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A review of intelligent methods for condition monitoring and fault diagnosis of stator and rotor faults of induction machines

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ABSTRACT

Nowadays, induction motor (IM) is extensively used in industry, including mechanical and electrical applications. However, three main types of IM faults have been discussed in the literature, bearing, stator, and rotor. Importantly, stator and rotor (S/R) faults represent approximately 50%. Traditional condition monitoring (CM) and fault diagnosis (FD) methods require a high processing cost and much experience knowledge. To tackle this challenge, artificial intelligent (AI) based CM and FD techniques are extensively developed. However, there have been many review research papers for intelligent CM and FD machine learning methods of rolling elements bearings of IM in the literature. Whereas there is a lack in the literature, and there are not many review papers for both S/R intelligent CM and FD. Thus, the proposed study's main contribution is in reviewing the CM and FD of IM, especially for the stator and the rotor, based on AI methods. The paper also provides discussions on the main challenges and possible future works.

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1. INTRODUCTION

Recently, induction machines [1], such as induction motors (IM) [2, 3], are extensively used in several industrial processes and applications [4], including mining industries, chemical processes, gas and petroleum industries, transportation industries, compressor, and pumps [5, 6]. Importantly, IM has a vital and important use according to low price, reliability, robustness, and low maintenance cost [7, 8]. The performance and accuracy of IM can be impacted by three kinds of faults, such as electrical faults, mechanical faults, and environmental faults [9]. However, early and continuous condition monitoring (CM) and fault diagnosis (FD) of IM are crucial to increase availability, reliability, and safety, as well as reducing the risk of sudden accidents and failures [10, 11]. Recently, to follow up on the operating condition of IM and prevent faults and failures [12], CM and FD of IM have been developed by companies, scientists, researchers, and engineers [13-15]. However, several FD methodologies have been analyzed to achieve the best diagnostic results, including temperature analysis [16], vibration analysis [17], noise analysis [18], infrared analysis [19], current analysis [20], voltage analysis [21], electromagnetic field analysis [22], oil analysis [23], pressure analysis [24], ultrasound analysis [25], and also, sound and acoustic emission analysis [26].

Three main types of IM faults have been discussed in the literature, including bearing [27-29], stator [30, 31], and rotor [32-34] faults. Table 1 shows all types of faults of IM and their percentage [35]. However, bearing faults represent approximately 40%, while S/R faults represent approximately 50%. Figure 1 shows IM faults [36, 37].

