Fault Detection and Condition Monitoring in Induction Motors Utilizing Machine Learning Algorithms

Tareq Alqallai [1*]
[1]Department of Electrical-Electronics Engineering, Karabuk University, Karabuk Turkey
[1]tareg.elgallai@gmail.com

ABSTRACT

Electric induction motors (IM) are considered to be a highly significant and extensively utilized category of machinery within contemporary industrial settings. Typically, powerful motors, which are frequently essential to industrial processes, are equipped with integrated condition-monitoring systems to support proactive maintenance and the identification of faults. Typically, the cost-effectiveness of such capabilities is limited for tiny motors with a power output of less than ten horsepower, given their relatively low replacement costs. Nevertheless, it is worth noting that several little motors are commonly employed by large industrial facilities, mostly to operate cooling fans or lubricating pumps that support the functionality of larger machinery. It is possible to allocate multiple small motors to a single electrical circuit, so creating a situation where a malfunction in one motor could potentially cause damage to other motors connected to the same circuit. Hence, there exists a necessity to implement condition monitoring techniques for collections of small motors. This paper presents a comprehensive overview of a continuous effort aimed at the development of a machine learning-driven solution for the identification of faults in a multitude of small electric motors.

INTRODUCTION

Induction motors (IMs) play a significant role in the field of electric machines, serving as a primary means of converting energy into practical activity within contemporary industrial settings (Gangsar & Tiwar, 2020). Therefore, keeping track of these machines, which are frequently crucial, is of utmost significance. Numerous studies spanning over four decades have provided substantial evidence indicating the feasibility of identifying various fault types in motor sensor data before their occurrence, hence generating significant interest in leveraging this knowledge to mitigate the detrimental consequences associated with such failures.

Condition Monitoring (CM) refers to the utilization of non-destructive tests or sensed data to identify and assess alterations occurring inside a monitored system. Previous methodologies were limited to merely detecting the presence of a modification. However, contemporary methodologies have advanced to the point where they are capable of not only identifying the root cause of a fault but also pinpointing its specific location and assessing the extent of the harm that has been incurred thus far (Irfan, et al., 2017; Khaleel, et al., 2023). The methodologies discussed mostly include inferential sensing, which refers to the estimation of a dynamic system state that is complex and subject to change. This estimation is based on readings obtained from simpler sensors. Several instances of such approaches have been documented in the literature. Certain adaptive systems possess the capability to engage in self-repair endeavors, leveraging the aforementioned knowledge (Belrzaeg, et al., 2021 Sheikh, et al., 2017). Condition monitoring (CM) has gained significant recognition in contemporary times as an efficient and cost-effective strategy for managing extensive and costly systems. It enables the anticipation of maintenance requirements before the exacerbation of faults or the occurrence of failures (AlShorman, et al., 2020).

The technique of CM for small electric motors, namely those with a power rating of 10 HP or less, is not widely used due to their relatively low cost and lack of direct impact on important processes. Nevertheless, it is worth noting that a substantial industrial facility might potentially house a considerable number of these motors. There is a growing acknowledgment that the failure of these subcomponents or protection systems can have a significant influence on the overall functioning of the plant, as they are frequently responsible for operating crucial elements or safeguarding high-value systems. These may encompass the operation of cooling, lubrication, and HVAC (heating, ventilation, and air conditioning) equipment, which serve to safeguard the aforementioned bigger systems. A cost-effective CM system is vital for these motors. Therefore, it is recommended to adopt a practical strategy of simultaneously monitoring complete sets of small motors, such as those connected to a shared electrical circuit (Diab, et al., 2020).

LITERATURE REVIEW

By critically appraising existing literature, this review aims to contribute to the ongoing scholarly conversation and pave the way for the current study's unique contribution to the field. According to (Choudhary, et al., 2020) The imperative nature of condition-based monitoring in various industrial sectors, including railways, oil extraction mills, industrial drives, agriculture, and the mining industry, has underscored its significance for engineers and researchers. In response to the growing demand and impact of condition monitoring and fault diagnosis in induction motors (IMs), and with a forward-looking perspective for future research endeavors, this paper conducts a comprehensive state-of-the-art review. The review delineates various types of faults observed in IMs along with their respective diagnostic schemes. The identification and representation of diverse monitoring techniques for IM fault diagnosis are elucidated. The paper also underscores the potential of non-invasive techniques for data acquisition in facilitating automatic and timely maintenance scheduling, as well as predicting failure aspects of dynamic machines, thus presenting a promising avenue for future research in this domain.

