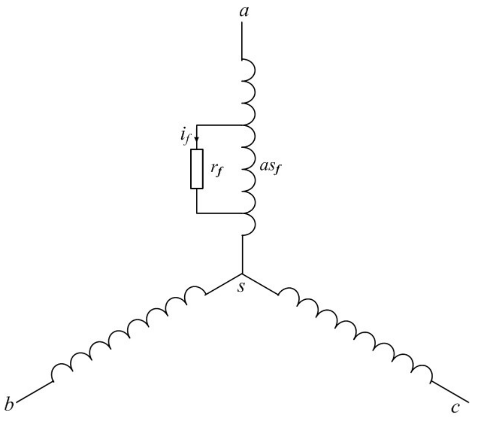

Figure 1. Stator winding under inter-turn short circuit fault in phase a.

2.2. Prognostic Parameter for Induction Machines

In this section, the sequence component model of a machine is employed to derive the proposed parameter. The equations of a faulty machine in the sequence component form are described in ((Nguyen et al., 2016, De Angelo et al., 2009).

$$\tilde{V}_{sp} = (R_s + j\omega_e L_s)\left(\tilde{I}_{sp} - \tfrac{1}{3}\mu\tilde{I}_f\right) + j\omega_e L_m \tilde{I}_{rp} \tag{2}$$

$$\tilde{V}_{sn} = (R_s + j\omega_e L_s)\left(\tilde{I}_{sn} - \frac{1}{3}\mu\tilde{I}_f\right) + j\omega_e L_m \tilde{I}_{rn} \tag{3}$$

$$0 = \left(\frac{R_r}{s} + j\omega_e L_r\right)\tilde{I}_{rp} + j\omega_e L_m\left(\tilde{I}_{sp} - \frac{1}{3}\mu\tilde{I}_f\right) \tag{4}$$

$$0 = \left(\frac{R_r}{2-s} + j\omega_e L_r\right)\tilde{I}_{rn} + j\omega_e L_m\left(\tilde{I}_{sn} - \frac{1}{3}\mu\tilde{I}_f\right) \tag{5}$$

$\tilde{V}_{sp}, \tilde{V}_{sn}$ are positive and negative components of stator voltages, respectively. $\tilde{I}_{sp}, \tilde{I}_{sn}$ are positive and negative components of stator currents, respectively. $\tilde{I}_{rp}, \tilde{I}_{rn}$ are positive and negative components of rotor currents, respectively. $\tilde{I}_f$ is fault loop current phasor. ω_e is the excited electrical frequency. s is motor slip. R_s, R_r are the stator and rotor resistances, respectively. L_s, L_r, L_m are the stator inductance, rotor inductance, and magnetizing inductance, respectively.

It can be observed from Eq. (3) and Eq. (5) that there exists an additional term, depending on fault parameters, due to the effect of fault. This fault-dependent quantity is $\frac{1}{3}\mu\tilde{I}_f$ and can be estimated as

$$\frac{1}{3}\mu\tilde{I}_f = \tilde{I}_{sn} - \frac{\tilde{V}_{sn}}{Z_{nn}} \tag{6}$$

where

$$Z_{nn} = (R_s + j\omega_e L_s) + \frac{\omega_e^2 L_m^2}{\frac{R_r}{2-s} + j\omega_e L_r} \tag{7}$$

When the machine is healthy, it takes a zero value. When the fault is present, it has a nonzero value. That is,

$$\Delta_n^h = 0 \tag{8}$$

$$\Delta_n^f = \frac{1}{3}\mu\tilde{I}_f \tag{9}$$

where superscripts h and f indicate the value of the indicator under healthy and faulty conditions, respectively, and

$$\Delta_n = \tilde{I}_{sn} - \frac{\tilde{V}_{sn}}{Z_{nn}} \tag{10}$$

For applications in which motors are operated near the rated speed, s is small, and hence Δ_n can be calculated assuming $(2-s) \approx 2$. That is, it is independent of slip, and can be used for sensor-less applications.

3. ACCELERATED TEST

3.1. Description of the Test and Data Collection

The machine used in the simulation is a squirrel cage induction motor of 1.5 kW, 415 V, and 10.2 Nm.

