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Intelligent fault diagnosis of synchronous generators

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ABSTRACT

Condition based maintenance (CBM) requires continuous monitoring of mechanical/electrical signals and various operating conditions of the machine to provide maintenance decisions. However, for expensive complex systems (e.g. aerospace), inducing faults and capturing the intelligence about the system is not possible. This necessitates to have a small working model (SWM) to learn about faults and capture the intelligence about the system, and then scale up the fault models to monitor the condition of the complex/prototype system, without ever injecting faults in the prototype system. We refer to this approach as scalable fault models.

We check the effectiveness of the proposed approach using a 3 kVA synchronous generator as SWM and a 5 kVA synchronous generator as the prototype system. In this work, we identify and remove the system-dependent features using a nuisance attribute projection (NAP) algorithm to model a system-independent feature space to make the features robust across the two different capacity synchronous generators. The frequency domain statistical features are extracted from the current signals of the synchronous generators. Classification and regression tree (CART) is used as a back-end classifier. NAP improves the performance of the baseline system by 2.05%, 5.94%, and 9.55% for the R, Y, and B phase faults respectively.

1. Introduction

In recent years, condition based maintenance (CBM) became popular in an effort to reduce downtime and maintenance cost. CBM can be implemented through condition monitoring of the machine and the maintenance is scheduled at the optimum time. i.e., maintenance is recommended when any abnormal behavior is anticipated in the system performance. Thus, condition monitoring of systems has become an essential component for enhancing production and profit in industries, and avoid expensive casualties in mission critical applications (Jardine, Lin, & Banjevic, 2006).

Condition monitoring of machines can be done using model based (using physics based mathematical models), data driven or hybrid approaches (Narasimhan, Roychoudhury, Balaban, & Saxena, 2010). A model based approach is recommended for the simple and well known systems. i.e., the mathematical model of the system should be available to analyze the components of the machine. But, for complex systems in aerospace applications, when such mathematical models are not easily available, the model based approach is not feasible (Narasimhan et al., 2010). A data driven approach does not depend on any mathematical model and it is easier to analyze complex systems using data driven approaches than using model based techniques, when sufficient data from the system is available under fault and no fault conditions.

A review of literature (Nandi, Toliyat, & Li, 2005; Siddique, Yadava, & Singh, 2005) reveals that fault modeling has to be done using exactly similar machine/machines as that for which diagnosis is to be performed. Gunal et al. used two healthy three phase induction motors having different specifications and five faulty motors with the same specifications for diagnosis (Günal, Ece, & Nezih Gerek, 2009). However, the focus was to test the generality and applicability of the algorithm to distinguish the healthy motor when it was clustered together with different healthy and faulty motors. The task in this work may be considered as a novelty detection from the knowledge of the machine under normal conditions, rather than doing any elaborate diagnosis of the condition of the motor. If a data driven fault diagnosis model generated using a lower capacity system could be used for the condition monitoring of higher capacity system, without injecting any faults in the higher capacity system, then we may be able to develop universal fault diagnosis systems.

Wang et al. proposed a novel approach to extract features from the envelope of the motor current (Wang, Liu, Gao, & Yan, 2012). Current signals were collected from six identical motors to diagnose various faults using three pattern classifiers such as Naive Bayes, *k* nearest

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neighbor and support vector machine (SVM). Seera et al. developed a hybrid intelligent model using the fuzzy min max (FMM) neural network and the random forest (RF) ensemble (FMM-RFE) for condition monitoring of induction motors using the motor current signature analysis (MCSA) method under noisy and noise-free environments (Seera, Lim, Nahavandi, & Loo, 2014). In (Karabadji, Seridi, Khelf, Azizi, & Boulkroune, 2014), an improved unpruned decision tree was constructed by combining the attribute selection and data reduction process to overcome the decision tree size and over-fitting problems for machine fault diagnosis.

Awind turbine simulator plays an important role in condition monitoring of wind turbines, to verify and test the fault detection algorithms before introducing them into the health monitoring system. Oh et al. developed a 20 kW wind turbine simulator with similarities to a 3 MW wind turbine. It was reported that the measured vibration and strain values at the gear box and blade root in the simulator have similarities to the actual wind turbine. The authors also suggested that the quantitative values measured from simulator could be used to develop intelligent system for fault diagnosis (Oh et al., 2014). However, no study has been made in the reported work, on fault diagnosis using the quantitative values measured from the simulator.

Godoy et al. compared the performance of machine learning techniques such as fuzzy adaptive resonance theory (ARTMAP) network, multilayer perceptron network, and support vector machine to diagnose the stator short circuit faults in the induction motors. The current signals are collected from 1 hp and 2 hp induction motors at various loading conditions. However, in this study, faults are diagnosed in a machine dependent manner (Godoy, da Silva, Goedtel, & Palcios, 2015). Blanquez et al. demonstrated that the frequency response analysis technique could be used to diagnose the inter-turn faults effectively in the field windings of synchronous machines at different operating speeds (Blánquez, Platero, Rebollo, & Blázquez, 2015).