This study (Gangsar, et al., 2020) critically examines the traditional time and spectrum signal analyses applied to two primary signals, namely vibration and current, which are highly effective indicators of various faults in induction motors (IMs). The analyses involve scrutinizing time and spectral characteristics of vibration and current signals obtained from diverse faulty IMs within a laboratory setting. The ensuing discussion delves into both the advantages and challenges inherent in these conventional analytical procedures. Furthermore, the paper systematically outlines and consolidates the current state of research and development within the realm of signal-based automation for condition monitoring methodologies. Specifically, the focus is on the fault detection and diagnosis of diverse electrical and mechanical anomalies prevalent in induction motors. This paper (Kumar, et al., 2022) provides a succinct overview of traditional approaches and meticulously examines intelligent methodologies for fault diagnosis (FD) and condition monitoring (CM) in electrical drives, with a specific focus on those prevalent in the context of Industry 4.0. Commencing with an exploration of fault statistics, the paper initially delves into standard techniques employed for the FD and CM of rotating machines. Subsequently, it directs its attention towards the intelligent approaches emerging in this domain. The paper meticulously addresses major diagnostic procedures, providing a thorough analysis of their advancements up to the present. Notably, particular emphasis is placed on motor current signature analysis (MCSA) and the application of digital signal processing techniques (DSPTs), predominantly utilized for feature engineering in this context.

METHOD

The methodology for the investigation into fault detection and condition monitoring in induction motors utilizing machine learning algorithms involves a systematic approach. Beginning with a comprehensive literature review to understand existing methodologies, the research design includes the selection of induction motors, identification of fault types, and the choice of machine learning algorithms. Data collection entails acquiring performance data and generating fault-injected datasets. Preprocessing steps involve data cleaning and feature extraction. The implementation of machine learning algorithms encompasses model training, validation, and parameter fine-tuning. Performance evaluation is conducted through metrics analysis and robustness testing. The integration of condition monitoring techniques, examination of false positives and negatives, and case studies ensure a holistic investigation. Ethical considerations guide the research process, and the methodology concludes with a summary of findings and recommendations for future research, providing a comprehensive framework for a thorough investigation into fault detection and condition monitoring in induction motors.

CM IN ELECTRIC MOTORS

Figure 1, illustrates a simplified representation of a conventional induction motor. The wire windings contained within the stator structure constitute a series of electromagnets. By applying distinct phases to individual windings, a rotating magnetic field is generated. The process of induction of a current within the windings of the rotor is initiated by the rotating field. Consequently, this current generates a magnetic field that acts in opposition to the rotation of the stator magnetic field. The presence of a rotor and its corresponding shaft, which possess the ability to rotate independently within the stator, leads to the generation of rotational motion due to the counteracting force (Cirrincione, et al., 2020; Belrzaeg, et al., 2023). Bearings serve the purpose of offering lubricated assistance to the rotor and shaft throughout their rotational movement, enabling the shaft to effectively carry out productive tasks. Approximately 40% of faults observed in induction motors are attributed to bearing failures (Gundewar, et al., 2020; Ahmed, et al., 2022). Figure 2 illustrates the many categories of defects which can potentially develop in an induction motor.
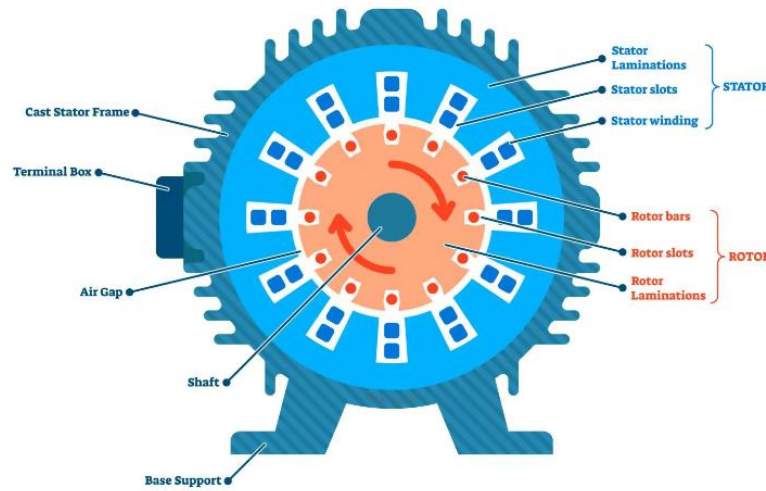
Figure 1. Induction motor

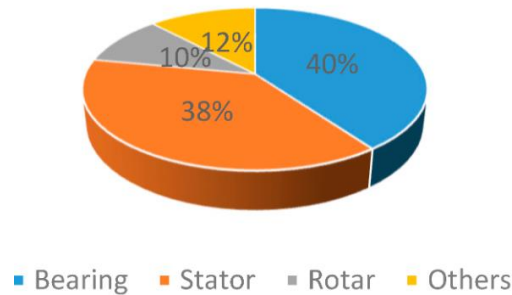- Bearing - Stator - Rotar - Others

Fig. 1.   The various types of faults that might occur in an induction motor.

