Applied Soft Computing 21 (2014) 647–653

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Fault detection in dynamic systems by a Fuzzy/Bayesian network formulation

Marcos F.S.V. D'Angelo [a,*], Reinaldo M. Palhares [b], Luciana B. Cosme [c], Lucas A. Aguiar [a], Felipe S. Fonseca [a], Walmir M. Caminhas [b]

[a] Department of Computer Science – UNIMONTES, Av. Rui Braga, sn, Vila Mauricéia, 39401-089 Montes Claros, MG, Brazil
[b] Department of Electronics Engineering, Federal University of Minas Gerais, Av. Antônio Carlos, 6627, 31270-901 Belo Horizonte, MG, Brazil
[c] IFNMG Campus Montes Claros, Rua Dois, 300, Village do Lago I, 39404-058 Montes Claros, MG, Brazil

ARTICLE INFO

Article history:
Received 11 June 2013
Received in revised form 7 March 2014
Accepted 3 April 2014
Available online 24 April 2014

Keywords:
Fault detection
Inter-turn faults
Induction machine
Fuzzy sets
Bayesian networks

ABSTRACT

In this paper the fault detection problem is solved using an alternative methodology based on a fuzzy/Bayesian strategy combining a Bayesian network and the fuzzy set theory. The new important issue in this proposed methodology is to address uncertainties in the input of the Bayesian Network. This contribution is possible since the fuzzy set theory is used as the knowledge representation. To illustrate the technique, the fault detection problem in induction machine stator-winding is considered. Specifically, the faults in the induction machine stator-winding are detected by a state change of stator current. Simulation results are presented to illustrate the advance of the proposed methodology when compared to standard Bayesian network.

1. Introduction

Fault detection and analysis is a very important strategy that is commonly employed in the industry with the purpose of allowing a cost–effective maintenance policy, keeping productivity standards and ensuring safety. The fault analysis gives support for the design of corrective actions, system redundancies, and safety policies in order to mitigate the effects of a fault [1]. A fault diagnosis procedure is typically divided into three tasks: (i) the fault detection, indicating the occurrence of some fault in a monitored system; (ii) the fault isolation, establishing the type and/or location of the fault; and (iii) the fault identification, determining the magnitude of the fault. After a fault has been detected and diagnosed, in some applications it is required that the fault be self-corrected, usually through controller reconfiguration. This is usually referred to as fault accommodation.

The literature presents several classes of strategies to deal with fault detection and isolation (FDI) [2]. These strategies can be, in general, divided in quantitative approach. These strategies are, in general, divided into two kind of approaches: (i) quantitative [3] and qualitative [4,5].

Most of the quantitative approaches are based on the knowledge of mathematical models of the plant. Many survey papers with different emphasis on various quantitative approaches have been published over the past years. The main approaches in this context are based on (unknown input) observers [2,6–10], parity relations [2,11] and Kalman or robust filters [2,12–15]. The requirement of a mathematical model of the plant can lead to several difficulties in the implementation of these approaches, for instance due to factors such as system complexity, high dimensionality, nonlinearities and parametric uncertainties. Further, in the case the neural network plays a role as an observer, it falls into the class of quantitative approaches [16,17].

On the other hand, most of the qualitative approaches are based on some pattern analysis of the historic process data. The main related approaches are: signed directed graph [18–20], fault tree [21], fuzzy system [22–24], qualitative trend analysis [25–28], mutual information [29], neural networks [30,31] (in the case of classification), artificial immune systems [32–34], Bayesian networks [35–39] and the combination of techniques [40].

In this paper, a new qualitative approach for fault detection is presented. This new approach is based on a Fuzzy/Bayesian representation. Unlike the traditional Bayesian networks as reported in [37–39], the Fuzzy/Bayesian proposed in this paper combine

* Corresponding author. Tel.:+55 38 3229 8273.
E-mail addresses: marcos.dangelo@unimontes.br, kimmarcos@yahoo.com.br (M.F.S.V. D'Angelo).

http://dx.doi.org/10.1016/j.asoc.2014.04.007
1568-4946/

the potential for aggregation of information/knowledge of the fuzzy sets theory for processing input uncertainties in the Bayesian network – for simplicity we will call this combination of fuzzy/Bayesian network. The approach proposed in this paper was motivated by the approaches presented in [41,42]. Although references [41,42] deal with the problem proposed in this paper, the approach proposed in [42] solve the problem of only one unknown evidence, and [41] needs several traditional Bayesian network information, beyond the necessity of conditional independence of evidence. In the next section this topic is considered deeply. To illustrate the efficiency of the proposed methodology, the problem of fault detection in the stator winding of induction machine is presented.

The paper is organized as follows. Section 2 shows a new Fuzzy/Bayesian Network approach. Section 3 presents and analyzes the induction machine simulation considering the case of fault on stator-winding and shows the results for fault detection in induction machine stator-winding. Finally, Section 4 presents the concluding remarks.