In this test, a portion of the stator winding is scratched, clearly shown in Fig. 2. The machine is run under full load and rated voltages after that. A dynamometer is used as the load on the motor under test. The measured stator currents and stator voltages are transferred to a computer through NI data acquisition module and LabVIEW software. The measurements of stator voltages and currents are collected according to the sequence, described in Fig. 3. The machine is run and stopped daily until complete failure occurs. Data is collected regularly after twenty minutes for a fixed interval of five minutes. The first data bundle is grouped in Group 1, the second data bundle is grouped in Group 2, and so on. The reason for this grouping is to compare data under homogeneous condition of same operational temperature. The machine is run until the shorted turns became charred. This is accompanied by a melting of grease, as shown in Fig. 4.

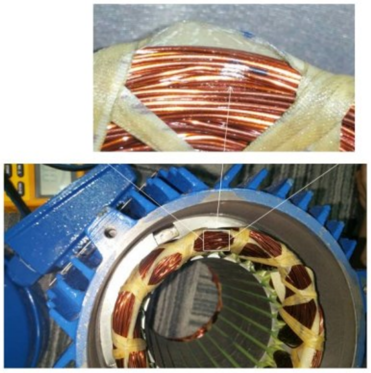

Figure 2. The stator winding is scratched to generate the initial degradation.

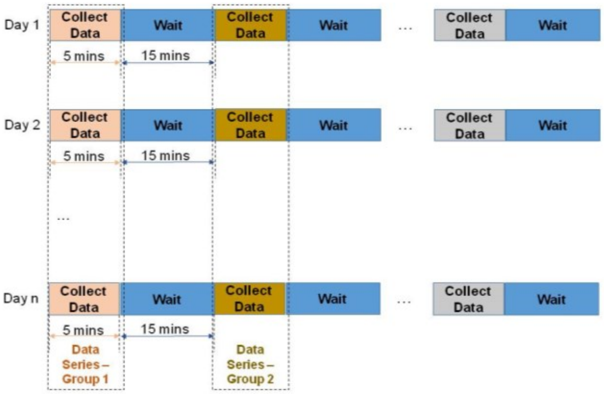

Figure 3. Data collection sequence and the grouping of data in ALT test.

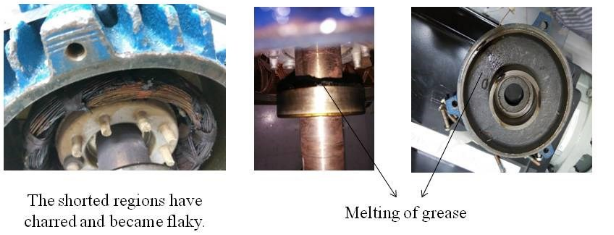

Figure 4. Machine is damaged.

4. EXPERIMENTAL RESULTS

4.1. Data Analysis and Pro-processing for Prognostic Purpose

Fig. 5 shows the magnitude of Δ_n for different groups. They have the same pattern, independent of the group order. Therefore, the average of the data of groups can be used as a single data for analysis and other steps. However, they are not monotonic. This is very interesting since it seems the data can be divided into two stages. The first stage is characterized by monotonic trend, but the second stage is noticed by higher peaks. The increase trend is there, but in the values and peaks, for the first stage and second stage, respectively.

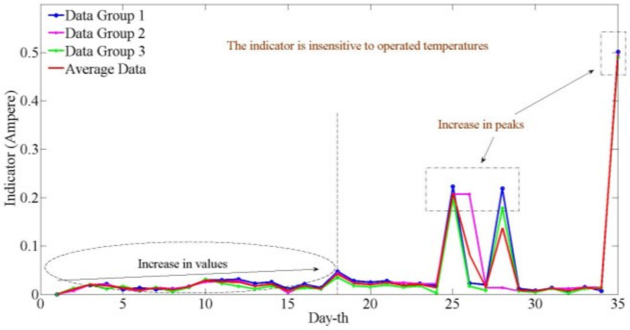

Figure 5. Magnitude of Δ_n in the test.

Such kind of characteristic shows the degradation trend, but is inconvenient for data modeling and RUL estimation since the data values are not always monotonic.