The study by (Jain, et al., 2020) provided is in the format of a numerical reference, indicating that the user is referring In a more comprehensive analysis, [8] categorizes failures of induction motors into two main types: mechanical problems and electrical defects. Mechanical faults encompass a range of issues, such as bearing failures resulting from factors like improper lubrication, mechanical stresses, incorrect assembly, and misalignment (Ghayth, et al., 2023; Glowacz, 2019). In the case of motors equipped with gearboxes, gearbox failures are also considered mechanical faults. Given that induction motors are classified as rotating devices, it is worth noting that some signals that indicate the presence of potential or existing flaws have periodic characteristics. Frequency-domain analysis has been a prominent method for detecting motor faults for a considerable period. The initial focus of the research was on Fourier transforms; however, contemporary methodologies now investigate signals in the combined time-frequency domain (Diarra, et al., 2022; Alsharif, et al., 2022). Certain flaws can be readily identified and analyzed in the frequency domain. However, it is more typical to utilize time-frequency band coefficients as features in a classifier algorithm inside the conventional inferential-sensing methodology.

ANOMALY DETECTION AND DEEP LEARNING

After understanding the significant achievements of deep learning across multiple domains, researchers have dedicated their efforts to exploring deep anomaly detection (AD) techniques. These studies have demonstrated promising outcomes. However, it is important to note that this particular subject remains relatively unexplored in academic research (Ciabattoni, et al., 2018). In terms of the training methodology and data accessibility, the techniques mentioned earlier can be classified as supervised, semi-supervised, and unsupervised deep anomaly detection. Researcher has focused their endeavors on examining solutions for deep anomaly detection (AD) following their recognition of the significant achievements of deep learning in various fields. Prior studies have produced positive outcomes. However, it is imperative to recognize that this particular subject has been the focus of scant scholarly research. The techniques above can be classified into three categories: supervised, semi-supervised, and unsupervised deep anomaly detection, depending on their training methodology and data accessibility. To train a deep classifier using supervised anomaly detection (AD) methods, it is crucial to have access to labeled data that includes both normal and anomalous classifications.

MACHINE LEARNING METHODS FOR CONDITION MONITORING

Machine Learning (ML) is a specific field within the realm of artificial intelligence that focuses on the development of algorithms capable of acquiring knowledge from data and enhancing their performance autonomously, without the need for human involvement. The trend study conducted in 2020 revealed that the predominant direction in the field of Predictive Maintenance (PdM) is the use of machine learning (ML)-driven solutions. The authors of the paper placed significant emphasis on the pivotal role of machine learning (ML) in facilitating several breakthroughs. These include the reduction of stoppages, decrease in maintenance costs, extension of spare-part life, enhancement of operator safety, increase in production levels, and verification of repairs (Alsharif, et al., 2023; Ahmed et al., 2021; Cerrada, et al., 2018).

Classification analysis

Classification analysis is a machine learning technique that involves predicting the class value of studied data based on previous observations. The aforementioned methodology can be categorized into two main types: supervised and unsupervised. The process of classification plays a crucial role in the framework of machine fault identification and classification. In the field of condition monitoring, the process of identifying faults can be described as a binary classification task, where the objective is to categorize a given case as either faulty or healthy. Multiple standard measurement methodologies, often known as indicators of performance, exist to evaluate the performance of a model. If the diagnostic technique employed by the model is classification-based, the often-used measures are reliability, precision, recall, and sensitivity.