2. Fuzzy/Bayesian network approach

Bayesian theorem is an effective tool for reasoning under the condition of uncertainty. Propositions are given numerical parameters representing their degree of beliefs under some body of knowledge, these parameters are then combined and manipulated based on the rules of probability theory. $P(H_i \mid \epsilon_j)$ represents the subjective belief in the hypothesis, H_i, given the knowledge of the evidence, ϵ_j. However, if there is uncertainty in the evidence, the application of the traditional Bayes rule implies to fix the knowledge of the evidence to belong a given set. Clearly this a drawback of this kind of approach. In order to solve this problem, a new Fuzzy/Bayesian inference is proposed in this paper. Other papers deal with the problem proposed, as in [41,42]. It is observed that the approach proposed in [42] solve the problem of only one unknown evidence and [41] needs several traditional Bayesian network information, beyond the necessity of conditional independence of evidence ϵ_j. The proposed approach is more simple and differs from [41] because the inference in Fuzzy/Bayesian network needs only the conditional probability table $P(H_i \mid \epsilon_1, \epsilon_2, \ldots, \epsilon_k)$ and it is given by:

$$P(H_i \mid \tilde{\epsilon}_1, \tilde{\epsilon}_2, \ldots, \tilde{\epsilon}_k) = \frac{\sum_{j=1}^{2k} \left(P(H_i \mid \epsilon_{j1}, \epsilon_{j2}, \ldots, \epsilon_{jk}) * \prod_{m=1}^{k} \mu_{\tilde{\epsilon}_{jm}} \right)}{\sum_{j=1}^{2k} \left(\prod_{m=1}^{k} \mu_{\tilde{\epsilon}_{jm}} \right)} \tag{1}$$

where: H_i is the hypothesis to be tested, $\tilde{\epsilon}_k$ is the fuzzy evidences. For each evidence $\tilde{\epsilon}_k$ a pair of membership functions ($\mu_{\tilde{\epsilon}}$) is defined that describes the uncertainty inherent in the evidence description.

The next Theorem plays a crucial rule since it shows that the summation of the hypothesis given fuzzy evidences is also unitary. This result allows to make the proposed approach consistent.

Theorem 2.1. *The summation of the hypothesis probabilities related to a set of fuzzy evidences is*

$$\sum_{i=1}^{n} P(H_i \mid \tilde{\epsilon}_1, \tilde{\epsilon}_2, \ldots, \tilde{\epsilon}_k) = 1 \tag{2}$$

where n is the number of hypothesis.

Proof. To show that (2) is true take the summation in (1), namely:

$$\sum_{i=1}^{n} \left\{ \frac{\sum_{j=1}^{2k} \left(P(H_i \mid \epsilon_{j1}, \epsilon_{j2}, \ldots, \epsilon_{jk}) * \prod_{m=1}^{k} \mu_{\tilde{\epsilon}_{jm}} \right)}{\sum_{j=1}^{2k} \left(\prod_{m=1}^{k} \mu_{\tilde{\epsilon}_{jm}} \right)} \right\} \tag{3}$$

Define $P(H_{ij}) \triangleq P(H_i \mid \epsilon_{j1}, \epsilon_{j2}, \ldots, \epsilon_{jk})$ and

$$M_j \triangleq \frac{\prod_{m=1}^{k} \mu_{\tilde{\epsilon}_{jm}}}{\sum_{j=1}^{2k} \left(\prod_{m=1}^{k} \mu_{\tilde{\epsilon}_{jm}} \right)}$$

with $p \triangleq 2^k$ in (3).

Thus (3) may be rewritten as:

$$\begin{aligned} \sum_{i=1}^{n}\sum_{j=1}^{p} P(H_{ij})M_j = {} & P(H_{11})M_1 + P(H_{12})M_2 + P(H_{13})M_3 + \cdots + P(H_{1p})M_p \\ & + P(H_{21})M_1 + P(H_{22})M_2 + P(H_{33})M_3 + \cdots + P(H_{2p})M_p \\ & \vdots \\ & + P(H_{n1})M_1 + P(H_{n2})M_2 + P(H_{n3})M_3 + \cdots + P(H_{np})M_p \end{aligned}$$

which is equivalent to:

$$\begin{aligned} \sum_{i=1}^{n}\sum_{j=1}^{p} P(H_{ij})M_j = {} & P(H_{11})M_1 + P(H_{21})M_1 + P(H_{31})M_1 + \cdots + P(H_{n1})M_1 \\ & + P(H_{12})M_2 + P(H_{22})M_2 + P(H_{32})M_2 + \cdots + P(H_{n2})M_2 \\ & \vdots \\ & + P(H_{1p})M_p + P(H_{2p})M_p + P(H_{3p})M_p + \cdots + P(H_{np})M_p \end{aligned}$$

Rewriting the previous equation as:

$$\begin{aligned} \sum_{i=1}^{n}\sum_{j=1}^{p} P(H_{ij})M_j = {} & [P(H_{11}) + P(H_{21}) + P(H_{31}) + \cdots + P(H_{n1})]\, M_1 \\ & + [P(H_{12}) + P(H_{22}) + P(H_{32}) + \cdots + P(H_{n2})]\, M_2 \\ & \vdots \\ & + [P(H_{1p}) + P(H_{2p}) + P(H_{3p}) + \cdots + P(H_{np})]\, M_p \end{aligned}$$

Notice that by definition $\sum_{i=1}^{n} P(H_i \mid \epsilon_{1i}, \epsilon_{2i}, \ldots, \epsilon_{ki}) = 1$, thus:

$$\sum_{j=1}^{p} M_j = 1$$

and from the definition of M_j, it follows that:

$$\sum_{j=1}^{2^k} \left(\frac{\prod_{m=1}^{k} \mu_{\tilde{\epsilon}_{jm}}}{\sum_{j=1}^{2k} \left(\prod_{m=1}^{k} \mu_{\tilde{\epsilon}_{jm}} \right)} \right) = 1$$

or

$$\sum_{j=1}^{2^k} \prod_{m=1}^{k} \mu_{\tilde{\epsilon}_{jm}} \left(\frac{1}{\sum_{j=1}^{2k} \left(\prod_{m=1}^{k} \mu_{\tilde{\epsilon}_{jm}} \right)} \right) = 1$$

This shows that (2) is unitary as proposed. □

3. 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 [43–46]. The induction machine stator-winding is subject to stress due to many factors, which include thermal overload, mechanical vibration and