Title: Condition monitoring of induction motors: a review and an application of an ensemble of hybrid intelligent models

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Keywords: Condition monitoring, induction motor, motor current signature analysis, fuzzy min-max neural network, random forest

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Response to Comments by Reviewers

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Title: Condition monitoring of induction motors: a review and an application of an ensemble of hybrid intelligent models

Reviewer #1

The paper is interesting from the practical point of view. Through the methodological pov I haven't found any new idea. In my opinion a few improvements are necessary

1. Author should argue why they choose the presented classifiers, because the plethora of other models could be applied.

Response
We have explained the reasons for formulating a hybrid model comprising FMM and an RF ensemble of CART decision trees. The details are presented in Section 1 (paragraph 5), as follows:

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 et al., 2002). In particular, the Classification and Regression Tree (CART) is useful for handling large and noisy data samples (Breiman et al., 1984) while the Random Forest (RF) model is beneficial for improving the performance of a learning model using an ensemble technique (Verikas et al., 2011). As reported in Park & 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.

2. I understand that diversity of the ensemble was assured by using different models. I suggest authors to present (in the experimental analysis) values of a chosen diversity measure.

Response
A total of six non-pairwise diversity measures have been computed and added in the revised manuscript. They are (1) entropy measure $E$, (2) Kohavi-Wolpert variance, (3) $k$ statistic, (4) measure of difficulty, $\theta$, (5) generalized diversity, and (6) coincident failure diversity. The results are presented in Table 4, and the details are presented in Section 6.4 (paragraph 3).

3. Author chose the line-up of the ensembles arbitrary - I think that it requires argumentation. In my opinion authors should use an ensemble pruning method to find the best line-up.

Response
In accordance with the suggestion, a pruning version of the Random Forest ensemble (RFE) has been implemented. The experimental results have also been updated using the pruned RFE model (coupled with FMM). Details of the pruned RFE model are presented in Section 4.5 (paragraphs 1 and 2).

4. The setup of experiment is unclear - this section should be rewritten.

Response
The experimental setup has been clarified in the revised manuscript, as in Section 6.1. A flowchart to illustrate the condition monitoring procedure has also been included, i.e. Fig. 4.

5. The statistical analysis of the results are required - please use e.g., 5x2 t-test to compare the ensembles and individual models (see e.g., handbook by Alpaydin) + a rank test.

Response
The 5x2 cross-validation method has been used for performance comparison between individual and ensemble models in the revised manuscript, i.e., as explained in Section 6.4 (paragraph 1). In addition, for performance evaluation, the Wilcoxon signed rank test has been used, as explained in Section 6.4 (paragraph 4). The overall results are presented in Table 5, and the details are presented in Section 6.4 (paragraph 4). The findings indicate that the FMM-RFE model performs well as compared with those from its constituents, especially in noisy environments (i.e. at 30% and 50% noise levels).
6. The deeper discussion about feature extraction for the problem under consideration should be included.

**Response**

The feature extraction procedure has been further clarified in Section 6.3, which includes explanation pertaining to the PSD (power spectral density) profiles as well as selection of important harmonic features for classification. The PSD profiles of different induction motor conditions are shown graphically too, i.e. in Figures 7 to 9.

We thank the reviewer for the constructive comments.

**Reviewer #2**

Thanks for the nice work. The topic is important and interesting, but I would suggest the following comments for improvements:

1. Please give a frank account of the strengths and weaknesses of the proposed research method.

**Response**

The proposed research method is based on both MCSA and FMM-RFE. The strengths and weaknesses of the proposed method is given in Section 6 (paragraph 1), as follows:

In this study, we propose a hybrid intelligent model, namely FMM-RFE, for condition monitoring of induction motors using the MCSA method. The strengths and weaknesses of the proposed approach are analyzed, as follows. FMM-RFE possesses a number of advantages, which include its online learning and rule extraction capabilities. These two capabilities are important to tackle condition monitoring problems with comprehensible and convincing predictions (through rule extraction) in changing environments without the need for re-training (through online learning). Nevertheless, FMM-RFE is a complex model involving three constituents, i.e., FMM, RF, and CART. This, in turn, leads to another disadvantage, i.e., a longer computational time (as shown in Table 3). These limitations (high complexity and long computational time) can be a concern when FMM-RFE is used in real-time. One solution is to design dedicated hardware chips to implement FMM-RFE for real-time applications. On the other hand, the MCSA method for condition monitoring has its strengths and weaknesses too. MCSA requires only one input source (i.e., current signals) to detect various faults, instead of using multiple input sources as in other methods. In addition, the non-invasive characteristic of MCSA is appealing as an induction motor does not need to be stopped for the current measurements to be taken. Although MCSA can be used to detect bearing and eccentricity faults, methods based on vibration signals are regarded as the best for these faults (Li & Mechefse, 2006). Besides that, as MCSA uses an external current probe to gather current signals, it is susceptible to noise (Milenkovic et al., 2005). As such, we evaluate the effectiveness of MCSA coupled with FMM-RFE under noisy environments, with 10% to 50% noise levels in the data samples.

2. The research motivations are unclear and rather vague. The authors must clearly discuss the significance of the research problem in the first section.

**Response**

The main research motivation, i.e., to design and develop a reliable condition monitoring system for induction motors, has been clarified in Section 1 (paragraph 3), as follows:

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 et al., 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 et al., 2008). Indeed, as reported in Almeida (2006) and by Commission EC (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 et al., 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 et al., 2005); therefore reducing maintenance costs as well as unscheduled downtimes (Martins et al., 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.
3. The authors will need to clearly address your research contributions in theory. The research contributions in theory must be fully stated in at least one paragraph.

Response
The main theoretical contributions of this research are related to the proposed FMM-RFE model for condition monitoring of induction motors, which has been clarified in Section 1 (paragraph 6), as follows:

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).

