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Incipient fault detection in induction machine stator-winding using a fuzzy-Bayesian change point detection approach

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ABSTRACT

In this paper the incipient fault detection problem in induction machine stator-winding is considered. The problem is solved using a new technique of change point detection in time series, based on a two-step formulation. The first step consists of a fuzzy clustering to transform the initial data, with arbitrary distribution, into a new one that can be approximated by a beta distribution. The fuzzy cluster centers are determined by using a Kohonen neural network. The second step consists in using the Metropolis–Hastings algorithm for performing the change point detection in the transformed time series generated by the first step with that known distribution. The incipient faults are detected as long as they characterize change points in such transformed time series. The main contribution of the proposed approach is the enhanced resilience of the new failure detection procedure against false alarms, combined with a good sensitivity that allows the detection of rather small fault signals. Simulation and practical results are presented to illustrate the proposed methodology.

1. Introduction

Induction motors are the most important electric machinery for different industrial applications. Faults in the stator windings of three-phase induction motor represent a significant part of the failures that arise during the motor lifetime. When these motors are fed through an inverter, the situation tends to become even worse due to the voltage stresses imposed by the fast switching of the inverter [1]. From a number of surveys, it can be realized that, for the induction motors, stator winding failures account for approximately 30% of all failures [2,3].

The stator winding of induction machine is subject to stress induced by a variety of factors, which include thermal overload, mechanical vibrations and voltage spikes. Deterioration of winding insulation usually begins as an inter-turn short circuit in one of the stator coils. The increased heating due to this short circuit will eventually cause turn to turn and turn to ground faults which finally lead the stator to break down [4].

Although there is no experimental data that indicate the time delay between inter-turn and ground insulation failure, it is believed that the transition between the two states is not instantaneous. Therefore, early detection of inter turn short circuit during motor operation can be of great significance as it would eliminate subsequent damage to adjacent coils and the stator core, reducing repairing cost and motor outage time [5,6].

However, early stages of deterioration are difficult to detect. In general, most of the previous references present approaches for dealing with abrupt faults in the stator winding, which are easier to be detected than incipient faults. In spite of these difficulties, a great deal of progress has been made on induction machine stator-winding incipient fault detection. Methods that use voltage and current measurements offer several advantages over test procedures that require machine to be taken off line or techniques that require special sensors to be mounted on the motor [7]. Other methods, in the context of abrupt fault detection related to the stator-winding, can be found in [8–12]. Other types of faults in induction machines, such as dynamic eccentricity, unbalanced rotors, bearing defects and broken rotor bars have been tackled via other approaches of fault detection that are specific for each case (see [13] for details and further references).

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In this paper, a new two-step formulation for incipient fault detection in the stator windings of induction machines is proposed. The proposed methodology deals with the fault detection problem as a change point detection problem over the time series of the root mean square (rms) values of stator currents. The change point detection algorithm is based on a fuzzy set technique and a Markov Chain Monte Carlo (MCMC) method. The proposed method, differently from former techniques, does not require any prior knowledge about statistical properties of the time series before the application of the MCMC procedure. This is made possible by the first step, in which a fuzzy set technique is applied in order to cluster and to transform the initial time series (about which there is no *a priori* knowledge of its distribution) into a time series whose probability distribution can be approximated by a beta distribution. Specifically in the first step, a Kohonen network is used to find centers of the clusters, and in the sequel the fuzzy membership degree is computed for each point of the initial time series, generating a time series with beta distribution. This new time series, generated in the first step, allows to systematically apply the same strategy to detect the change point via a MCMC method with a fixed reference distribution: the beta distribution. The Metropolis–Hastings algorithm [14] is used to perform the change point detection. The main idea in this paper is to apply the change point detection strategy in a data sequence that carries information of relevant physical variables of the dynamic system. A change point detection gives support to the hypothesis of fault occurrence.