Multilayer perceptron

Artificial Neural Networks (ANNs) are computational algorithms rooted in deep learning that emulate the operational mechanisms of the human brain. The processing units, referred to as neurons, are comprised of weights and biases (Khaleel, et al., 2023). Every individual neuron is specifically structured to facilitate the transmission of signals to adjacent neurons, analogous to the synaptic connections within the human brain. It operates by transmitting information exclusively forward, starting from the input layer, by way of the hidden layers, and ultimately reaching the output layer. Figure 3, illustrates multilayer perceptions.
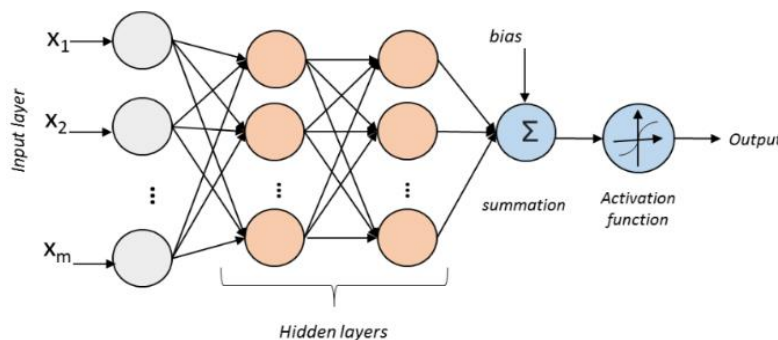

Figure 3. Multilayer perceptrons

The Radial Basis Function neural network (RBFNN)

The RBFNN belongs to the feedforward neural network category and is commonly employed as a supervised classifier in many monitoring applications within the business. The RBFNN shares a structural resemblance with the Multilayer Perceptron (MLP), with a single hidden layer. However, the RBFNN distinguishes itself by employing the radial basis function (RBF) as an activation function, hence generating a hidden space characterized by increased dimensions. Figure 4, shows Architecture of the RBFNN model. Similar to artificial neural networks (ANN), during the training process, the model commonly involves two distinct steps: the adjustment of the parameters of the kernel function and the optimization of the weights and biases of the network. Following the completion of the tuning phase, the network is now prepared to address classification or regression tasks. Consequently, the RBFNN algorithm can be readily employed for fault classification or identification tasks.
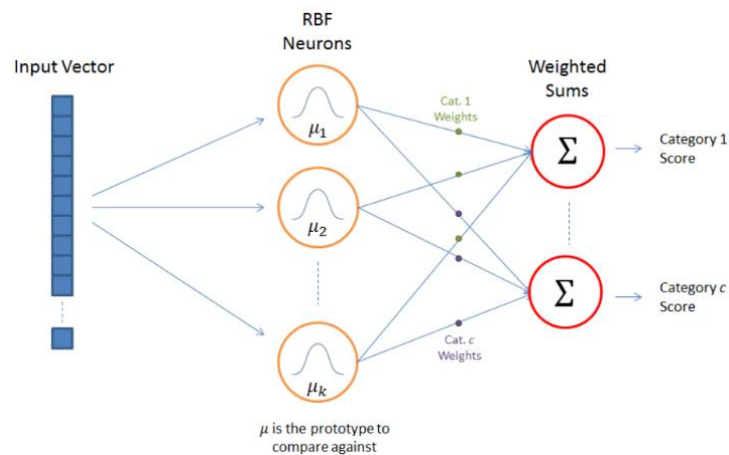
Figure 4. Architecture of the RBFNN model

Convolutional neural network

The Convolutional Network, often known as the Convolutional Neural Network (CNN), is a supervised deep learning technique used for the analysis of topological datasets. It draws its initial inspiration from the visual brain, as demonstrated by Hubel and Wiesel in 1968. A typical CNN is composed of convolutional, pooling, and fully connected layers, as depicted in Figure 5. The initial phase of the neural network architecture involves the utilization of a convolutional layer, which is responsible for extracting distinctive characteristics from the input dataset. This process is accomplished by convolving the input data with kernels of reduced dimensions, resulting in the generation of an activation map. Therefore, a Convolutional Neural Network (CNN) possesses the capability to effectively identify and analyze localized patterns within a given dataset, in contrast to a Multilayer Perceptron (MLP) that primarily focuses on learning global patterns.
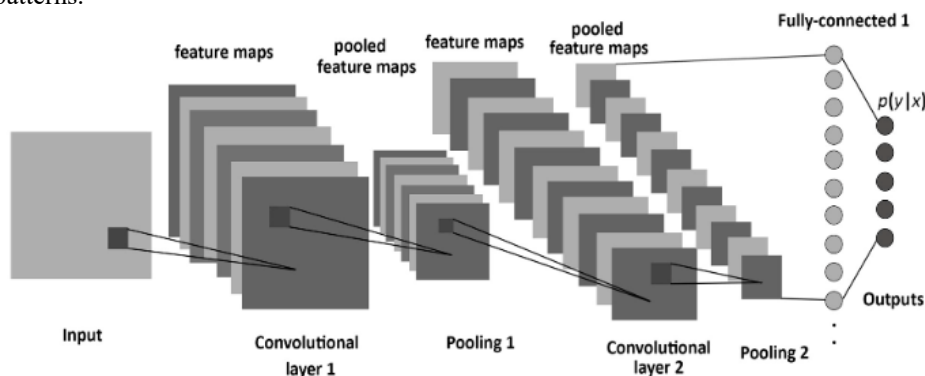