4. The authors need to fully discuss insightful practical implications. The discussions must be fully stated in at least one paragraph.

Response
The practical implications of this research is to ensure a useful condition-based maintenance (CBM) system using a hybrid intelligent model for the manufacturing industry, as clarified in Section 1 (paragraph 2), as follows:

In general, machine maintenance can be in the form of reactive, preventive, or predictive maintenance (Chen et al., 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 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.

We thank the reviewer for the constructive comments.
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.

Keywords Condition monitoring, induction motor, motor current signature analysis, fuzzy min-max neural network, random forest

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 et al., 2007). A proper maintenance strategy is important to avoid machine and/or process failures (Conney et al., 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 et al., 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 (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 et al., 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 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 et al., 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 et al., 2008). Indeed, as reported in Almeida (2006) and by Commission EC (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 et al., 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 et al., 2005); therefore reducing maintenance costs as well as unscheduled downtimes (Martins et al., 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 et al., 2012), monitoring of water and wastewater facilities using intelligent networks (Davis et al., 2012), monitoring of nuclear power plant reactor cores using intelligent systems (West et al., 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 et al., 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 et al., 2008). From the literature, it can be concluded that neural networks with learning capabilities are useful models for tackling CBM problems (Tallam et al., 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 et al., 2002). In particular, the Classification and Regression Tree (CART) is useful for handling large and noisy data samples (Breiman et al., 1984) while the Random Forest (RF) model is beneficial for improving the performance of a learning model using an ensemble technique (Verikas et al., 2011). As reported in Park & 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 et al., 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 et al., 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 commonly used condition monitoring methods for induction motors is presented in the following section.
2.1. Vibration

A fault-free induction motor produces very little vibration signals during its normal condition. When faults in the internal parts of an induction motor occur, large vibration signals are generated. For condition monitoring of bearing faults in induction motors, vibration signals can be exploited (Kral et al., 2003). Indeed, monitoring vibration signals is considered to be one of the best methods in bearing faults detection (Li & Mechefske, 2006). By attaching transducers to bearings, radial or axial vibration signals can be measured. This method is useful for detecting not just bearing faults, but also unbalanced mass, misalignment of rotors, as well as gear mesh problems of induction motors (Kral et al., 2003).

2.2. Electromagnetic Field

When an induction motor operates under the normal condition, sinusoidal variations in the air gap flux occur. However, asymmetric rotors or stators can lead to changes in signal variations (Thorsen & Dalva, 1999). For condition monitoring of stators, a search coil (attached to the motor shaft) can be used to measure the distortion pertaining to the flux density of the air gap (Cameron et al., 1986). For condition monitoring of rotors, an internal or external search coil can be used (Elkasabgy et al., 1992). It is preferred to detect signal variations by using an external stray flux sensor. The internal search coil method is invasive, and is not practical in condition monitoring.

2.3. Induced Voltage

The stator currents of an induction motor diminish quickly when the power supply is disengaged. Sinusoidal mmf (magneto-motive force) is induced by the rotor currents (Elkasabgy et al., 1992). When there are broken rotor bars, the voltages induced in the stator windings are affected, providing an indicator of faults. However, changes in terms of loads, temperature of rotors, inertia, and supply voltage affect the usefulness of this method (Supangat et al., 2007). In addition, continuous monitoring using this method is deemed impractical as faults cannot be measured reliably. Besides that, the method is invasive as the motor core or winding needs to be damaged in order to detect faults (Mehrjou et al., 2011).

2.4. Surge Test

In condition monitoring of stator winding, a surge test can be used (Kohler et al., 1999). To perform the test, two identical high-voltage, high-frequency pulses are imposed, while grounding is applied to the remaining phase of the motor winding (Thorsen & Dalva, 1997). Any insulation faults between the winding and coils can be detected by the reflected pulses. In Huang et al. (2007), the surge test was used to detect eccentricity problems in rotors. The eccentricity problem could lead to an asymmetric air gap. As a result, the shape of the surge waveform is altered in each revolution; therefore signifying the air gap problem.

2.5. Motor Circuit Analysis

In this method, the electromagnetic characteristics of an induction motor are measured. By applying a small amount of power, the amplified responses are compared, which in turn allows the rotor and winding conditions to be evaluated (Penrose & Jette, 2000). This method is useful for detecting variations from electromagnetic characteristics in the motor. By using a de-energized induction motor, a number of inductance- and resistance-based tests can be performed. The motor conditions can then be accurately evaluated by combining the measurement taken from inductance, impedance, resistance, as well as phase angle (Penrose & Jette, 2000).

2.6. Acoustic Emission

Acoustic emission can be generated by altering the structure of a solid material (Tandon & Choudhury, 1999). This method can be exploited for detecting rotor and bearing problems. However, the accuracy rate of using acoustic measurements for detecting rotor problems can be compromised in noisy environments (Li & Mechefske, 2006), e.g. a rise of 12dB in electromagnetic noise can occur when the speed of an induction motor is doubled (Singal et al., 1987). On the other hand, an ultrasonic wave can be launched for monitoring faults related to stator bars (Lee et al., 1994).

2.7. Air Gap Torque

When an induction motor rotates, the current and flux linkages produce an air gap torque. Harmonics (at some specific frequency) in the air gap torque emerge when the motor is subject to an unbalanced supply (Mehrjou et al., 2011). The air gap torque can be analyzed such that unbalanced stator winding and rotor bar faults can be differentiated (Hsu et al., 1992).
Nonetheless, it is difficult to measure the air gap torque precisely, or in a direct way (Mehrjou et al., 2011). Owing to the natural frequency of the motor frame, shaft, and rotor, some variations between the measured pulsating torque and the actual air gap torque is expected.

