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Multiple incipient fault diagnosis in three-phase electrical systems using multivariate statistical signal processing

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ABSTRACT

This paper presents and evaluates a methodology to detect and diagnose single or multiple faults at their earliest stage in electrical systems. The faults affect the gain, the offset and the phase shifting of the output currents. Following the general Fault Detection and Diagnosis process, the methodology is based on data driven approach for modeling the currents in the time domain, pre-processing with the Park transform and univariate statistical feature extraction and analysis.

In the case of incipient faults, the Park transformed currents are more sensitive. Therefore we use their Cumulated Sum (CUSUM) (CUSUM mean or CUSUM variance) for the fault detection. Within the incipient fault ranges ($\leq 10\%$) and a threshold set to have zero false alarm rate, intensive simulations show that these features successfully detect the fault(s) with a probability of miss detection around 5%.

The classification of the seven fault classes that have been identified (3 single and 4 multiple) is successfully done with Linear Discriminant Analysis and Support Vector Machines (SVM) when data is linearly separable or kernel-based SVM when data is non linearly separable. The simulation results show that the misclassification errors are lower than 3%.

For the fault estimation, the slope of the CUSUM decision has been identified as a relevant feature. For the different faults (single or multiple), from the evolution of the slope along with the fault severity, an analytical model has been derived. The inversion of this model allows an accurate estimation of the fault level.

1. Introduction

Nowadays, health monitoring of sensible systems is a hot issue in industrial and academic research. Due to increasing safety rules, and in order to avoid unwanted stops it is crucial to detect failures at their earliest stage (Trigeassou, 2011; Benbouzid, 2000). Among the most sensitive applications, we can cite transportation and electrical energy production.

Every unexpected behavior (fault) needs to be detected and diagnosed (identification and estimation) (Isermann, 2006).

Indeed, to monitor a process, we need to evaluate the deviation of its current behavior from a reference one assumed to be the healthy one. The deviation due to faults or noise variations can be evaluated from collected information(data-driven approach), from the theoretical physics-based modeling or from linguistic rules (Teo and Gooi, 1997; Venkatasubramanian et al., 2003a, b; Chatti et al., 2016). The main steps (Modeling, Preprocessing, Feature extraction, and Feature analysis) are recalled in Fig. 1. For the aforementioned sensitive applications, the modeling is mainly done using physics laws or data.

However, due to their increasing complexity accurate physics-based models are tedious to develop over all the operating range without weak assumption. Data-driven approach based on numerical models or experimental data can then provide additional knowledge and support effective oversight (Cai et al., 2017). This last approach is based on signal processing techniques, statistical analysis, estimation and detection theory (Basseville and Nikiforov, 1993; Lehman, 1996; Kay, 1993, 1998).

Indeed, using qualitative information the Fault Detection and Diagnosis (FDD) procedure mainly consists in the residual/feature extraction and analysis. Several kind of faults can be considered: abrupt, intermittent or gradual (Isermann, 2006; Yin et al., 2014). When the gradual failure is a modification that slowly grows in a very low range of values, they are denoted as incipient faults (Ren et al., 2011). Such types of

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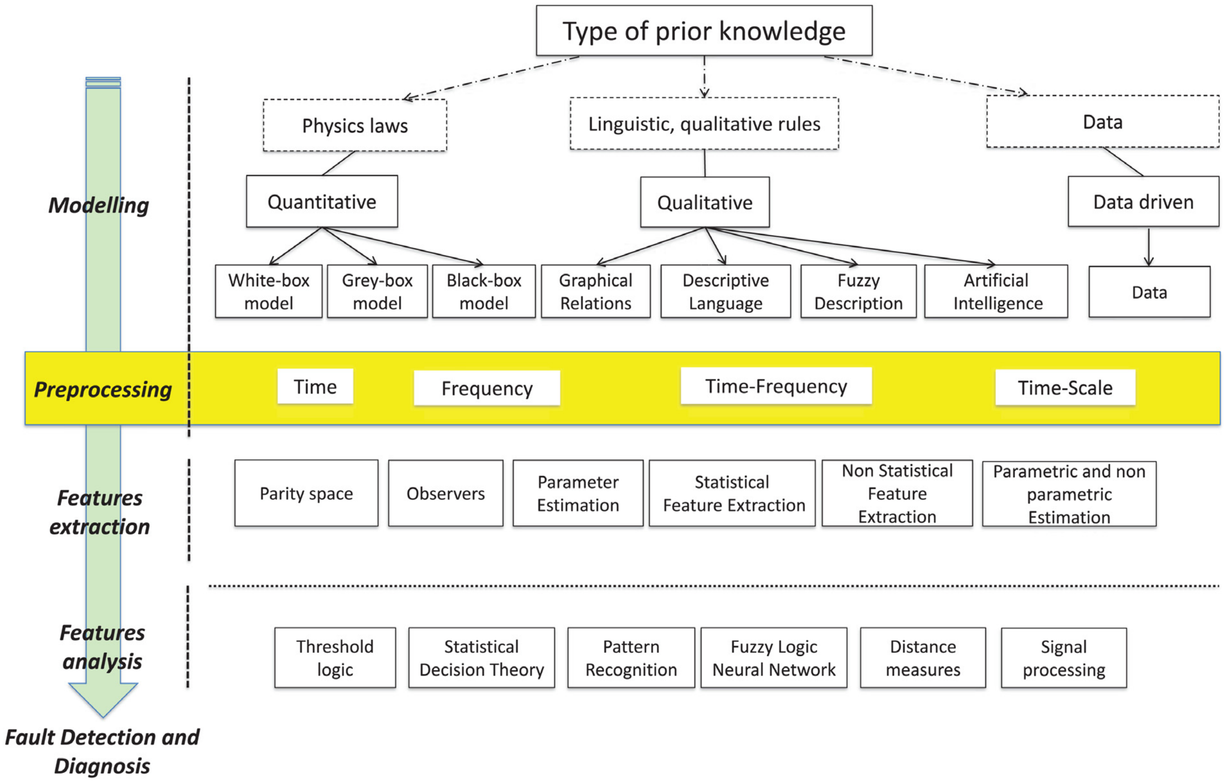