Table 1. IM faults and their percentage

Fault type	Percentage
Stator	38%
Rotor	10%
Bearing	40%
Others	12%

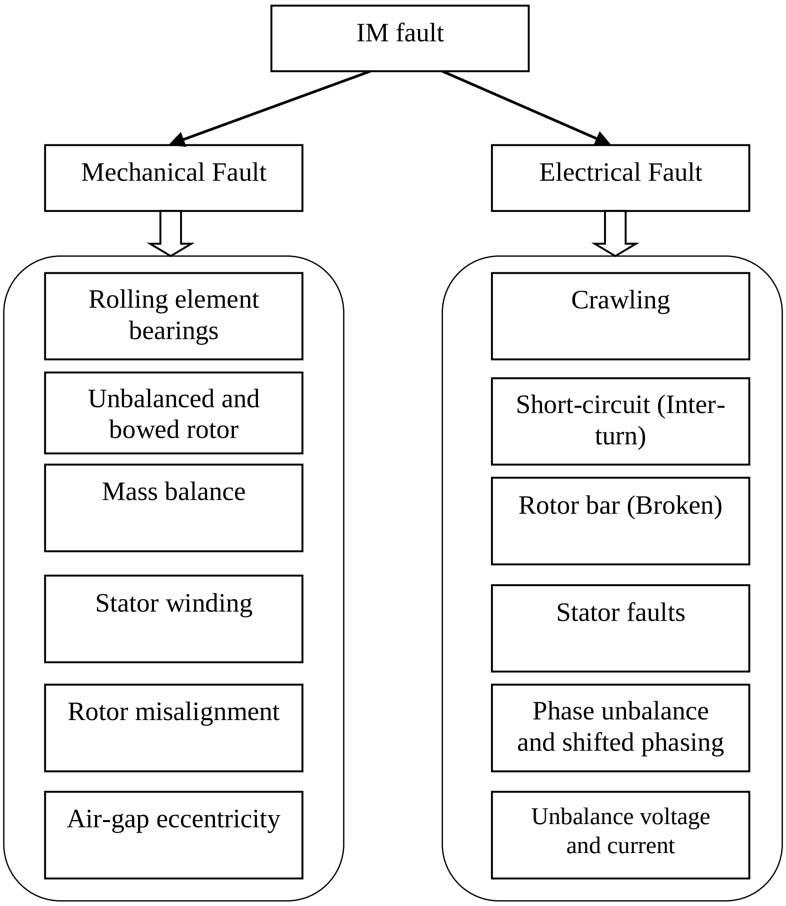

Figure 1. Fault classification of IM

Recently, in the industrial internet of things (IIoT) [38, 39], big data [40-42], and recent information and communications technologies (ICTs) [43] era, many CM and FD methods are based on different techniques are employed. That includes the internet of things [44], machine and deep learnings [45], advanced signal and image processing for time, frequency, and time-frequency domains [46, 47], and expert systems [48]. In recent literature, there have been many review papers for intelligence CM and FD machine learning methods of rolling elements bearings of IM [49, 50]. However, there is a lack in the literature and there are not many review papers for both S/R intelligent CM and FD. The S/R CM and FD framework are shown in Figure 2. This study aims to propose a systematic literature review for CM and FD of the IM, especially for S/R based on artificial intelligent (AI) methods shown in Figure 3. The study also points out the advantages and drawbacks of each method. Finally, challenges and possible future trends are also addressed.

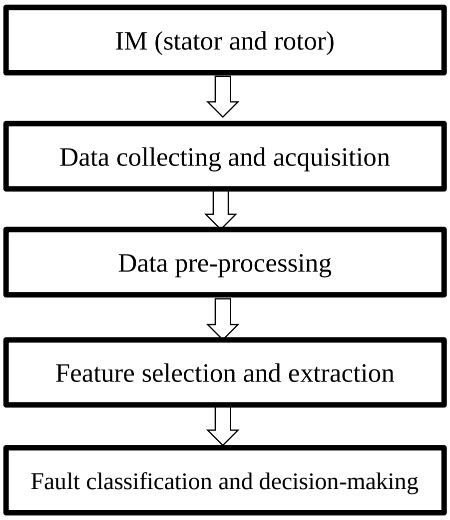

Figure 2. S/R CM and FD framework

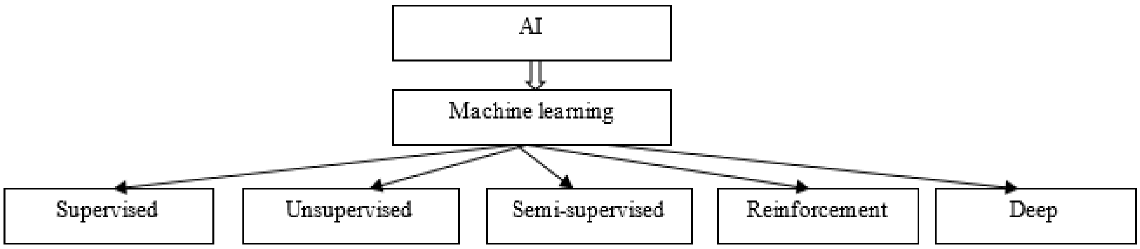

Figure 3. Types of AI methods in CM and FD [51, 52]

2. RELATED WORKS

2.1. Stator faults (SFs) diagnosis

Stator faults are considered to be one of the most faults of the IM [53, 54]. Consequently, in [55], the feature extraction method applied to the thermal images is used to diagnose SFs of the IM. This method is depended on the states of the selected area. The primary use of AI algorithms in this study is in the classification stage. Notably, two types of classifiers, the nearest neighbor (NN) and the Gaussian mixture models (GMM) achieved the obtained feature vectors' classification stage. As a result, the effectiveness of AI recognition and classification algorithms used in this study research was very high. In [56], a neuro-fuzzy classifier for boundary detection is used to diagnose IM's SF using line current vector obtained from stator current. Moreover, this simple method is applied as an FD of rotor faults based on the image's obtained pattern. In [57], a stator-winding-fault prediction approach of IM using fuzzy optimization and multi-scale entropy is introduced.