2.8. Instantaneous Angular Speed

The instantaneous angular speed refers to the variation of the angular speed within one revolution of the motor shaft (Sasi et al., 2006). It can be used to monitor stator core vibrations (due to asymmetry faults). This method is also useful for condition monitoring of rotors (Feldman & Siobold, 1999), with the assumption that the speed is constant. However, it is not practical because the rotating speed normally varies during motor operations.

2.9. Motor Current Signature Analysis

MCSA works by measuring currents from the stators of induction motor. The measured currents are processed to produce their power spectrum profiles. Motor faults can then be detected by analyzing the resulting power spectrum profiles (Siddique et al., 2005). Currents are restricted from flowing through a cracked rotor bar; therefore no magnetic flux can be sensed from the bar. When asymmetric rotor bars occur, a non-zero backward rotating field is formed. As a result, harmonics pertaining to the stator winding currents are induced (Mehrjou et al., 2011). In Siau et al. (2004), a formulation to determine the number of broken rotor bars based on stator currents is provided.

2.10. Summary

Table 1 shows a comparison of the above-mentioned methods for condition monitoring of induction motors. The first two (vibration and electromagnetic field) are invasive methods because they require sensors to be attached internally in the motor. The next three (induced voltage, surge test, and motor circuit analysis) are off-line methods generally. The last four are online and non-invasive methods. On one hand, direct attachment of sensors to the motor is often needed for the air gap torque and acoustic emission methods. On the other hand, a constant motor speed is often required for the instantaneous angular speed method. Comparatively, the MCSA method is cost-effective and easy to implement, as it only requires clamping the current sensors to the cables of the incoming power supply of the induction motors. As a result, MCSA is chosen for use in the case study conducted in this research.

<table>
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<tr>
<th>Method</th>
<th>Online</th>
<th>Offline</th>
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<td>Vibration</td>
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<td>Acoustic Emission</td>
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<td>Air Gap Torque</td>
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<td>Instantaneous Angular Speed</td>
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<td>Motor Current Signature Analysis</td>
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3. Intelligent Systems for Condition Monitoring of Induction Motors

A survey of intelligent learning models for condition monitoring of induction motors is presented in the following section. A number of key input sources of induction motors, i.e., current signals, vibration signals, and combination of multiple input signals, are covered.

3.1. Current Signals

Current signals constitute a useful source in condition monitoring of various induction motor faults, which include stator, rotor, and bearing problems. In induction motors, bearing faults are a common cause for eccentricity-related problems (Haji & Toliyat, 2001). In Önel et al. (2009), a Concordia transform algorithm was developed, and the radial basis function (RBF) neural network was employed for condition monitoring of bearings. Using three-phase current signals, an accuracy rate of 93.75% was reported. In Ghate & Dudul (2010), the principal component analysis (PCA) was used to extract the input features from three-phase current signals of the stator. The aim was to detect eccentricity and stator winding faults using the RBF-based multi-layer perceptron (MLP) network. The accuracy rates obtained were between 98.11% – 98.41%. On the other hand, multiple discriminant analysis was deployed to detect broken rotor bars based on the input features extracted from stator current signals (Ayhan et al., 2005). The reported accuracy rates from six different tests were between 73.12% – 99.38%.
In Rodríguez et al. (2008), a predictive filter was used to separate the harmonic components extracted from current signals. A fuzzy model was used to detect short circuits in the coils. Two different tests were conducted, and the accuracy rates were: 92% for the coil short circuit test and 100% for the open phase and coil short circuit test. In Pires et al. (2010), stator currents were used to produce eigen-related information, with were used for detecting broken rotor bars as well as stator winding faults. Different fault severity levels were obtained based on the analysis of eigenvalues and eigenvectors of stator currents. In Widodo & Yang (2008), PCA and kernel PCA were used to extract useful information from start-up transient currents. The wavelet-based support vector machine (SVM) was deployed for condition monitoring of eccentricity problems, unbalanced phase, and bearing faults. The accuracy rates of PCA and kernel PCA were 83% and 96%, respectively.

3.2. Vibration Signals

In addition to current signals, vibration signals are another common source for condition monitoring of induction motors. In Lei et al. (2008), the adaptive neural fuzzy inference system (ANFIS) was used for condition monitoring of bearing faults. The input features comprised vibration signals extracted from time-domain and frequency-domain statistics. Two evaluations based on four randomly chosen features and four useful features were conducted. The accuracy rates achieved were 83.42% and 100%, respectively. In Taplak et al. (2006), the back-propagation neural network was applied to detect bearing faults. The input features comprised amplitude, velocity, and acceleration measurements from vibration signals. Two evaluations based on load-free and centered loads on the shaft were conducted. The accuracy rates achieved were 76% – 83% and 67% – 74%, respectively. The back-propagation neural network was also used to detect bearing faults in Hwang et al. (2009). The Cepstrum coefficients from vibration signals were used to form the input features. The network was able to produce perfect accuracy in detecting bearing faults.

An improved fuzzy ARTMAP network was used to detect rolling element bearing faults in Xu et al. (2009). A series of input features from time-domain and frequency-domain signals as well as wavelet moments were obtained from vibration signals. Two evaluations based on the original and optimized feature sets were conducted. The accuracy rates achieved were 89.382% and 99.541%, respectively. In Samanta & Nataraj (2009), the particle swarm optimization algorithm was used to process and extract time-domain vibration signals. Linear and nonlinear proximal SVM models were deployed to detect bearing faults. The accuracy rates achieved were 91% – 93% and 92% – 95%, respectively. In Su & Chong (2007), the short time Fourier transform was used to process vibration signals. The extracted information was provided to a neural network trained with the Levenberg-Marquardt algorithm. The accuracy rates for detecting broken rotor bars and eccentricity problems were between 97% – 100%. In Nguyen et al. (2008), time-domain features from vibration signals were used to detect faults related to unbalanced rotors and damaged bearings. The genetic algorithm with a decision tree and a multi-class SVM were used. Two tests, i.e. with and without feature selection, were conducted. The reported accuracy rates were 94.14% and 94.79% – 99.67%, respectively.

