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PEM fuel cell fault diagnosis via a hybrid methodology based on fuzzy and pattern recognition techniques

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ABSTRACT

In this work, a fault diagnosis methodology termed VisualBlock-Fuzzy Inductive Reasoning, i.e. VisualBlock-FIR, based on fuzzy and pattern recognition approaches is presented and applied to PEM fuel cell power systems. The innovation of this methodology is based on the hybridization of an artificial intelligence methodology that combines fuzzy approaches with well known pattern recognition techniques. To illustrate the potentiality of VisualBlock-FIR, a non-linear fuel cell simulator that has been proposed in the literature is employed. This simulator includes a set of five fault scenarios with some of the most frequent faults in fuel cell systems. The fault detection and identification results obtained for these scenarios are presented in this paper. It is remarkable that the proposed methodology compares favorably to the model-based methodology based on computing residuals while detecting and identifying all the proposed faults much more rapidly. Moreover, the robustness of the hybrid fault diagnosis methodology is also studied, showing good behavior even with a level of noise of 20 dB.

1. Introduction

Polymer electrolyte membrane (PEM) fuel cells are devices that allow the direct transformation of chemical energy (hydrogen) into electrical energy (Pukrushpan et al., 2004). This energy conversion is clean because the only by-products are water and heat. Moreover, this process is very efficient and has the same level of performance than the main fossil alternatives. Amongst others, these advantages are behind the recent increase in scientific production in the field in the last years. Potential applications are grouped into three categories: generation of electricity for stationary applications; residential and electronic applications and automotive applications. Applications in the automotive sector have been particularly attractive due to the fact that there is practically null emission of polluting agents (Rajashekara, 2000). This means that fuel cells are environmentally-friendly alternative to conventional fossil fuels that significantly reduce pollution and man-made greenhouse gases.

With all, PEM fuel cells are complex and interrelated systems and, as stated in recent research efforts (Feroldi, 2009), efficiency in control is crucial. Different control problems must be solved to obtain a correct operation of the system, i.e. control of the power flows in the system to fulfill the power load, conditioning of the generated power, handling of heat and water and suitable hydrogen and air supply. Therefore, a set of auxiliary elements such as valves, compressors, sensors, regulators, etc., are needed to guarantee that the fuel cell works in an optimal way. For this reason, fuel cell systems are vulnerable to different set of faults that can imply its temporal or permanent damage. Fault diagnosis systems (FDS) become, therefore, fundamental in order to reduce as much as possible this vulnerability.

There has been intensive research activity in the fault diagnosis of fuel cell stack systems that includes quantitative as well as qualitative approaches. According to Aitouche et al. (2012), fault diagnosis methods can be classified on two types: model-based and knowledge-based approaches. In model-based approaches a priori knowledge about the model of the process is assumed. However, this information is not always available and the dynamic fuel cell model is characterized by multiple variables and a strong coupling with profound dynamics. Model-based approaches are primarily based on statistical techniques, first order logic, control theory, mathematical modeling, and computer simulation (Aitouche et al., 2011; Escobet et al., 2009; Rosich et al., 2014; Wu et al., 2008a, 2008b; Wang et al., 2011; Zhang and Huang, 2011). Knowledge-based approaches are based on the data available from the system to perform learning. Examples of knowledge-based approaches are signal processing, experimental methods and artificial intelligence. There is a large amount of research done in the area of knowledge-based FDS for fuel cell stack systems, specially using artificial intelligence methods, like expert systems, neural networks, and genetic programming (Chavez-Ramírez et al.,

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Nomenclature

PEM	polymer electrolyte membrane
FDS	fault diagnosis system
ANFIS	neural-networks fuzzy infer system
FIR	Fuzzy Inductive Reasoning
KNN	k-nearest neighbor
5NN	5-nearest neighbor
EFP	equal frequency partition
MSE	mean square error
LPV	linear parameter varying
Q	acceptability measure
C	partial acceptability measure
C_{rel}	relative confidence
I_a	computing the maximum number of local cumulative errors possible
λ_{o_2}	oxygen excess ratio
$o_2 in$	oxygen input
$o_2 react$	oxygen reacted
I_{cm}	compressor current
ω_{cm}	compressor speed
V_{fc}	voltages applied to the cell
I_{fc}	stack current
V_{cm}	voltages applied to the compressor

2010; Kamal et al., 2014; Liu and Wang, 2003; Nitsche et al., 2004; Yousfi Steiner et al., 2011; Zheng et al., 2013). However in recent years, the demand has arisen to develop FDS that are more robust to uncertainty. In this context, fuzzy logic and hybrid fuzzy approaches appear to offer a good alternative to other qualitative FDS methodologies (Hissel et al., 2004, 2007; Olteanu et al., 2012; Tao et al., 2005; Vural et al., 2009; Becker and Karri, 2010). Let us look a little closer to this research that is clearly related to our interests.