In order to overcome this limitation, in this paper, the magnitude of Δn is integrated to ensure the monotonic trend of the data. The integral is shown in Fig. 6. The interesting observation is that the degradation process progresses gradually at the early stage, accelerates, but goes gradually again after that (however, with shorted time than the first stage), and finally runs very fast to the complete failure.

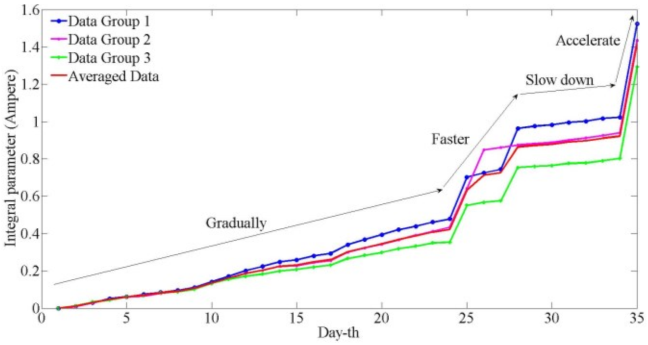

Figure 6. The integral of the magnitude of Δ_n.

4.2. Degradation Model Identification and RUL Estimation

A scheme for degradation model identification and RUL estimation includes the step of calculating the sequence component-based diagnosis and prognostic parameter, data pre-processing, data modeling, data prediction and RUL estimation. In order to avoid outliers, the data can be smoothed before modeling step is implemented. Based on the identified degradation model, the RUL can be predicted. The threshold for complete failure is taken as the value of data on the last day of test when the failure signature is significant.

Various techniques have been proposed and can be applied to identify the model of the degradation process based on the calculated data. In this paper, the Curve Fitting Toolbox in MATLAB software is used for this purpose. The degradation process can take various forms. As in (Saxena et al., 2008, Babel et al. 2014), exponential form can be considered to be a candidate for stator winding inter-turn fault. Also, based on the characteristic of the calculated data (the integral of the magnitude of Δn), exponential form is assumed for the degradation process. The prediction step is triggered at different instants, as shown in Table. I.

Fig. 7 shows the identification and prediction results for different cases of time instants for starting the prediction process. It can be observed that when more data are used for model identification, the estimated curve better matches the curve representing actual measured data. When the number of data is ten, the deviation between the two curves is significant, but it reduces considerably for other numbers of data. The RUL estimation errors for different cases are shown in Table 1. The data of twenty days and more can be considered to provide acceptable results (equal and less than 38.2 %).

5. CONCLUSION

This paper presents the characteristic of the winding degradation process and its estimation of RUL using an accelerated test. The diagnostic and prognostic parameter is proposed using the sequence components of stator voltages and currents. The integral method allows the monotonic trend in the values of the data so that model identification and RUL estimation are convenient. The progression of the prognostic parameter shows the various rates of degradation process with gradual development between higher rate process. The experimental results show the suitability of the parameter and its application to estimate RUL. The data identification step is implemented for an assumption of exponential decay, but other methods can be applied to more general forms of degradation process. This will be considered in future work.

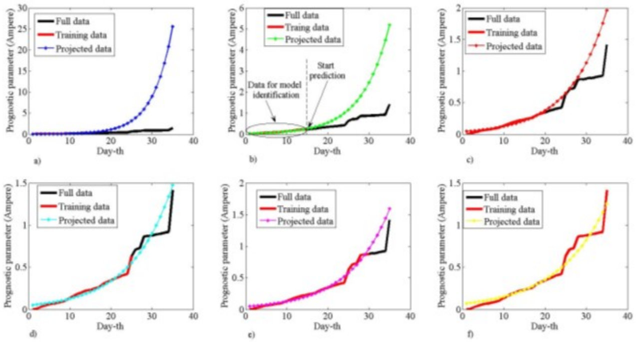

Figure 7. Identified curves for various cases of time instants for starting prediction steps. a) 10-th day, b) 15-th day, c) 20-th day (d), 25-th day, (e) 30-th day, f) 35-th day

Table 1. RUL estimation performance under different prediction instants.

Prediction Moment (day-th)	10	15	20	25	30	35
Estimated RUL error (%)	1704.6	265.4	38.2	4.1	12.3	11.5

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BIOGRAPHIES

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