3.3. Multiple Input Signals

Both current and vibration signals were used for classification of eccentricity problems and unbalanced phases in Han et al. (2007). The genetic algorithm was used for feature reduction, and a hybrid adaptive resonance theory and Kohonen self-organizing map model was employed as an effective classifier for condition monitoring. In Tran et al. (2009), both current and vibration signals were used to form the input features for detecting eccentricity, rotor, and bearing faults. The CART model was deployed to choose useful input features. The ANFIS model with fuzzy if-then rules was used for fault identification. The accuracy rate achieved was 91.11%. Both current and vibration signals were used to classify bearing faults and broken rotor bars in Liu et al. (2009). A fusion model comprising fuzzy measures and fuzzy integrals was devised, and a perfect accuracy rate was reported. In Bouzid et al. (2008), three-phase shifts between the phase voltage and line currents were monitored. The MLP network with back-propagation training was useful for detecting inter-turn short-circuit faults in stator windings.

3.4. Summary

Based on the survey of single and multiple input sources (current and vibration signals), it is evidenced that intelligent systems are useful for monitoring various types of induction motor faults. While various intelligent systems, which include neural networks, fuzzy systems, support vector machines, decision trees, and evolutionary algorithms, are able to achieve good results, they normally learn the fault characteristics of induction motors in an offline learning mode. As a result, FMM, which is able to perform online learning, is investigated in this study. Another important property of a useful condition monitoring model, is absent from most of the intelligent systems covered in the review, i.e. the ability to provide explanation for justifying the predictions. Indeed, the capability of providing explanatory rules to domain users is very important in condition monitoring applications. A useful condition monitoring system needs to produce convincing predictions to domain users. Therefore, FMM is equipped with a rule extraction technique by using the CART-based RF ensemble in this paper. Besides that, the majority voting scheme is adopted to improve the overall performance. Therefore, the resulting FMM-RFE model is capable of learning online, providing useful justification for its predictions, and producing high classification accuracy.
4. The Hybrid Intelligent Model

In our previous work (Seera & Lim, 2014, an initial investigation on combining FMM, CART, and RF has been fruitful, and the resulting hybrid model has been shown to be useful in tackling medical data classification problems. Leveraging on the previous findings, we further improve the initial model and formulate the proposed FMM-RFE model in this study. A number of useful modifications are introduced in FMM-RFE in order to ensure that its constituents are integrated efficiently. Table 1 shows the procedure of the proposed FMM-RFE model. The details are explained in the following sections.

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4.1. The FMM Neural Network

The hyperbox fuzzy sets are used in the learning algorithm of FMM. A user-defined expansion parameter, \( \theta \in [0, 1] \), is employed to regulate the hyperbox size. The minimum (min) and maximum (max) points of a hyperbox are deployed to measure the extent an input pattern falls within the hyperbox through a fuzzy membership function. Given a unit hypercube, \( I^n \), in an n-dimensional pattern space, the hyperbox fuzzy set, \( B_j \), is defined as follows (Simpson, 1992).

\[
B_j = \{ X, V, W, f(X, V, W) \} \quad \forall X \in I^n,
\]

where \( V=(v_{j1}, v_{j2}, \ldots, v_{jn}) \) and \( W=(w_{j1}, w_{j2}, \ldots, w_{jn}) \) are the min and max points of \( B_j \), respectively. Fig. 1 illustrates the min and max points of a three-dimensional box. The joint fuzzy set that categories the \( k^{th} \) output class, i.e., \( C_k \), is:

\[
C_k = \bigcup_{j \in k} B_j,
\]

where \( K \) denotes all hyperboxes that belong to class \( k \).

![Fig. 1. A three-dimensional hyperbox](image)

The FMM learning algorithm aims to construct nonlinear boundaries for different output classes. It should be noted that overlapped regions among hyperboxes from the same class are allowed, but not for hyperboxes from different classes. For the \( j^{th} \) hyperbox, its membership function, i.e., \( b_j(A_h) \in [0, 1] \), is employed to compute the degree of the \( h^{th} \) input pattern, \( A_h \), being outside hyperbox \( B_j \). As \( b_j(A_h) \) becomes closer to unity, the pattern is considered to be more contained by the hyperbox. The membership function is computed using (Simpson, 1992):

\[
b_j(A_h) = \frac{1}{2^n} \sum_{m} \left[ \max(0, 1 - \max(0, \gamma \min(1, a_{hm} - w_{jm}))
+ \max(0, 1 - \max(0, \gamma \min(1, v_{jm} - a_{hm})))\right],
\]

where \( A_h=(a_{h1}, a_{h2}, \ldots, a_{hn}) \) is the \( h^{th} \) input pattern; \( \gamma \) (the sensitivity parameter) regulates the speed the membership function diminishes with respect to the distance between \( A_h \) and \( B_j \).

The FMM network has three layers of nodes. The input, hidden, and output layers are denoted as \( F_A \), \( F_B \), and \( F_C \), respectively. The numbers of \( F_A \) and \( F_C \) nodes correspond to the input dimension and the number of output (target) classes, respectively. \( F_B \) is the hyperbox layer. Each hyperbox fuzzy set is denoted by one \( F_B \) node (with its membership function in equation (3)). The min-max points are stored within the \( F_A \) and \( F_B \) connections. Matrix \( U \) stores the binary-valued connections between \( F_B \) and \( F_C \) nodes, i.e.
where $b_j$ is the $j^{th}$ hidden node in $F_B$ and $C_k$ is the $k^{th}$ target class in $F_C$. In each $F_C$ node, a fuzzy union operation is performed, i.e.

$$\sum_{i=1}^{m} c_k = \max_{j=1}^{u_{jk}} b_j u_{jk}$$

(5)

Note that $F_C$ nodes can be used in two modes. While the outputs can be used directly to produce a soft decision, the winner-take-all principle is applied to reach a hard decision (the highest value in $F_i$ is set to 1 for the target class, with the remaining set to 0).