Figure 5. Convolutional neural network

Autoencoder

An autoencoder is a type of artificial neural network (ANN) that is employed to encode the underlying patterns of a given dataset and subsequently reconstruct it with minimal deviation. As depicted in Figure 6, the structure of the encoder primarily comprises three components: the encoder stage, which encompasses a collection of linear feed-forward filters known as MLP. In general, an error term is allocated to quantify the discrepancy induced by the intermediary layer. Various ways exist for integrating autoencoders into systems as a whole including stacked sparse autoencoders, eliminating autoencoders, adversarial autoencoders, and numerous others.
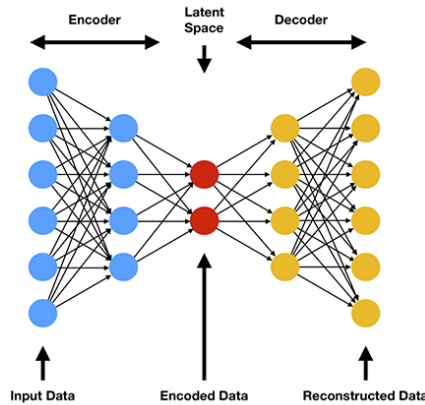
Figure 6. Architecture of the autoencoders

Support vector machine (SVM)

The support vector machine (SVM) is a statistical machine-learning technique that is widely utilized in various classification tasks. The algorithm in question serves as a means of establishing a correspondence between input and output variables within the training dataset, so functions as a supervised machine-learning technique. SVMs can effectively handle large volumes of data and effectively address complex categorization challenges in several industrial domains. Figure 7, shows the architecture of the SVM classifier. The classification technique is founded around the construction of an optimal hyperplane that effectively separates the latent classes within the dataset. The algorithm takes into account the data points as vectors of p dimensions. The objective is to identify a hyperplane with p + 1 dimensions.
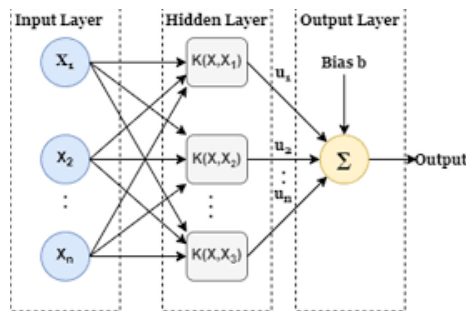

Figure 7. Architecture of SVM classifier

Fuzzy logic

Fuzzy logic (FL) or Fuzzy set theory is a robust approach for accurately transforming ambiguous inputs into a well-defined output through the utilization of linguistic norms. As previously stated, the available real-world information is characterized by its lack of specificity and partial accuracy, resulting in an inherently ambiguous environment (Khaleel, et al., 2022). Fuzzy logic (FL) plays a crucial role in decision-making situations that include an environment of uncertainty, where existing decision theories lack robustness. Figure 8, presents fuzzy logic system structure.
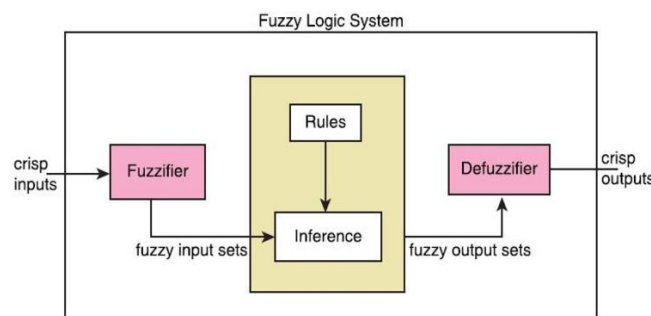

Figure 8. Fuzzy logic system structure

FL is a derivative of four essential components. The membership function (MF) is responsible for assigning a fuzzy membership value, ranging from 0 to 1, to each data element in the input space. Fuzzy sets are a type of class that

encompasses a range of membership grades. If the signal is at a low level and the inaccuracy is minimal, it can be inferred that the tool wear will be minimal as well. If the signal is of medium intensity and the error rate is low, then the level of tool wear is expected to be medium (Khaleel, et al., 2023). Ultimately, to achieve convergence towards a final output, it becomes necessary to employ the process of defuzzification to reduce the system output to a single value. A system that follows a set of rules to imitate the reasoning process of a human expert, which incorporates fuzzy logic, is commonly referred to as a fuzzy inference system (FIS). In the field of Predictive Maintenance (PdM), Mamdanior or Sugeno fuzzy rule systems are commonly employed. The implementation of this potent technique can be used in other industrial systems, such as microcontrollers, to augment their capabilities.

