Incipient fault detection in induction machine stator-winding using a fuzzy-Bayesian two change points 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 three-step formulation. The technique can detect up to two change points in the time series. The first step consists of a Kohonen neural network classification algorithm that defines the model to be used, one change point or two change points. The second 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 the Kohonen neural network classification algorithm used in the first step. The last step consists in using the Metropolis-Hastings algorithm for performing the change point detection in the transformed time series generated by the second 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 in this paper, related to previous one in the Literature, is to detect up to two change points in the time series considered, besides the enhanced resilience of the new fault detection procedure against false alarms, combined with a good sensitivity that allows the detection of rather small fault signals. Simulation results are presented to illustrate the proposed methodology.

I. 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 [2]. From a number of surveys, it can be realized that, for the induction motors, stator winding failures account for approximately 30% of all failures [3] [4].

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 [5].

In this paper, the work presented by [1] is improved by adding the detection of two change points and an algorithm to define which model will be used: one change point or two change points. Now there is a three-step formulation for incipient fault detection. The first step is responsible for choose the most suitable model for the time series studied. The other two steps deal with the fault detection problem as a change point detection problem over the time series of the rms (root mean square) 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 second 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 [14] is used to find the model and the cluster centers, in the second step the fuzzy membership degree is computed for each point of the initial time series, generating a time series with beta distribution. The new time series generated in the second 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, as shown in [1]. The Metropolis-Hastings algorithm [11] 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 paper is organized as follows. Section II presents and analyzes the induction machine simulation considering the case of incipient fault on stator-winding. Section III describes...
the methodology used for change point detection. Section IV shows the simulations results for on-line incipient fault detection in induction machine stator-winding. Finally, section V presents the concluding remarks.

II. 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 [6], [7], [8], [9]. 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 [10], [16], valid for any dq (direct and quadrature) axis speed obtained by the Park’s transformation [12]. Representing the current values are illustrated by i, v and λ, the resistance, leakage and mutual inductance by r, Ld and Lq, 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:

\[ [v_s] = [r_s][i_s] + \frac{d[\lambda_s]}{dt} \] (1)
\[ [v_r] = [r_r][i_r] + \frac{d[\lambda_r]}{dt} \] (2)

where

\[ [v_s] = \begin{bmatrix} v_{sa1} & v_{sa2} & v_{sb} & v_{sc} \end{bmatrix}^T \]
\[ [v_r] = \begin{bmatrix} v_{ra} & v_{rb} & v_{rc} \end{bmatrix}^T \]
\[ [i_s] = \begin{bmatrix} i_{sa} & i_{sb} & i_{sc} \end{bmatrix} \]
\[ [i_r] = \begin{bmatrix} i_{ra} & i_{rb} & i_{rc} \end{bmatrix} \]
\[ [\lambda_s] = \begin{bmatrix} \lambda_{sa1} & \lambda_{sa2} & \lambda_{sb} & \lambda_{sc} \end{bmatrix} \]
\[ [\lambda_r] = \begin{bmatrix} \lambda_{ra} & \lambda_{rb} & \lambda_{rc} \end{bmatrix} \]

In the above, the index as2 represents the shorted turns and \( i_f \) is the current in the short-circuit. Figure 1 represents the schematic diagram of a motor with an inter-turn short-circuit.

In the model proposed in reference [10], the stator windings voltages are given by:

\[ V_{ds} + \frac{2}{3} \mu r_s i_f \cos\theta = r_s i_{ds} + \frac{d\lambda_{as2}}{dt} + \omega \lambda_{qs} \] (3)
\[ V_{qs} + \frac{2}{3} \mu r_s i_f \sin\theta = r_s i_{qs} + \frac{d\lambda_{qs}}{dt} + \omega \lambda_{ds} \] (4)
\[ V_{qs} + \frac{1}{3} \mu r_s i_f = r_s i_{0s} + \frac{d\lambda_{ds}}{dt} \] (5)

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

The stator and the rotor electromagnetic flows of stator in dq axis, are given by:

\[ \lambda_{ds} = L_s i_{ds} + L_m i_{dr} - \frac{2}{3} \mu L_s i_f \cos\theta \] (6)
\[ \lambda_{qs} = L_s i_{qs} + L_m i_{qr} - \frac{2}{3} \mu L_s i_f \sin\theta \] (7)
\[ \lambda_{0s} = L_{ts} i_{0s} + \frac{\mu}{3} L_{ts} i_f \sin\theta \] (8)
\[ \lambda_{dr} = L_r i_{dr} + L_m i_{ds} - \frac{2}{3} \mu L_m i_f \cos\theta \] (9)
\[ \lambda_{qr} = L_r i_{qr} + L_m i_{qs} - \frac{2}{3} \mu L_m i_f \sin\theta \] (10)

The voltage and the induced electromagnetic flow in the short-circuit turns are given by:

\[ v_{as2} = \mu r_s (i_{ds} \cos\theta + i_{qs} \sin\theta - i_f) + \frac{d\lambda_{as2}}{dt} \] (11)
\[ \lambda_{as2} = \mu L_s (i_{qs} \sin\theta + i_{dr} \cos\theta - i_f) + \mu L_m (i_{qs} \sin\theta + i_{dr} \cos\theta - \frac{2}{3} \mu i_f) \] (12)

