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# Condition monitoring of induction motors: A review and an application of an ensemble of hybrid intelligent models

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ABSTRACT

In this paper, a review on condition monitoring of induction motors is first presented. Then, an ensemble of hybrid intelligent models that is useful for condition monitoring of induction motors is proposed. The review covers two parts, i.e., (i) a total of nine commonly used condition monitoring methods of induction motors; and (ii) intelligent learning models for condition monitoring of induction motors subject to single and multiple input signals. Based on the review findings, the Motor Current Signature Analysis (MCSA) method is selected for this study owing to its online, non-invasive properties and its requirement of only single input source; therefore leading to a cost-effective condition monitoring method. A hybrid intelligent model that consists of the Fuzzy Min–Max (FMM) neural network and the Random Forest (RF) model comprising an ensemble of Classification and Regression Trees is developed. The majority voting scheme is used to combine the predictions produced by the resulting FMM–RF ensemble (or FMM–RFE) members. A benchmark problem is first deployed to evaluate the usefulness of the FMM–RFE model. Then, the model is applied to condition monitoring of induction motors using a set of real data samples. Specifically, the stator current signals of induction motors are obtained using the MCSA method. The signals are processed to produce a set of harmonic-based features for classification using the FMM–RFE model. The experimental results show good performances in both noise-free and noisy environments. More importantly, a set of explanatory rules in the form of a decision tree can be extracted from the FMM–RFE model to justify its predictions. The outcomes ascertain the effectiveness of the proposed FMM–RFE model in undertaking condition monitoring tasks, especially for induction motors, under different environments.



## 1. Introduction

In the manufacturing environment, condition monitoring is important for machine maintenance, with the aim to safeguard the reliability and efficiency of machinery for production purposes (Venugopal, Wagstaff, & Sharma, 2007). A proper maintenance strategy is important to avoid machine and/or process failures (Cooney, Mann, & Winkless, 2003); therefore minimizing production cost and time (Portioli-Staudacher & Tantardini, 2012). Traditionally, fault diagnostic techniques in complex machines or processes use either *prior* knowledge or historical data (Cholette, Liu, Djurdjanovic, & Marko, 2012). However, detecting, locating, and isolating faults can be a challenging task, which is especially true in operations where dependent failures occur (Weber & Wotawa, 2012). In this aspect, the loss of output due to unplanned shutdown caused by machine or process failures cannot be recovered without incurring additional cost and time, e.g. wages for workers in overtime periods (Alsyouf, 2007). Besides that, as reported in Rockwell Automation (2012), enhancing the capabilities of detecting and monitoring machine faults can lead to reduction of maintenance cost as well as improvement of process uptime by up to 25%. Therefore, condition monitoring has become an integral part in modern production planning and operations.

In general, machine maintenance can be in the form of reactive, preventive, or predictive maintenance (Chen, Ding, Jin, & Ceglarek, 2006). The fix-upon-failure strategy is considered as reactive maintenance, while the pre-planned strategy is related to preventive maintenance. Predictive maintenance, which is also known as condition-based maintenance (CBM), adopts the forecasting strategy. Owing to the immense practical implications of CBM, we focus on designing and developing a useful CBM system for induction motors using a hybrid intelligent model in this study. The goal of CBM is to minimize redundant maintenance activities and, at the

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same time, prevent machine failures (Camci & Chinnam, 2010). As stated in Zhou et al. (2012), an established CBM method is able to avoid non-essential maintenance tasks and to reduce the maintenance cost. As a result, subject to an accurate forecasting technique, CBM offers practical benefits in terms of cost (as compared with reactive maintenance) and time (as compared with preventive maintenance) in machine maintenance. In this aspect, a combination of different intelligent models can be used in CBM to devise a robust forecasting technique and ensure a high predictive accuracy (Camci & Chinnam, 2010). As such, the use of CBM can help increase the availability and reliability of machines for production operations, which is of practical importance in the manufacturing industry.

In production facilities, induction motors are widely used in many processes, e.g. manufacturing machines, belt conveyors, cranes, lifts, compressors, trolleys, electric vehicles, pumps, and fans (Montanari, Peresada, Rossi, & Tilli, 2007). Owing to numerous advantages of induction motors, which include high reliability, high performance, and simple design (Almeida, 2006), they are used in many critical applications where the motor reliability must be at a high level (Ayhan, Trussell, Chow, & Song, 2008). Indeed, as reported in Almeida (2006) and by Commission of the European Communities (2009), three-phase induction motors make up 87% of the total AC motors used in Europe. While induction motors are the workhorses in a lot of production processes, the running cost of induction motors actually greatly exceeds their initial purchase prices (Nagornyy, Wallace, & Jouanne, 2004). Therefore, it is vital to minimize the running cost of induction motors. One useful way is to employ an effective condition monitoring system so that unexpected induction motor failures can be minimized (Siddique, Yadava, & Singh, 2005); therefore reducing maintenance costs as well as unscheduled downtimes (Martins, Pires, & Amaral, 2011). As such, the main motivation of this research is to design and develop a highly reliable intelligent model for condition monitoring of induction motors.