K-means clustering

The algorithm for K-means clustering is a recursively unsupervised approach used to categorize a set of n observations into k clusters. In this method, the new data is assigned to the cluster center that is closest to it, and the method then modifies the cluster centers after every iteration. The efficacy of K-means clustering was evaluated in different circumstances to demonstrate its ability to recognize and recognize faults in rolling bearings. Figure 9 illustrates the flowchart of the k-means clustering algorithm. The mathematical dynamic model of the system was employed to differentiate the data. Subsequently, the researchers performed calculations to determine the initial centroid locations of the pre-clusters.
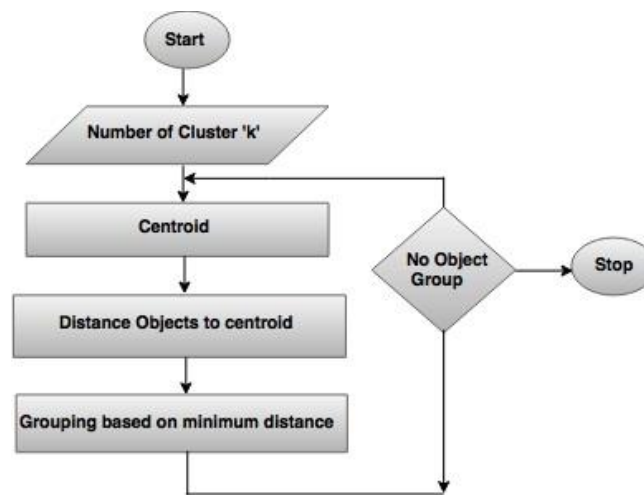

Figure 9. Flowchart of k-means clustering algorithm

RESULT

The result of this investigation unveils the successful development of a condition monitoring solution tailored for diminutive electric motors commonly employed in industrial contexts. The chosen design integrates an anomaly-detection framework, where the normal model is instantiated through a sophisticated time series forecasting method. A comprehensive exploration of both shallow and deep learning methodologies for the normal model elucidates that the deep network, while achieving a significantly diminished false alarm rate, concurrently incurs a marginally heightened false-negative rate. In essence, this study not only introduces an efficacious solution for condition monitoring in small electric motors but also lays the groundwork for broader applications of the proposed architecture. The strategic infusion of advanced techniques underscores a commitment to advancing monitoring systems within industrial realms, with the overarching goal of augmenting efficiency and reliability across diverse domains.

CONCLUSION AND FUTURE WORK

A condition monitoring solution has been developed for tiny electric motors commonly utilized in industrial settings. The used design utilizes an anomaly-detection framework, where the normal model is implemented as a time series forecasting method. This study examines both shallow and deep learning methodologies for the normal model, finding that the deep network yields a much-reduced false alarm rate, albeit with a somewhat elevated false-negative rate. In subsequent research, we will initially investigate the potential enhancement of fault identification by incorporating supplementary sensing modalities into our dataset, through the utilization of data fusion techniques. The aforementioned layout is frequently observed in expansive industrial facilities, whereby it presents the potential for abnormalities or damage in a single motor to propagate and result in subsequent harm to additional interconnected motors as a consequence of current or voltage surges. The monitoring problem is conceptualized as consisting of three distinct stages: failure detection, defect localization to one or more specific motors, and fault diagnosis or prediction of

remaining life, as deemed suitable. In addition to the application of condition monitoring in induction motors, these works intend to employ this fundamental architecture, utilizing deep learning for the normal model and shallow learning for the anomaly detector, in various other monitoring scenarios and domains.

REFERENCES

Ahmed, A. A., Alsharif, A., Triwiyanto, T., Khaleel, M., Tan, C. W., & Ayop, R. (2022). Using of neural network-based controller to obtain the effect of hub motors weight on electric vehicle ride comfort. *2022 IEEE 2nd International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA)*. IEEE.

Ahmed, A. A., Masood, M. A., Almabrouk, A. Q., Sheggaf, Z. M., Khaleel, M. M., & Belrzaeg, M. (2021). An investigation of the effect of the hub motor weight on vehicle suspension and passenger comfort. *International Journal of Mechanical and Production Engineering Research and Development*, *11*(5), 51–64.