### 4.2. Modifications to the FMM Neural Network

In Quteishat & Lim (2008), two modifications were incorporated into FMM, i.e., computation of the hyperbox confidence factor and hyperbox centroid. These modifications are adopted owing to their usefulness in ensuring that FMM and CART are integrated efficiently. Each hyperbox $B_j$ is tagged with a confidence factor, $CF_j$. The confidence factor is computed as follows (Carpenter & Tan, 1995; Quteishat & Lim, 2008):

$$CF_j = (1 - \eta)U_{j} + \eta A_{j}$$

(6)

where $U_j$ are $A_j$ are the usage and accuracy measures of hyperbox $j$, respectively; $\eta \in [0, 1]$ is a weighting factor. The confidence factor is useful for identifying regularly used and fairly accurate hyperboxes as well as rarely used and highly accurate hyperboxes. Notice that each FMM hyperbox contains only the min-max points. As such, the centroid of each hyperbox needs to be established, which can be computed as follows (Quteishat & Lim, 2008):

$$C_{mj} = C_j + \frac{\left(a_{hji} - C_j\right)}{N_j},$$

(7)

where $C_j$ is centroid of the $j^{th}$ hyperbox in the $i^{th}$ dimension; $a_{hji}$ is the $h$-th input data; $N_j$ is the number of data contained in the $j^{th}$ hyperbox. These two modifications are useful for the CART formation procedure, as follows.

### 4.3. Classification and Regression Tree

A training set containing data features (also known as attributes) and their target classes are required to build a decision tree (i.e., CART). In general, the greedy approach is deployed to partition the training data into smaller groups. Initially, the whole training set is used at the root node. If all data samples are from the same class, no further partitioning is needed. Otherwise, it is necessary to find the best feature so that the node can be split into two leaf nodes. This applies to every new leaf node, until a full tree is constructed. The Gini impurity index is used to measure the degree of impurity pertaining to the data set, $D$, as follows (Han et al., 2012):

$$Gini(D) = 1 - \sum_{i} p^2(i),$$

(8)

$p(i)$ is the observed fraction of classes.

An impurity function of each node is used to measure the goodness-of-split. In the ideal situation, every leaf node should be dominated by one class (i.e., pure). When there is a split at node $t$, the goodness-of-split is computed as follows:

$$\Delta(i(s,t)) = i(t) - p_L[i(t_L)] - p_R[i(t_R)],$$

(9)

$s$ is a particular split, $p_L$ and $p_R$ denote the data proportions at node $t$ that flow to the left (i.e., $t_L$) and right (i.e., $t_R$) child nodes, $i(t_L)$ and $i(t_R)$ denote the impurity measures of the left and right child nodes, respectively (Yohannes & Webb, 1999).

### 4.4. Modifications to CART

The FMM hyperbox centroid is used as a confidence factor in CART. The aim is to overcome the problem associated with incorrect branches in CART taken by a learning sample, which can lead to classification errors. A useful modification to the Gini index is therefore introduced, i.e.

$$Gini(D) = 1 - \sum_{i} w^2(i),$$

(10)

$w(i)$ is the normalized weights of the classes. This proposed modification is able to enhance the CART performance, as shown in case studies in the next section.
4.5. Random Forest

The general structure of RF is shown in Fig. 2, where \( k_1, k_2, \ldots, k_T \), are \( k \) are classes, and \( T \) is the number of trees (Verikas et al., 2011). RF is constructed using the bagging method with random attribute selection. Consider a data set, \( D \), with \( d \) tuples, and \( k \) CART trees in the ensemble. In each iteration, a data set, \( D_i \), is formed by drawing \( d \) tuples using the sample replacement method (Han et al., 2012), i.e., \( D_i \) constitutes a bootstrap sample of \( D \). The CART algorithm is applied to grow the RF tree to its maximum size. Then, pruning is performed in order to find a good subset of ensemble members.

Pruning reduces a tree size by removing leaf nodes under the original branch and/or turning the branch nodes into leaf nodes. In this study, the cost complexity pruning algorithm, which considers the cost complexity of a tree as a function of the number of leafs in the tree and the error rate based on the tree, is utilized (Han et al., 2012). The pruning procedure starts from the bottom of the tree, where the cost complexity of sub-tree at an internal node is computed. If the sub-tree at an internal node results in a smaller cost complexity, the sub-tree is pruned, otherwise it is kept (Han et al., 2012). Finally, the majority voting scheme is adopted to combine the predictions from an ensemble of pruned trees, as shown in Fig. 2.

![Fig. 2. The structure of a random forest (adopted from Verikas et al., 2011)]

5. A Benchmark Problem

Before conducting the evaluation using real induction motors, a benchmark study related to the steel plate faults was first carried out. The purpose of the benchmark study was to compare FMM-RFE with its constituents as well as other models in the literature. Obtained from the UCI Machine Learning Repository (Bache & Lichman, 2013), the steel plate data set comprised 1941 samples, each with 27 features. The outputs comprised 7 types of faults, i.e., pastry, z-scratch, k-scratch, stains, dirtiness, bumps, and other faults. A similar study with three different models, i.e., logistic regression, the MLP neural network, and the C5.0 decision tree, was reported in Fakhr & Elsayad (2012). For comparison purposes, the same data distribution as used in Fakhr & Elsayad (2012) was followed in this study. Four different models, i.e., FMM, CART, and FMM-CART, and FMM-RFE, were compared. To indicate the computational complexity of each model, the execution time from one test run using an Intel Core i5-4200U 2.30 GHz processor, 4GB RAM and the MATLAB® R2013a software was recorded. The overall results are presented in Table 2.