Fig. 1. Fault Detection and Diagnosis general scheme.

faults are difficult to detect and diagnose due to their low severity close to the noise variance (Delpha and Diallo, 2015). Nevertheless their detection and diagnosis are important in early FDD.

1.1. Problem statement

Recent works have been proposed for the detection, classification and estimation of incipient faults with data-driven approach (Ren et al., 2011; Namdari and Jazayeri-Rad, 2014; Ferracuti et al., 2015; Delpha and Diallo, 2015; Harmouche et al., 2016; Youssef et al., 2016b; Delpha et al., 2017). They have highlighted the benefit of statistical based approaches for an efficient fault detection. In these papers, the Kullback–Leibler Divergence (KLD) and the Principal Component Analysis (PCA) have proved their ability to properly detect and diagnose an incipient fault using the Probability Density Functions (PDF). However, there is one restriction for using the KLD : the two PDF should share the same sample space (Kullback and Leibler, 1951; Cover and Thomas, 2005). Moreover, the incipient fault detection performances can be degraded by the projection error and the uncorrelated variables that can be yield using PCA (Youssef et al., 2016a).

In this work, we are also interested in the detection and diagnosis of incipient fault for a three-phase electrical drive. Misfiring of the power converter switches or malfunctions of sensors (currents or voltages) are common faults in electrical systems (Trigeassou, 2011). The effect of these faults can be observed in the currents flowing out of the power converter. Therefore they can be modeled as a modification of the amplitude, the phase and the offset of a sinusoidal variable.

To cope with the limitations of the statistical techniques mentioned in the former paragraph, we propose here to perform the fault detection using the Cumulated Sum (CUSUM) technique that has already proved its efficiency in other contexts for abrupt fault detection (Bodnar and Schmid, 2011; Basseville and Nikiforov, 1993).

In this paper, we are interested in incipient fault detection and diagnosis of a three-phase electrical system fed by an inverter, in star coupling mode with an isolated neutral. The failure under consideration are gain fault, offset fault, phase shifting fault or their combination. First, the detection is done using CUSUM. Secondly, we focus on the fault classification. We propose to consider the statistical moments as features for performing the fault isolation (fault type classification) based on a combination of multivariate statistical techniques (Costamagna et al., 2016): Principal Component Analysis (PCA) for representation (Diana and Tommasi, 2002; Harrou et al., 2013), Linear Discriminant Analysis (LDA) (Delpha et al., 2008; Haddad and Strangas, 2016) and the Support Vector Machines (SVM) (Delpha et al., 2012; Namdari and Jazayeri-Rad, 2014) for fault classification. The fault classification accuracy is evaluated based on the classification confusion matrix. Third, we propose to estimate the fault severity using the slope of the CUSUM and we show its efficiency for the main considered faults.

1.2. Paper organization

The rest of the paper will be organized as described in Fig. 1. The methodology is based :

- Modeling using data collected from the process;
- Preprocessing in the time domain;
- Statistical features extraction and analysis for fault detection and diagnosis

Fault Detection and Diagnosis (FDD) process can be decomposed in three main operations: Detection, Isolation and estimation (see Fig. 2). The *Detection* operation consists of analyzing the process and decides if a fault (anomaly in the behavior) has occurred or not (Isermann, 2006). For the *Isolation*, it can be considered as the localization or the characterization of the fault type. The *Estimation* consists in evaluating the fault severity (amplitude, length, . . .).

In Section 2, the fault modeling is presented. Section 3 is devoted to the fault detection. Then, the Fault Isolation and its performances are described in Section 4. The fault estimation is then performed in Section 5. Finally, concluding remarks in Section 6 close the paper.