Alsharif, A., Ahmed, A. A., Khaleel, M. M., Alarga, A. S. D., Jomah, O. S. M., & Alrashed, A. B. E. (2023). Stochastic method and sensitivity analysis assessments for vehicle-to-home integration based on renewable energy sources. *2023 IEEE 3rd International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA)*. IEEE.

Alsharif, A., Ahmed, A. A., Khaleel, M. M., & Altayib, M. A. (2023). Ancillary services and energy management for electric Vehicle: Mini-review. *(NAJSP)*, 9–12.

Alsharif, A., Ahmed, A. A., Khaleel, M. M., Daw Alarga, A. S., Jomah, O. S. M., & Imbayah, I. (2023). Comprehensive state-of-the-art of vehicle-to-grid technology. *2023 IEEE 3rd International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA)*. IEEE.

Alsharif, A., Tan, C. W., Ayop, R., Ahmed, A. A. A., Alanssari, A., & Khaleel, M. M. (2022). Energy management strategy for Vehicle-to-grid technology integration with energy sources: Mini review. *African Journal of Advanced Pure and Applied Sciences (AJAPAS)*, 12–16.

Alsharif, A., Tan, C. W., Ayop, R., Ahmed, A. A., & Khaleel, M. M. (2022). Electric vehicle integration with energy sources: Problem and solution review. *African Journal of Advanced Pure and Applied Sciences (AJAPAS)*, 17–20.

Alsharif, A., Tan, C. W., Ayop, R., Al Smin, A., Ali Ahmed, A., Kuwil, F. H., & Khaleel, M. M. (2023). Impact of electric Vehicle on residential power distribution considering energy management strategy and stochastic Monte Carlo algorithm. *Energies*, *16*(3), 1358.

AlShorman, O., Irfan, M., Saad, N., Zhen, D., Haider, N., Glowacz, A., & AlShorman, A. (2020). A review of artificial intelligence methods for condition monitoring and fault diagnosis of rolling element bearings for induction motor. *Shock and Vibration*, *2020*, 1–20.

Belrzaeg, M., Ahmed, A. A., Almabrouk, A. Q., Khaleel, M. M., Ahmed, A. A., & Almukhtar, M. (2021). Vehicle dynamics and tire models: An overview. *World Journal of Advanced Research and Reviews*, *12*(1), 331–348.

Belrzaeg, M., Ahmed, A. A., Khaleel, M. M., Alsharif, A., Rahmah, M. M., & Alarga, A. S. D. (2023). Suspension system control process for buses with in-wheel motors. *ICCEIS 2022*. Basel Switzerland: MDPI.

Cerrada, M., Sánchez, R.-V., Li, C., Pacheco, F., Cabrera, D., Valente de Oliveira, J., & Vásquez, R. E. (2018). A review on data-driven fault severity assessment in rolling bearings. *Mechanical Systems and Signal Processing*, *99*, 169–196.

Choudhary, A., Goyal, D., Shimi, S. L., & Akula, A. (2019). Condition monitoring and fault diagnosis of induction motors: A review. *Archives of Computational Methods in Engineering. State of the Art Reviews*, *26*(4), 1221–1238.

Ciabattoni, L., Ferracuti, F., Freddi, A., & Monteriu, A. (2018). Statistical spectral analysis for fault diagnosis of rotating machines. *IEEE Transactions on Industrial Electronics (1982)*, *65*(5), 4301–4310.

Cirrincione, G., Randazzo, V., Kumar, R. R., Cirrincione, M., & Pasero, E. (2020). Growing curvilinear component analysis (GCCA) for Stator fault detection in induction machines. In *Neural Approaches to Dynamics of Signal Exchanges* (pp. 235–244).

Diab, A. A. Z., Al-Sayed, A.-H. M., Mohammed, H. H. A., & Mohammed, Y. S. (Eds.). (2020). *Literature review of induction motor drives," in Development of Adaptive Speed Observers for Induction Machine System Stabilization*. Berlin, Germany: Springer.

Diarra, M. N., Yao, Y., Li, Z., Niasse, M., Li, Y., & Zhao, H. (2022). In-situ efficiency estimation of induction motors based on Quantum Particle Swarm Optimization-Trust Region Algorithm (QPSO-TRA). *Energies*, *15*(13), 4905.

Gangsar, P., & Tiwari, R. (2020). Signal-based condition monitoring techniques for fault detection and diagnosis of induction motors: A state-of-the-art review. *Mech. Syst. Signal Process*, *144*(106908).