As can be observed in Table 2, the FMM accuracy rate is the lowest, and its network structure is the most complex. However, its computational time is the shortest. FMM-RFE is able to produce the best result (i.e., 98.9% accuracy) with the least complex structure. But, it has the longest computational time. The accuracy rates reported in Fakhr & Elsayad (2012) are as follows: 72.59% for logistic regression, 79.14% for the MLP neural network, 90.57% (without boosting) and 98.09% (with boosting) for the C5.0 decision tree. As such, FMM-RFE produces a better performance as compared with the results reported in Fakhr & Elsayad (2012).

6. Condition Monitoring of Induction Motors

In this study, we propose a hybrid intelligent model, namely FMM-RFE, for condition monitoring of induction motors using the MCSA method. The strengths and weaknesses of the proposed approach are analyzed, as follows. FMM-RFE possesses a number of advantages, which include its online learning and rule extraction capabilities. These two capabilities are important to tackle condition monitoring problems with comprehensible and convincing predictions (through rule extraction) in changing...
environments without the need for re-training (through online learning). Nevertheless, FMM-RFE is a complex model involving three constituents, i.e., FMM, RF, and CART. This, in turn, leads to another disadvantage, i.e., a longer computational time (as shown in Table 3). These limitations (high complexity and long computational time) can be a concern when FMM-RFE is used in real-time. One solution is to design dedicated hardware chips to implement FMM-RFE for real-time applications. On the other hand, the MCSA method for condition monitoring has its strengths and weaknesses too. MCSA requires only one input source (i.e., current signals) to detect various faults, instead of using multiple input sources as in other methods. In addition, the non-invasive characteristic of MCSA is appealing as an induction motor does not need to be stopped for the current measurements to be taken. Although MCSA can be used to detect bearing and eccentricity faults, methods based on vibration signals are regarded as the best for these faults (Li & Mechefske, 2006). Besides that, as MCSA uses an external current probe to gather current signals, it is susceptible to noise (Milenkovic et al., 2005). As such, we evaluate the effectiveness of MCSA coupled with FMM-RFE under noisy environments, with 10% to 50% noise levels in the data samples.

In the following section, the experimental setup is first presented, which is followed by the details of stator winding faults and eccentricity problems. Next, the feature extraction process pertaining to the two faults is explained. The results are then presented and discussed.

6.1. Experimental Setup

After establishing the usefulness of FMM-RFE with the benchmark study, a condition monitoring task of induction motor using real data was conducted. Two common induction motor fault conditions, i.e., stator winding faults and eccentricity problems were evaluated. A database comprising real current signals was established. A series of experiments with a laboratory-scale test rig comprising an oscilloscope, three current probes, and an induction motor, was conducted, as shown in Fig. 3. A database comprising real current signals from induction motors was established for condition monitoring using FMM-RFE.

![Fig. 3. A test rig for monitoring and detecting induction motor faults](image)

In this study, a total of three induction motors were tested. One of the induction motors was in a healthy (fault-free) condition, which was used for comparison purposes with faulty motors. Other two induction motors were operated with various fault conditions. The induction motors were first operated with turn shorts in one of the three phases having stator windings short. Then, eccentricity was produced for experimentation. A number of tests were performed at 25%, 50%, 75%, and full load conditions. The load was electronically controlled, whereby the load conditions could be increased or decreased by turning the controller knob accordingly. Three probes were used to measure the stator currents, and the maximum measurement frequency was set at 50 kHz.

The three-phase stator currents from an induction motor were measured using three current probes connected to an oscilloscope as a data acquisition unit. The data samples were acquired using a network connection and stored in a computer. A total of 20 cycles, which was equivalent to 0.4 seconds, of unfiltered three-phase stator currents, i.e. phase A, phase B, and phase C, were transformed using Fast Fourier Transform (FFT) to the respective Power Spectrum Density (PSD) profiles for feature extraction. During feature extraction, selected pairs of harmonic magnitudes from the frequency spectrum were used as the input features of FMM-RFE. The output of FMM-RFE was a prediction of different motor conditions, i.e. fault-free, stator winding faults, or eccentricity problems. An overview of the procedure for condition monitoring is shown in Fig. 4.
6.2. Induction Motor Faults

In this section, two main induction motor faults, i.e. stator winding and eccentricity, are explained.

6.2.1. Stator Winding Faults

According to Rodríguez et al. (2008), approximately 38% of induction motor faults are related to stator windings. One of the common causes of this fault is short circuits between windings from two different phases, or between the ground and one of the phase windings (Awadallah & Morcos, 2003). When the turn-to-turn faults are undetected at the early stage, major short circuits can eventually occur, resulting in damages in the stator coils. Fig. 5 shows two induction motors, one with stator windings in a good condition and another with winding shorts. In this study, the induction motor used in the experiment was inflicted with the condition of about 10% windings turn shorts in one phase.

6.2.2. Eccentricity Problems

The common cause of eccentricity is bearing faults (Rosero et al., 2006), which contribute approximately 40% of induction motor problems (Rodriguez et al., 2008). Eccentricity problems result in a non-uniform air gap. There are two types of eccentricity conditions pertaining to the rotors of induction motors, i.e., static and dynamic eccentricity. In static eccentricity, the position of the air gap is fixed. In dynamic eccentricity, the air gap position rotates in correspondence with the rotor. In general, a maximum of 10% eccentricity condition is tolerable, owing to imperfect design and manufacturing processes (Awadallah & Morcos, 2003). However, a higher degree of eccentricity condition can result in rotor-to-stator rub, leading to damages for the rotor and/or windings or core of the stator (Nandi et al., 2011).