Hissel et al. (2004) presented a first step in the direction of fuel cell systems diagnosis, by proposing a Sugeno-type fuzzy model for two faults, i.e. an accumulation of nitrogen and/or water in the anode compartment and an important drying of the proton exchange membrane. The Sugeno model has been tuned using a genetic algorithm. The conclusions obtained state that the fuzzy diagnosis models help to improve the results. For instance, the authors point out that thanks to the fuzzy model only 150 s are needed to detect the accumulation of nitrogen and water in the anode component fault. Hissel et al. (2007) present a new approach to PEM diagnosis based on fuzzy k-means clustering. The fuzzy clustering algorithm produces three clusters on the two dimension feature space, each one corresponding to a specific fault, i.e. a specific behavior of the fuel cell stuck. Olteanu and co-workers also proposed a Sugeno-type fuzzy model. In this case the goal was to model the polyelectrolyte membrane fuel cell by means of a set of fuzzy rules built based on physical principles. Therefore, this research follows a model-based approach and it is not focused on fault diagnosis. Tao et al. use the adaptive neural-networks fuzzy infer system (ANFIS) to build the temperature model of PEM fuel cell which is used as the reference model of the control system, and adjusts the model parameters to control it online. Vural et al. also uses the ANFIS to model the PEM fuel cell under various operational conditions. The models obtained are able to predict fuel cell performance with a high accuracy in an easy, rapid and cost effective way. Becker and Karri also build predictive ANFIS models, in this case for hydrogen flow rate, electrolyzer system-efficiency and stack-efficiency. They found that these models are reliable predictive tools with an excellent accuracy. Notice that neither Tao et al. nor Vural et al. nor Becker and Karri research are focused on fault diagnosis.

Therefore, the number of works that can be found in the literature that propose fuzzy or hybrid fuzzy FDS for PEM fuel cells is quite low. This is the reason why we propose a FDS based on the Fuzzy Inductive Reasoning (FIR) methodology.

The main motivation of our research is to explore the added value of using a fuzzy knowledge-based approach as an alternative to other knowledge-based and model-based approaches, for cases in which the non-linear dynamics are insufficiently known. The goal of this research is to allow a tolerant fuel cell control by means of the addition of a fuzzy fault diagnosis system operating in real-time. With this idea in mind, the VisualBlock-FIR FDS based on the Fuzzy Inductive Reasoning (FIR) methodology is presented in this work. The FIR methodology is based on a hybrid fuzzy pattern recognition approach and its conceptualization arises of the General System Problem Solving (Klir and Elias, 2002). This methodology of modeling and qualitative simulation is based on systems behavior rather than structural knowledge. It has the ability to describe systems that cannot easily be described by classical methods (e.g. differential equations), i.e., systems, whose physical processes are awkward to model.

The novelty of this work lies in using the FIR methodology to model the different fault scenarios and the plant without faults, and applying the detection and identification VisualBlock-FIR algorithm to detect and isolate the faults occurred as fast as possible.

Most of the inductive model identification techniques, such are neural networks and its hybridizations, assume a fixed (although often arbitrary) structure and map the knowledge contained in the training data set onto a set of parameter values. The training data are only used during the model identification phase, i.e., the modeling phase. Once the model has been identified, simulation runs are based solely upon the previously optimized parameter values. Such techniques suffer from the problem that they normally are unable to recognize, when the testing data lie outside the range, for which the model has been validated.

In contrast, FIR is a non-parametric technique. The training data are characterized and classified during the model identification phase, but they are not mapped onto parameter sets. Therefore, FIR refers back to the classified training data set also during the simulation or prediction phase. This property makes it impossible for FIR to extrapolate "generously" during simulation and, therefore, to predict values that are not physically possible. Finally, FIR has self-assessment capabilities that enable it to warn the user of the methodology if it makes "risky" predictions, i.e. predictions that are not well founded on the basis of the available training data.

To prove the usefulness and robustness of the proposed methodology, the PEM system simulator developed by Pukrushpan et al. (2004) and modified by Escobet et al. (2009), to include a set of typical fault scenarios, has been used. This allows comparison of the results obtained by the VisualBlock-FIR methodology to the results achieved by the model-based fault diagnosis methodology presented by Escobet et al. (2009). It is important to mention that we have chosen the fault scenarios described by Escobet et al. (2009), because the data was easily available. Moreover, in that work, the detection and identification of the faults is reported not only taking into account whether it is possible or not to detect and identify them; they also take into account the time needed to do it. We could not find many papers that present the time needed by the proposed methodologies to detect and identify the faults of PEM fuel cells.

The VisualBlock-FIR fault diagnosis methodology is introduced in Section 2. Section 3 describes the PEM fuel cell system. Section 4 presents the application of VisualBlock-FIR to the fuel cell system and the results obtained. Section 5 presents the study of robustness of