Furthermore, vibration signals along with the motor's current signature are utilized to diagnose the SFs under different operating speeds. The wavelet transform technique is applied in order to removing noise. Notably, neuro-fuzzy is applied to model and predict the SFs. As a result, the grey-fuzzy investigation showed the effectiveness in the on-line predicting of the stator winding faults. In [58], a short circuit stator-fault analysis approach of IM using information measures and ANN is introduced.

Moreover, feature vectors are measured as a mutual information technique. Importantly, two ANN topologies are used in this proposed approach. Multilayer perceptron (MLP) along with radial basis function (RBF) are applied as pattern recognition and classification processes. As a result, the error margin of the MLP networks is less than the margin of the RBF. However, the MLP is considered as the best ANN topology where experimental accuracy is 99%. According to [59], the FD approach based on AI is presented using both vibration and stator current analyses. Discrete wavelet transform (DWT) and matching pursuit are applied in the feature extraction stage. Following that, five classifiers are applied: subspace, fine and weighted nearest neighbor (NN), bagged trees, and support vector machine (SVM). As a result, the proposed study shows high classification accuracy (around 100%). In [60], a stator inter-turn FD tool based on ANN is presented. Moreover, the tool is developed under several fault sizes and loads. A steady-state electromechanical torque signature in time and frequency domains is applied as feature extraction method. As a classification method, a neural network is employed. As a result, 88-96% classification accuracy is obtained in this research study. Table 2 summarizes AI studies of CM and FD SFs.

Table 2. AI studies of CM and FD for SFs

Reference	Analysis type	Feature extraction	Classification	Highlights
[55]	Thermal images	Method of Area Selection of States	NN and GMM	- Reliable diagnostic method - The efficiency of the proposed method is 100 % - Diagnosing multiple states and faults - Several types of motors (DC, IM, and synchronous) could be benefited using this method
[56]	Current analysis	Image processing-based pattern recognition method	Neuro-fuzzy classifier	- Current vector image pattern-based automatic technique is proposed - No expert is needed - The average recognition rate was 99%
[57]	Current and vibration analyses	Multi-scale entropy (MSE) algorithm	Grey fuzzy classifier	- SF prediction technique is presented - Diagnose the SFs under different operating speeds - Fuzzy logic along with grey relational analysis (GRA) and are applied - The proposed method can be used as on-line monitoring to reduce the risk of SFs - The multi-performance index (GFRG) is 0.6 for faulty stator
[58]	Current analysis	Pattern recognition based mutual information method	Artificial neural networks (ANN)	- The method to detect stator short circuit method is presented - Several load levels and power supply voltage unbalance-based method - The classification accuracy is 99%
[59]	Current and vibration analyses	Matching pursuit, and discrete wavelet transform (DWT)	SVM, KNN, and bagging	- Two types of analyses (current and vibration) - Several electrical and mechanical faults are analyzed - The classification accuracy is 99%
[60]	Current analysis	Steady-state electromechanical torque signature	NN	- On-line detection method for stator inter-turn faults is proposed - Fault severity estimation are applied - 88-96% classification accuracy is obtained
[61]	External magnetic field	DWT		- Energy evaluation-based FD technique is proposed - The transient state and the severity of the fault are analyzed - The energy level is increased (89.19%) at start-up state
[62]	Current analysis	Fourier transform (FFT) along with DWT		- FD based on FFT and DWT is presented to diagnose inter-turn short circuit faults. - DWT is applied to deal with frequency spectrum for different load and speed - The proposed method cannot show a clear indication of fault severity.
[63]	Current analysis	Optimal wavelet tree and predator search genetic algorithm (PSGA)	Backpropagation NN	- Stator winding inter-turn short circuit FD technique is proposed - Improving the speed and precision of network training is occurred - Diagnosing multiple rotor faults - accurate results are achieved compared with the wavelet package method