In this study, the motor used in the experiment was inflicted with mixed eccentricity (Nandi et al., 2011), i.e., both static and dynamic eccentricity co-existed in the motor. One way to create mixed eccentricity was to use non-concentric support parts between the shaft and bearing (Rodriguez et al., 2008). This method was used in Sahraoui et al. (2008), as well as in this experiment, as shown in Fig. 6. During the experiment, the induction motor operated with approximately 30% dynamic eccentricity and 10% static eccentricity, under four load conditions (25%, 50%, 75%, and 100%).
6.3. Feature Extraction

The MCSA method relies on the spectral analysis of stator currents, or more precisely the supply currents of a motor, to detect an incipient motor fault (Siddique et al., 2005). Specifically, the spectral density is exploited to extract useful information from the current signal and to encode the associated power distribution in the frequency domain. The PSD profile is Fourier transform of the auto-correlation function of a signal when the signal is stationary (Herman et al., 2008). On the other hand, FFT allows a fast computation of the Fourier coefficients (Proakis & Monalakis, 1995). As such, FFT is used in this study to produce the PSD profile of the current signals. The Fourier transform values are, in general, complex quantities with both real and imaginary components. As such, the PSD profile is generated by multiplying the FFT function with its complex conjugates. It is then normalized by dividing the profile with the series length. Figs. 7 to 9 show the PSD profiles comprising different signal harmonics from three different motor conditions, i.e., a fault-free, stator winding faults, and eccentricity problems, respectively. Selection of important signal harmonics as useful discriminative input features for classification is explained next.

For a squirrel-caged induction motor, rotor slotting induces additional harmonics in the rotor magnetic field (Sharifi & Ebrahimi, 2011). Equation (11) shows the Rotor Slot Harmonics (RSHs) order:

\[
\text{RSHs order} = n \times (p + 1)
\]
where \( k \) is the slot index, \( p \) and \( N_r \) denote that number of pole pairs and rotor slots, respectively. When there is short circuit in stator windings, an increase in the current spectrum magnitude of the third-order RSHs can be observed (Sharifi & Ebrahimi, 2011). It should be noted that the 13\textsuperscript{th} harmonic is important because of its significant magnitude change in different motor conditions, i.e. fault-free, stator winding faults, unbalanced supply. As stated in Sharifi & Ebrahimi (2011), when a stator winding fault occurs, the standard deviation of the 13\textsuperscript{th} harmonic is six times larger than that of a fault-free motor.

Since the rotor magnetic field has extra components (besides the fundamental harmonic) in the phase current of an induction motor, it is difficult to differentiate between unbalanced problems and stator winding faults. As a result, the currents from all three phases need to be considered. In a normal motor, a fault-free winding condition is assumed, and the currents are assumed in a balanced state. The conductor distribution is (Sharifi & Ebrahimi, 2011):

\[
\begin{align*}
n_{r}(\theta) &= \sum_{i} n_{ak} \delta(\theta-\theta_{i}) \\
n_{s}(\theta) &= \sum_{i} n_{ak} \delta(\theta-\theta_{i}) - \frac{2\pi}{3} \\
n_{o}(\theta) &= \sum_{i} n_{ck} \delta(\theta-\theta_{i}) + \frac{2\pi}{3}
\end{align*}
\]

(12)

where \( n \) is the number of conductors in the stator slot, \( \theta \) is the angular position along the stator inner surface, \( k \) is the slot index, and \( \delta \) is a step function. For a fault-free motor, the windings in all three phases have the same number of conductors, i.e. \( n_{ak} = n_{ak} = n_{ak} \). However, when the stator windings have inter-turn shorts, \( n_{ak} \neq n_{ak} \neq n_{ak} \). According to Amara & Barakat (2011), a fault-free induction motor and one with stator winding faults (inter turn shorts) show different patterns in harmonics 3 and 5. Besides that, the findings in Faiz et al. (2010) indicate that the RSH amplitudes from harmonics 5 and 7 of a fault-free induction motor are different from those from (i) static eccentricity; (ii) broken rotor bars and static eccentricity. The findings in Faiz & Ojaghi (2009) denote that the harmonic amplitudes can be used to differentiate between unbalanced supply and static and dynamic eccentricity. Cusido et al. (2005) also state that visible effects around harmonic 5 are induced by rotor eccentricity. In this study, based on the above analysis, harmonics 3, 5, 7, and 13, and the standard deviation of harmonic 13 were used as the discriminative input features for condition monitoring of induction motors using FMM-RFE.

6.4. Results and Discussion

The experiment aimed to monitor and predict three different induction motor conditions using FMM-RFE, i.e., fault-free, stator winding faults, and eccentricity problems. For all data samples, normalization was first performed to ensure that the values were between 0 and 1. Note that because the data set size was small (1000 samples), considerable variations in the prediction error estimate could occur. Besides that, outliers could cause variations in the prediction error estimate too (Kewley et al., 2010). To tackle this problem, the cross-validation method was adopted to produce a reliable estimate of the performance (Kewley et al., 2010). By using the 5x2 cross-validation method (Dietterich, 1998), the data samples were divided equally into two sub-sets, one for learning and another for test, respectively. The role of the two sub-sets was swapped (Alpaydin, 2004). The same process with randomized data samples was then repeated for five times. To further assess the robustness of FMM-RFE in noisy environments, the test samples were corrupted with Gaussian white noise at different levels (10% to 50%, with an increment of 20%). The aim was to evaluate the robustness of FMM-RFE in noisy environments.