The research on the theme of change point detection in time series has been performed in the context of several applications, such as financial series [15], ecological series [16], hydrometeorological time series [17], etc. The main techniques presented in the literature are statistical tests and Bayesian analysis. In the change point detection problem the standard statistical test is the Cumulative Sum (CUSUM). The CUSUM test proposed by [18] is widely used in the change point detection, and applications of this method can be seen in [19–21], as well as its modifications and extensions. However other type of statistical approaches can be considered as the two-step presented in [22] which is based on learning the statistical properties of the process. In the context of Bayesian analysis different MCMC methods may be used as, for example, the Metropolis–Hastings, Gibbs sampling (see [14] and references therein), and reversible jump MCMC (see [23] and references therein). In the Bayesian analysis context, the product partition model (PPM) proposed by [24] may be used to model uncertainties that exist in a sequence of random quantities. The PPM has also been applied to the identification of multiple change points in the mean of data modeled by Gaussian distribution, as presented in [25,26]. In [27] the PPM has been extended to identify multiple change points both in the mean and variance of Gaussian-distribution data. However, all those previous approaches necessarily demand some type of prior knowledge about the time series, namely the type of distribution that models the data set. An important contribution of the approach proposed in this paper is the possibility of dealing with data with unknown probability distributions.

The main contribution of the proposed approach, however, is related to the enhanced resilience of the new failure detection procedure against false alarms, combined with a good sensitivity that allows the detection of rather small fault signals. This property comes from the adopted PPM model, which assumes explicitly that just one change can occur within the time window under analysis, performing a search for the most provable change point, and calculating the probability of such point being effectively a change point. The behavior of the resulting failure detection system contrasts with the outcome of other approaches, which search for any change point, assuming implicitly that several change points can occur: such approaches lead either to too sensitive systems (which cause false alarms) or to too insensitive systems (which will not detect several faults). Simulation and experimental results illustrate such comparison of the proposed method with other approaches.

The paper is organized as follows. Section 2 presents and analyzes the induction machine simulation considering the case of incipient fault on stator-winding. Section 3 describes the methodology used for change point detection. Section 4 shows the simulations and experimental results for on-line incipient fault detection in induction machine stator-winding. Finally, Section 5 presents the concluding remarks.

2. Induction machine modeling and simulation with turn-to-turn short-circuit in stator winding

Many studies have shown that a large proportion of induction machine faults are related to the stator-winding [8–11]. The induction machine stator-winding is subject to stress due to many factors, which include thermal overload, mechanical vibration and peak voltage caused by a speed controller. The deterioration of insulation usually begins as a short-circuit fault of the stator-winding. This section describes the model that is employed here for the simulation of inter-turn short-circuits in the stator windings of induction machines.

This work employs a generic model for the machine [12], valid for any *dq* (direct and quadrature) axis speed obtained by the Park's transformation [28]. Representing the currents, voltages and electromagnetic flows by i, v and λ, the resistance, leakage and mutual inductance by r, L_l and L_m, the phases a, b and c by indexes a, b and c, the windings of the stator and rotor by indexes s and r, the stator and rotor voltages equations become:

$$[v_s] = [r_s][i_s] + \frac{d[\lambda_s]}{dt} \tag{1}$$

$$[v_r] = [r_r][i_r] + \frac{d[\lambda_r]}{dt} \tag{2}$$

where

$$[v_s] = [\, v_{as1} \quad v_{as2} \quad v_{bs} \quad v_{cs} \,]^T$$

$$[v_r] = [\, v_{ar} \quad v_{br} \quad v_{cr} \,]^T$$

$$[i_s] = [\, i_{as} \quad i_{as} - i_f \quad i_{bs} \quad i_{cs} \,]^T$$

$$[i_r] = [\, i_{ar} \quad i_{br} \quad i_{cr} \,]^T$$

$$[\lambda_s] = [\, \lambda_{as1} \quad \lambda_{as2} \quad \lambda_{bs} \quad \lambda_{cs} \,]^T$$

$$[\lambda_r] = [\, \lambda_{ar} \quad \lambda_{br} \quad \lambda_{cr} \,]^T$$

In the above, the index as_2 represents the shorted turns and i_f is the current in the short-circuit. Fig. 1 represents the schematic diagram of a motor with an inter-turn short-circuit.

In the model proposed in reference [12], the stator windings voltages are given by:

$$V_{ds} + \frac{2}{3}\mu r_s i_f \sin\theta = r_s i_{ds} + \frac{d\lambda_{ds}}{dt} + \omega\lambda_{qs} \tag{3}$$

$$V_{qs} + \frac{2}{3}\mu r_s i_f \cos\theta = r_s i_{qs} + \frac{d\lambda_{qs}}{dt} + \omega\lambda_{ds} \tag{4}$$

$$V_{0s} + \frac{1}{3}\mu r_s i_f = r_s i_{0s} + \frac{d\lambda_{0s}}{dt} \tag{5}$$

The rotor circuit equations are the same as for traditional symmetrical model.