Zhang et al. proposed a rotor dynamic model to simulate the operations of machinery and generate fault conditions since fault data is difficult to obtain in real applications such as aero-engines. A dynamic model of aero-engine rotor test kit was used to simulate the unbalance, rub impact, and misalignment faults for generation of data. Time-frequency features are extracted using an improved empirical mode decomposition (EMD) and statistical parameters. The fuzzy support vector machine (FSVM) optimized by the multi-population genetic algorithm was used to diagnose the condition of the system automatically (Zhang, Ma, Lin, Ma, & Jia, 2015).

CBM requires continuous monitoring at different operating conditions of the machine to provide maintenance decisions. In most of the aerospace applications, components are too expensive, and may not be possible to subject them to faulty conditions to be able to capture the intelligence about the faults from the data. Thus, in order to develop an intelligent system to monitor the condition of the machine, there must be sufficient knowledge about the system failure mechanisms (Engel, Gilmartin, Bongort, & Hess, 2000). This necessitates the need for capturing intelligence about the faults using a small working model (SWM), and being able to scale up the models to the prototype system to be monitored.

In this paper, we address the problem of diagnosing faults using fault models generated using the data from a small working model (SWM) under fault and no-fault conditions, and the data from prototype system under no-fault condition alone. With this, we are able to get away with the requirement of the need for data from prototype system under faulty conditions, and thus be able to generate the models for diagnosis using the data from the prototype system working under no-fault conditions alone. In the proposed approach, we do not need to ever inject faults in the expensive prototype system. We refer to the proposed approach as scalable fault models for the fact that the fault models generated using an SWM could be used in the prototype system, and thus the models are effectively scaled up.

Duque-Perez et al. used the statistical tools such as box plots and analysis of variance (ANOVA) to analyze the data obtained from the induction motors fed by different power supplies. This study also reveals that the same fault condition generates different fault signatures depending upon the type of power supply, motor, and load conditions. Additive models were used to identify and eliminate the influence of these factors in the fault signatures for developing the universal fault diagnosis system (Duque-Perez, Garcia-Escudero, Morinigo-Sotelo, Gardel, & Perez-Alonso, 2015).

Nuisance attribute projection (NAP) (Solomonoff, Campbell, & Quillen, 2007) is a popular algorithm widely used in speaker recognition systems. Cross-channel degradation is an important factor that affects the performance of speaker recognition systems. For example, a person speaking through a carbon button handset and mobile phone will sound differently. The same speaker from the different channels could cause those two utterances to be classified as different speakers. NAP filters out the effect of the nuisance attributes (channel types) using an eigenvalue analysis. Solomonoff et al. used the NAP to identify and remove the nuisance attributes in the support vector machine (SVM) expansion space to improve the speaker recognition system performance (Solomonoff, Campbell, & Boardman, 2005). NAP is also used in face recognition systems to remove the illumination artifacts from face images (Štruc, Vesnicer, Mihelič, & Pavešić, 2010). Tome et al. presented a general variability compensation scheme based on NAP to compensate the factors affecting the face recognition systems (Tome, Vera-Rodriguez, Fierrez, & Ortega-Garca, 2012). Yifrach et al. proposed a modified NAP to simplify the training process in face recognition systems (Yifrach, Novoselsky, Solewicz, & Yitzhaky, 2014).

From this literature review, we can correlate the factors affecting the speaker recognition systems with the study reported in (Duque-Perez et al., 2015) for the machine fault diagnosis applications, where the same fault condition generates different fault signatures depending upon the factors such as type of power supply, motor, and loads. In this work, we experiment with NAP to diagnose the faults in a system-independent manner. In our work, we consider that the fault is expressing itself through the system as a channel. Therefore, if we can remove the effect of channel from the features used for the classification, we may be able to make the fault models robust across the SWM and the prototype system.

To verify the effectiveness of the approach, we used a 3 kVA synchronous generator as SWM and a 5 kVA synchronous generator as the prototype system. We model the system using 3 kVA generator data (no-fault & fault conditions) and 5 kVA generator (no-fault data), considering the fact that fault injection is not possible in the prototype system. We use NAP to identify the system-dependent dimensions in the feature space and remove those dimensions to make features system-independent across 3 kVA and 5 kVA generator. The system-independent features thus derived are used to diagnose the faults in the 5 kVA synchronous generator. Inter-turn short circuit faults are induced in the R, Y, and B phases of the stator winding to collect the fault conditions of the generator. The frequency domain statistical features are extracted from the current signals. Classification and regression tree (CART) is used as a back-end classifier.

Section 2 discusses the details of our experimental setup, data collection, feature extraction, classification and regression tree (CART) algorithm, and nuisance attribute projection (NAP). Experiments and results are discussed in Section 3, and finally, Section 4 concludes.

2. System description

2.1. Experimental setup

Several researchers have worked on condition monitoring of synchronous generators (Auckland, Pickup, Shuttleworth, Wu, & Zhou, 1995; Batzel & Swanson, 2009; Bruzzese, Giordani, & Santini, 2008; Penman & Jiang, 1996; Tavner, 2008). In synchronous generators,