2.2. Rotor faults (RFs) diagnosis

Open and broken bar rotor FD of the IM is vital [64, 65]. In [66], intelligent FD of broken rotor bar for IM using acoustic signals analysis is introduced. Two feature extraction methods are applied. The first one is based on frequency selection, and the second one is called SMOFS-32-MULTIEXPANDED-1-GROUP. KNN, backpropagation NN, and a modified classifier called word's coding are trained and applied in the classification stage.. High classification accuracy for real data is the main advantage of the proposed method. However, the backpropagation NN showed the best results as a classifier in this research study. In [67], AI experimental comparative evaluation FD study under various operating conditions using current signals is proposed.

Moreover, a feature-based method for automatic rotor FD of IM is developed. As feature extraction and selection stages, statistical measures on the signal's time and frequency domains are applied. Importantly, six machine-learning techniques are used in this study, naive Bayes, KNN, bootstrap aggregating (bagging), boosting algorithms (AdaBoost), multilayer perceptron (MLP) neural network, and SVM. However, KNN showed the worst results than the other classifiers just before MLP and SVM, whereas naive Bayes and bagging classifiers showed the best results. In [68], an on-line method for FD of broken rotor bars (BRP) using vibration analysis based on entropy is proposed.

Furthermore, the proposed method could deal with several operations. The Shannon entropy is applied to seek diagnostic vibration data. Significantly, the K-means cluster algorithm is employed. Importantly, as a result, in this study, K-means cluster-based Shannon entropy showed the ability to detect four severities of rotor damage, which include HLT condition, HBRB, 1BRB, and 2BRB. In [69], an early FD approach of the rotor based on empirical mode decomposition (EMD), ANN, and wavelet transform (WT) using vibration signals is proposed. WT is applied to decompose vibration signals into several bandwidths; then, EMD is applied to obtain corresponding frequency bandwidth from intrinsic mode functions (IMFs). Notably, in the classification stage, three layers back propagation neural network model is employed. However, the comprehensive approach of WPD, EMD and BPNN showed good diagnosis, extraction, and classification results less power signal. In [70], a data fusion technique for the rotor based on information entropy and NN using vibration signals is introduced. By applying the information entropy method, three characteristics could extract, namely, power spectrum, singular spectrum, and approximate entropies. A feature fusion model based on Probabilistic (PNN) is developed as an FD and classification. However, PNN based information entropy classifier showed significantly higher accuracy. In [71], a CM and FD approach for crack mentoring in the rotor using vibration signals is proposed.

Moreover, in this approach, WT and ANN are applied. The WT is applied as a feature extraction process. As a result, this method shows good diagnosis results. Furthermore, the signal-to-noise ratio increases as a result of speed's increasing; thus, the fault would be obvious. According to [72], a diagnostic approach for several loads based on the pseudo method and current signal is proposed. The pseudo-spectrum method is developed to diagnose fault frequency components. However, detecting fault at light load conditions is the main advantage of this method. Table 3 (see in Appendix) summarizes AI studies of CM and FD of RFs. Table 4 (see in Appendix) summarizes AI algorithms used for CM and FD for the rotor and the IM's stator.

3 CHALLENGES AND FUTURE TRENDS

Finding an intelligent CM and FD method for the rotor and IM's stator is considered a challenging task [76-78]. This section summarizes the challenges and future trends facing CM and FD of IM's stator and rotor.

- It is crucial to develop cost-effective, fast, non-invasive, non-intrusiveness, wireless, energy-efficient, and highly accurate sensors to solve conventional sensors problems [36].
- AI algorithms have to be used to build a better performance, low cost, continuous, and on-line CM and FD method [79].
- AI hybrid systems should be developed to deal with multiple faults [80].
- AI system that can diagnose all IM faults (bearing, stator, and rotor) should be developed [81].
- Fault’s size and severity based on AI techniques should be discussed more [82].
- Prognostic techniques should be developed based on AI [83].
- Big data analytics, expert systems, advanced signal processing algorithms, and data fusion should be used along with AI to develop CM and FD algorithms [84-86].
- Fuzzy-based fault-tolerant and internet of things (IoT) techniques based on advanced sensors technology should be developed [87-91].