The overall results (average accuracy and model complexity) are summarized in Figs. 10 and 11, respectively, while the average computational times for one run are shown in Table 3. As expected, the accuracy rates of all models deteriorated in correspondence with the level of noise. At the 50% noise level, FMM-RFE was able to produce about 91% accuracy, while FMM-CART, CART, and FMM yielded 87%, 84%, and 80%, respectively. Similarly, the model complexity increased in line with the level of noise, as can be seen in Fig. 11. FMM created the most complex network, and followed by CART and FMM-CART. FMM-RFE exhibited the least complex model with only 6 leaves (at the 50% noise level), while FMM, CART, and FMM-CART created 16 nodes, 9 leaves, and 8 leaves, respectively. However, the computational durations for all models, except FMM-RFE, were within 1 second. FMM-RFE consumed the maximum time, i.e., 1.21 second.

![Fig. 10](image.png) Performance comparison of different models with different noise levels
In addition to prediction accuracy, an ensemble diversity measure using six non-pairwise diversity indicators was further conducted for FMM-RFE. The results including average accuracy (as presented in Table 4) are shown in Table 4. The entropy measure, $E$ (between 0 and 1) indicates no difference in diversity (i.e., 0) and the highest possible diversity (i.e. 1). The Kohavi-Wolpert (KW) variance (Kohavi & Wolpert, 1996) constitutes a decomposition measure for the error rate of a classifier. A smaller KW variance indicates a more diverse classifier ensemble. The $\kappa$ statistic can be used as a measure of diversity between two classifiers (Dietterich, 2000). A value of 0 indicates the agreement between two classifiers equals to that as expected by chance, while a negative value indicates the agreement is less than that as expected by chance. The difficulty index, $\theta$, measures a fraction of classifiers that correctly categorize a random input pattern (Hansen & Salamon, 1990). The value of $\theta$ ranges from 0 (an ideal case, but unrealistic in real scenarios) to 1, where a higher $\theta$ value indicates a worse classifier ensemble. The Generalized Diversity (GD) measure, ranged between 0 (minimum diversity) and 1 (maximum diversity), occurs when the failure of one classifier is accompanied by correct labelling of another classifier (Partridge and Krzanowski, 1997). On the other hand, the Coincident Failure Diversity (CFD) measure is a modification of GD, whereby a value of 0 indicates all classifiers are always correct or incorrect, and a value of 1 indicates all misclassifications are unique (Partridge and Krzanowski, 1997). From the results in Table 4, it can be seen that FMM-RFE performs well in terms of a variety of ensemble diversity measures, even with 50% noise-induced data samples.

To further evaluate the performances statistically, the Wilcoxon signed rank test was performed. It is a nonparametric test which is used to determine whether two groups of indicators are different (Alpaydin, 2004). When the $p$-value is lower than the threshold (i.e., 0.05 or 95% confidence interval), the null hypothesis is rejected, and the outcome is considered significant. In this study, the null hypothesis claimed that the performances of both models under test were similar. Table 5 shows the results. As can be observed, FMM-RFE performed significantly better than (i) FMM for all tests; (ii) CART at 10%, 30%, and 50% noise levels; and (iii) FMM-CART at 30% and 50% noise levels. The results positively indicate the usefulness of FMM-RFE for condition monitoring of induction motors in noisy environments.

<table>
<thead>
<tr>
<th>Noise-level</th>
<th>Accuracy</th>
<th>$E$</th>
<th>KW</th>
<th>$\kappa$</th>
<th>$\theta$</th>
<th>GD</th>
<th>CFD</th>
</tr>
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<th>CART vs FMM-RFE</th>
<th>FMM-CART vs FMM-RFE</th>
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<td>0.0039</td>
<td>0.0078</td>
<td>0.0313</td>
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is in a fault-free condition. This decision tree is useful to domain users to understand the predictions provided by FMM-RFE. The extracted decision tree is also in agreement with analysis of harmonic patterns reported in the literature. For stator winding faults, different patterns occur in the 3rd and 5th harmonics (Amara & Barakat, 2011), while for eccentricity problems, the harmonic amplitudes differ in the 5th harmonic (Cusido et al. 2005, Faiz et al., 2010). Therefore, the decision tree is useful to assist domain users in understanding the conditions related to the induction motor under scrutiny.

Fig. 12. A decision tree for multiple faults with the noise-free data set

7. Conclusions

In this paper, a review on condition monitoring of induction motors has been presented. A case study pertaining to condition monitoring of induction motors using the FMM-RFE model has also been demonstrated. The usefulness of FMM-RFE is first evaluated using a benchmark problem. The results indicate its effectiveness as compared with those reported in the literature. A series of real experiments on condition monitoring of induction motors is conducted. The MCSA method is deployed to obtain stator current measurements from induction motors. The use of only one input source (i.e. stator currents) with the MCSA method leads to a cost-effective condition monitoring solution. Based on the output of MCSA, useful harmonic features are extracted and employed as the input features to FMM-RFE for condition monitoring. Different load conditions and noise levels are tested. The results are analyzed statistically. The findings ascertain efficacy of FMM-RFE in undertaking condition monitoring of induction motors under different load conditions and noisy environments.

For further work, real-time implementation of FMM-RFE is useful. With increasing numbers of induction motors in the industry, it is important to embed FMM-RFE into an appropriate hardware chip (e.g. FPGA or ASIC) for real-time condition monitoring using relevant data acquisition and signal conditioning circuits. Besides that, issues related to computational times have to be taken into consideration. All these challenges need to be overcome in order to realize a robust and useful real-time condition monitoring tool for induction motors using the FMM-RFE model.

Acknowledgements

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References

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

**Highlights**
- An ensemble of hybrid intelligent models is applied to condition monitoring tasks.
- A review on condition monitoring of induction motors is presented.
- The proposed model is able to learn incrementally and explain its predictions.
- The results ascertain the usefulness of the model for condition monitoring tasks.
- The knowledge base is presented as a decision tree for interpretation by users.