The electromagnetic torque is given by:

\[ T = \frac{3}{2} \frac{p}{2} L_m (i_{qs} i_{dr} - i_{ds} i_{qr}) - \frac{p}{2} \mu L_m i_f i_q \] (13)

The induction machine stator current simulation results for a fault in which 5% of turns in the phases a, b and c become in short-circuit after the time 0.72s are shown in the Figures 2–4. The root mean square (rms) current values are illustrated in Figures 5–7.
III. CHANGE POINT DETECTION METHODOLOGY

In this section, the three-step formulation to the change point detection problem is detailed. Consider a time series signal in which a change point is to be detected. The first step chooses the most suitable model for the time series studied, one change point model or two change points model. Its performed by a clusterization algorithm where cluster centers are pertinence function centers. The algorithm used is based on self-organized neural networks, a Kohonen network. Its initialized with three structures, each one corresponding to a pertinence function that is related to cluster centers. At the end of training those functions with big weight values represent time series centers and the other functions have small values close to zero. If there are two pertinence functions, then one change point model is used. If there are three, then two change point model is considered. As one change point model was presented in [1], let’s consider the two change points model for the sequence.

The second step consists in transforming the given time series into another one with beta distribution using a fuzzy set technique [13]. In order to illustrate how this is done, the following time series is used:
where $p_1$ is the first operation point (the mean value before the first change point), $p_2$ is the second operation point (the mean value after the first change point), $p_3$ is the third operation point (the mean value after the second change point), $\epsilon(t)$ is a noise signal with $\pi(\cdot)$ distribution and $m_1$ and $m_2$ are the change points. The figure 8 shows the time series $y(t)$ with fixed $p_1 = 1$, $p_2 = 10$, and $p_3 = 20$, $\epsilon(t) \sim U(0, 1)$ (uniform distribution in the interval $[0, 1]$), $m_1 = 20$, $m_2 = 50$ and 100 samples.

The proposed fuzzy clustering to transform a given time series into a new one is described below:

1) Input the time series $y(t)$;
2) Find $C_i$, $i = 1, 2, 3$, the elements of the cluster center set for $y(t)$ using the Kohonen network (considering, for example, the time series in (14)).
3) Compute the fuzzy membership degree for each sample of the time series, $y(t)$, with respect to each center $C_i$ (as illustrated in figure 9 considering, for example, the time series in (14)).

Further, it is clear that the distributions of $\mu_1(t)$, as shown in [1], are confined in the interval $[0, 1]$, and using the Kullback-Leibler divergence [15] one may conclude that the distributions of $\mu_1(t)$ shape a family of beta distribution with different input parameters: for $\mu_1(t)$, $t < m_1$, one obtains a beta$(a, b)$ distribution, or beta$(c, d)$ distribution, if $t > m_1$, or beta$(e, f)$ distribution, if $t > m_2$. This empirical test has been performed for several time series with different probability distributions, always leading to the same family of beta distributions after the clustering technique.

Since the clustering technique maps the original time series, with arbitrary probability distribution, into a new time series $\mu_1(t)$ with a beta probability distribution function, this fixed statistical model can be assumed in the Bayesian formulation to detect the change point in the transformed time series (third step). In this paper, the Metropolis-Hastings algorithm is used, since it is a powerful and simple strategy. The goal of the Metropolis-Hastings algorithm [11] is to construct a Markov chain that has a specified equilibrium distribution $\pi$.

Define a Markov chain as follows. If $X_i = x_i$, then draw a candidate value $Y$ from a distribution with density $f_{Y|X}(y) = q(x_i, y)$. The $q$ function is known as the transition kernel of the chain. It is a function of two variables, the current state of the chain $x_i$ and the candidate value $y$. For each $x_i$, the function $q(x_i, y)$ is a density which is a function of $y$.

The candidate value $Y$ is then accepted or rejected. The probability of acceptance is

$$
\alpha(x, y) = \min \left(1, \frac{\pi(y) q(y, x_i)}{\pi(x_i) q(x_i, y)} \right) \tag{15}
$$

If the candidate value is accepted, then set $X_{i+1} = Y$, otherwise set $X_{i+1} = X_i$. Thus, if the candidate value is rejected, the Markov chain has a repeat in the sequence. It is possible to show that under general conditions the sequence $X_0, X_1, X_2, \ldots$ is a Markov chain with equilibrium distribution $\pi$.

In practical terms, the Metropolis-Hastings algorithm can be specified by the following steps:

**Metropolis-Hastings Algorithm**

1) Choose a starting value $x_0$, the number of iterations, $R$, and set the iteration counter $r = 0$;
2) Generate a candidate value $y$ using the reference distribution given by $q(x_i, y)$;
3) Calculate the acceptance probability in (15) and generate $u \sim U(0, 1)$;
4) Compute the new value for the current state:

$$
x^{r+1} = \begin{cases} 
  y, & \text{if } \alpha(x, y) \geq u, \\
  x^r, & \text{otherwise}
\end{cases}
$$

5) If $r < R$, return to step 2. Otherwise stop.