Gangsar, Purushottam, & Tiwari, R. (2020). Signal based condition monitoring techniques for fault detection and diagnosis of induction motors: A state-of-the-art review. *Mechanical Systems and Signal Processing*, *144*(106908), 106908.

Ghayth, A., Şimşir, M., Khaleel, M., Ahmed, A., & Alsharif, A. (2023). An investigation of Inverse-Automatic Mechanical Transmission of EV using gear downshift approach. *Int. J. Electr. Eng. and Sustain.*, 1–9.

Ghayth, A., Yusupov, Z., & Khaleel, M. (2023). Performance enhancement of PV array utilizing Perturb & Observe algorithm. *Int. J. Electr. Eng. and Sustain.*, 29–37.

Glowacz, A. (2019). Detection of deterioration of three-phase induction motor using vibration signals," Meas. *Meas. Sci. Rev*, *19*(6), 241–249.

Gundewar, S. K., & Kane, P. V. (2020). *Fuzzy FMEA analysis of induction motor and overview of diagnostic techniques to reduce risk of failure," in Reliability, Safety and Hazard Assessment for Risk-Based Technologies*. Berlin, Germany: Springer.

Irfan, M., Saad, N., Ibrahim, R., Asirvadam, V. S., Alwadie, A. S., & Sheikh, M. A. (2017). An assessment on the non-invasive methods for condition monitoring of induction motors. In *Fault Diagnosis and Detection*. InTech.

Jain, J. K., Ghosh, S., & Maity, S. (2020). Concurrent PI controller design for indirect vector controlled induction motor. *Asian Journal of Control*, *22*(1), 130–142.

Khaleel, M., Abulifa, S. A., & Abulifa, A. A. (2023). Artificial intelligent techniques for identifying the cause of disturbances in the power grid. *Brilliance: Research of Artificial Intelligence*, *3*(1), 19–31.

Khaleel, M., Ahmed, A. A., & Alsharif, A. (2023a). Artificial Intelligence in Engineering. *Brilliance: Research of Artificial Intelligence*, *3*(1), 32–42.

Khaleel, M., Ahmed, A. A., & Alsharif, A. (2023b). Technology challenges and trends of electric motor and drive in electric vehicle. *Int. J. Electr. Eng. and Sustain.*, 41–48.

Khaleel, M. M., Adzman, M. R., & Zali, S. M. (2021). An integrated of hydrogen fuel cell to distribution network system: Challenging and opportunity for D-STATCOM. *Energies*, *14*(21), 7073.

Khaleel, M. M., Mohamed Ghandoori, T., Ali Ahmed, A., Alsharif, A., Ahmed Alnagrat, A. J., & Ali Abulifa, A. (2022). Impact of mechanical storage system technologies: A powerful combination to empowered the electrical grids application. *2022 IEEE 2nd International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA)*. IEEE.

Khaleel, M., Nassar, Y., El-Khozondar, H. J., Elmnifi, M., Rajab, Z., Yaghoubi, E., & Yaghoubi, E. (2024). Electric vehicles in China, Europe, and the United States: Current trend and market comparison. *Int. J. Electr. Eng. and Sustain.*, 1–20.

Khaleel, M., Şimşir, M., Yusupov, Z., Yasser, N., Elkhozondar, H., & Ahmed, A. A. (2023). The role of fault detection and diagnosis in induction motors. *Int. J. Electr. Eng. and Sustain.*, 31–40.

Khaleel, M., Yaghoubi, E., Yaghoubi, E., & Jahromi, M. Z. (2023). The role of mechanical energy storage systems based on artificial intelligence techniques in future sustainable energy systems. *Int. J. Electr. Eng. and Sustain.*, 01–31.

Khaleel, M., Yusupov, Z., Yasser, N., & El-Khozondar, H. J. (2023). Enhancing Microgrid performance through hybrid energy storage system integration: ANFIS and GA approaches. *Int. J. Electr. Eng. and Sustain.*, 38–48.

Kumar, R. R., Andriollo, M., Cirrincione, G., Cirrincione, M., & Tortella, A. (2022). A comprehensive review of conventional and intelligence-based approaches for the fault diagnosis and condition monitoring of induction motors. *Energies*, *15*(23), 8938. doi:10.3390/en15238938

Sheikh, M. A., Nor, N. M., Ibrahim, T., Bakhsh, S. T., Irfan, M., & Daud, H. B. (2017). Noninvasive methods for condition monitoring and electrical fault diagnosis of induction motors. In Fault Diagnosis and Detection. InTech.