4. CONCLUSION

Reducing maintenance costs and improving the availability and reliability of machines are crucial in the modern industrial world. CM and FD are being used to monitor the health of machines. Thus, the article presents a brief review of AI methods for CM and FD of S/R faults of induction machines such as IM. S/R faults represent approximately 50% of IM's total faults. However, developing non-invasive, early, continuous, and accurate fault diagnostic techniques based on AI methods is challenging. Thus, the proposed study discussed the literature methods and highlighted the advantages and disadvantages of each method.

APPENDIX

Table 3. AI studies of CM and FD for RFs

Reference	Analysis type	Feature extraction	Classification	Highlights
[66]	Acoustic signals	Frequencies Selection Multiexpand technique	BPNN, and words coding classifiers	- Intelligent FD technique based acoustic signals is proposed - Diagnosing multiple RFs - The proposed technique is inexpensive, instantly measurable, and non-invasive - 88.19-100% classification accuracy is achieved
[67]	Current analysis	Time and frequency domain analyses	KNN, NN, SVM, Naive Bayes, and Bagging	- Diagnosing multiple RFs - Four different power supplies and loaded are applied - Naive Bayes and Bagging (AUC=0.798, 0.900) achieved the best accuracy, and k-NN is the worst classifier.
[68]	Vibration signal	Shannon entropy	K- means cluster algorithm	- An on-line, low cost and simple monitoring method is proposed - The proposed method is implemented using FPGA - Start-up transient and three severities of damage are proposed - Low consumption of FPGA (11.67%) is achieved - The effectiveness of the proposed study is 100%
[69]	Vibration signal	WPD and EMD	BPNN	- An early fault diagnosis approach with a fault identification model is proposed - Diagnosing multiple RFs - The diagnosis result satisfies the actual condition.
[70]	Vibration signal	Information entropy	Probabilistic NN	- The fusion model for fault diagnosis approach is presented - Entropies (approximate, power spectrum, and singular spectrum) are obtained in the feature extraction stage - 80–95% classification accuracy is achieved
[71]	Vibration signal	WPT	ANN	- An automatic CM and FD approach based on the Wavelet packet technique for a cracked rotor is proposed - Severity level estimation is applied - High performance and low computational cost are the main advantages of this method
[72]	Current analysis	Pseudo-spectrum method	Multiple signal classification (MUSIC)	- Half broken rotor bar diagnostic approach is presented - Various load conditions are applied - light load condition fault capabilities - The proposed method shows effectiveness than motor current signature analysis (MCSA), especially for light load condition
[73]	Current analysis	Continuous transforms	-	- Start-up current analyzing based reliable detection FD method is presented - The proposed method improved visualization of the fault components - Better diagnostic results compared with discrete transforms are achieved - Tracking a larger number of fault harmonics is applied, and false alarms are obtained
[74]	Current analysis	Simulated Annealing algorithm and an ensemble composed of multivariate decision trees	KNN, random forest, and regression trees	- FD method with feature selection process and classification is proposed - Computational requirements of the diagnosis tool are decreased - The accuracy of the proposed study is approximately 100%
[75]	Electromagnetic torque monitoring	Finite element method	-	- The magnetic flux density is analyzed with a frequency range of 300 Hz - Different design variables are applied - Compared with traditional low-frequency torque signature methods, electromagnetic torque monitoring approach show best results

Table 4. AI studies for CM and FD for the rotor and the stator of IM

The method	Advantages	Drawbacks
SVM	Good performance and good classification accuracy	Efficient only with a small set of data
KNN	Simple	Low performance and classification accuracy
Random forest	Good classification accuracy	Over-fitting
Decision tree	High-dimensionality	More computational time is required
Regression	Simple and deal with small data	Low performance and classification accuracy
Bagging	Deal with big data	More computational time is required.
K- means clustering	Good performance and classification accuracy	Difficult to implement
Naive Bayes	Deal with big data	Low classification accuracy
Neuro-Fuzzy	Deal with big data and good diagnosis accuracy	More computational time is required.
ANN	Deal with big data, good performance, and good diagnosis accuracy	More training and computational time is required.

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