Notice that, as discussed previously, the clustering technique generates a transformed time series with the following distribution:

- $y(t) \sim \text{beta}(a, b)$, for $t = 1, \ldots, m_1$
- $y(t) \sim \text{beta}(c, d)$, for $t = m_1 + 1, \ldots, m_2$
- $y(t) \sim \text{beta}(e, f)$, for $t = m_2 + 1, \ldots, n$
The parameters to be estimated for the Metropolis-Hastings algorithm are \( a, b, c, d, e, f \) and the change points \( m_1 \) and \( m_2 \). In this type of algorithm, the choice of non-informative priors is performed usually from “flat” distributions, for example:

\[
\begin{align*}
    a & \sim \text{gamma}(0.1, 0.1), \\
    b & \sim \text{gamma}(0.1, 0.1), \\
    c & \sim \text{gamma}(0.1, 0.1), \\
    d & \sim \text{gamma}(0.1, 0.1), \\
    e & \sim \text{gamma}(0.1, 0.1), \\
    f & \sim \text{gamma}(0.1, 0.1)
\end{align*}
\]

\[
\begin{align*}
    m_1 & \sim U\{1, 2, ..., m_2 - 1\}, \quad \text{with } p(m) = \frac{1}{m_2 - 1}, \\
    m_2 & \sim U\{m_1 + 1, ..., n\}, \quad \text{with } p(m) = \frac{1}{n - m_2 + 1}
\end{align*}
\]

These distributions, with parameters 0.1, have been chosen for the purpose of spreading the whole parametric space.

The reference distribution, used in third step of the Metropolis-Hastings algorithm to generate the candidate value to the change points \( m_1 \) and \( m_2 \), considering two change points, are computed as:

\[
q(m_1, m_2 \mid a, b, c, d, e, f) \propto q(m_1, m_2, a, b, c, d, e, f) = \prod_{i=1}^{m_2} G(a+b) \big(\frac{a}{a+b}\big)^{y_i-1} \frac{y_i^{a-1}(1-y_i)^{b-1}}{G(a)G(b)} \prod_{i=m_1+1}^{m_2} G(c+d) \big(\frac{c}{c+d}\big)^{y_i-1} \frac{y_i^{c-1}(1-y_i)^{d-1}}{G(c)G(d)} \prod_{i=m_2+1}^{n} G(e+f) \big(\frac{e}{e+f}\big)^{y_i-1} \frac{y_i^{e-1}(1-y_i)^{f-1}}{G(e)G(f)}
\]

where \( a, b, c, d, e \) and \( f \) are generated by priors distribution and \( G(k) \sim \text{gamma}(k, 1) \).

The final analysis is performed as: the change point, \( m_1 \) and \( m_2 \), are obtained by checking where the maximum of \( q(m_1, m_2 \mid a, b, c, d, e, f) \) occurs, with the exception of the border points of the distribution (if the maximum occurs on such points, then there is no change point). Figure 10 and 11 shows the result when applying the proposed methodology for \( p_1 = 1, p_2 = 10, p_3 = 20, e(t) \sim U(0, 1), m_1 = 20 \) and \( m_2 = 50 \). The function \( q \), in the figure 10, can be interpreted as a histogram of change in the time series at the instant \( m_1 \) and, in the figure 11, \( m_2 \).

This methodology is applied in the next section, in the problem of incipient fault detection problem in induction machine stator winding — which is stated as a change point detection problem.

\[\text{IV. RESULTS OF THE PROPOSED METHODOLOGY}\]

The system simulation, described in Section II, calculates the instantaneous values of the motor currents \( i_{as}, i_{bs}, i_{cs} \) and the rotor speed \( \omega \) in an induction machine with star connection. After that, the root mean square (rms) value of each phase current is calculated over a period of time. The root mean square (rms) value is the input for change point detection algorithm. It should be noticed that the rms values of the stator currents in an induction motor change their values several times within a normal operation cycle, but the algorithm have to indicate only real changes.

The simulation results, for phase \( a \), are shown in Figures 12–14, considering 1% of turns in short-circuit for the first change point and 2% of turns in short-circuit for the second change point in phases \( a, b \) and \( c \).

As can be seen from Figures 13 and 14, the fault detection has been performed in the correct time, with the system indicating the higher value of probability of change, in the current of phase \( a \), for the first change point in figure 13, and higher value of probability of change, in the current of phase \( a \), for the second change point in figure 14. For the case of fault-free and noise-free simulation, the probability of change for each change point results in a high value near the border when using the proposed approach.

\[\text{V. CONCLUSION}\]

In this paper a extension of fuzzy/Bayesian methodology for two change points detection in time series has been used to treat the fault detection problem in induction machine stator-winding. This three-step formulation allows a systematic efficient way to solve change points detection problem, which is employed for detecting incipient faults such as change points that occur in some system signal.

The proposed methodology has as advantages, compared


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