In the CBM domain, intelligent learning models have been applied to tackle many different problems. These include monitoring of hydrostatic self-levitating bearings using a feedforward neural network (Garcia, Rolle, Gomez, & Catoira, 2012), monitoring of water and wastewater facilities using intelligent networks (Davis, Sullivan, Marlow, & Marney, 2012), monitoring of nuclear power plant reactor cores using intelligent systems (West, McArthur, & Towle, 2012), and monitoring of an aircraft air conditioning system using decision trees and a genetic algorithm (Gerdes, 2013). Other successful CBM applications include fault diagnosis of the Tennessee Eastman process using a hidden Markov model (Li, Fang, & Xia, 2014) and fault detection in industrial plants using the self-organizing map network (Domínguez et al., 2012). Besides that, intelligent learning models are useful for monitoring machine conditions through various sensor measurements, ranging from common malfunctions to rare emergency situations (Nadakatti, Ramachandra, & Santosh Kumar, 2008). From the literature, it can be concluded that neural networks with learning capabilities are useful models for tackling CBM problems (Tallam, Habetler, & Harley, 2003). They possess a number of advantages, such as the capability of learning from data samples, and the learning procedure does not require an exact mathematical model.

Among different neural network-based models, the Fuzzy Min–Max (FMM) network is designed specifically for solving data classification (Simpson, 1992) and data clustering (Simpson, 1993) problems. FMM is a hybrid model of neural network and fuzzy system. It inherits the advantages of both its constituents, i.e., the learning capabilities based on data samples (from neural networks) and the inference capabilities based on vague and imprecise information (from fuzzy systems). Besides that, FMM possesses several salient features for tackling data classification problems (Simpson, 1992), which include online learning, short learning time, and establishment of nonlinear decision boundaries. However, one of the key FMM limitations is its inability to provide explanation for its predictions. This is known as the black-box phenomenon (Kolman & Margaliot, 2005) – a problem suffered by many neural network models. One effective way to solve this black-box phenomenon is through rule extraction. In this aspect, decision trees offer a good rule extraction solution (Mitra, Konwar, & Pal, 2002). In particular, the Classification and Regression Tree (CART) is useful for handling large and noisy data samples (Breiman, Friedman, Olshen, & Stone, 1984) while the Random Forest (RF) model is beneficial for improving the performance of a learning model using an ensemble technique (Verikas, Gelzinis, & Bacauskiene, 2011). As reported in Park and Lee (2013), the ensemble technique is useful to improve the performance of constituent classifiers and/or predictors. Therefore, FMM is combined with an RF ensemble (RFE) comprising multiple CART decision trees to form a hybrid intelligent model known as FMM–RFE in this study.

The main contributions of this study are two-fold: a review of different condition monitoring methods for induction motors and a case study to demonstrate the applicability of the proposed FMM–RFE model using real data sets. It is worth mentioning that the case study covers two significant aspects pertaining to condition monitoring of induction motors. Firstly, we examine efficacy of FMM–RFE in monitoring multiple incipient faults from induction motors using information from only one source (i.e., stator currents) in both noise-free and noisy environments. The use of single input source leads to a cost-effective condition monitoring system. It should be noted that not many reports pertaining to monitoring multiple induction motor faults using information from only one source are available in the literature, owing to complexity of the task. Secondly, the ability of FMM–RFE to explain its prediction to domain users with a decision tree is another important aspect of this study. Again, it should be noted that the explanatory facility is absent from many condition monitoring systems reported in the literature (as explained in Section 3).

The organization of this paper is as follows. A total of nine common methods for condition monitoring of induction motors are explained in Section 2. They are compared in terms of the online/offline and invasive/non-invasive characteristics. Then, a review on condition monitoring of induction motors using intelligent learning models is presented in Section 3. The hybrid FMM–RFE model is described in detail in Section 4. To evaluate the effectiveness of FMM–RFE, a benchmark study is conducted, and the results are compared with those from other methods in the literature, as reported in Section 5. In Section 6, the applicability of FMM–RFE to condition monitoring of induction motor is evaluated empirically using real data sets. Concluding remarks and suggestions for further work are presented in Section 7.

## 2. Condition monitoring methods for induction motors

In condition monitoring, the role of intelligent sensors and sensor-based systems is important (Teti, Jemielniak, O'Donnell, & Dornfeld, 2010). Different sensing methods are applicable to condition monitoring of electrical motors in two ways: offline or online. On one hand, offline methods often require motor operations to be disturbed, or shutdown. On the other hand, online methods provide warnings of motor failures in advance. As such, the necessary replacement parts can be prepared before a failure occurs; therefore minimizing downtime of motors (Mehrjou, Mariun, Marhaban, & Misron, 2011). While induction motors are robust, certain faults can occur, which result in their failures (Siddique et al., 2005). As a result, it is essential to have effective and efficient condition monitoring methods for induction motors. A review pertaining to nine