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A Review on Model-Based Fault Diagnosis in Electric Drives Using Machine Learning Techniques

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***Abstract*—**Electric drives, as adequately described over years of development and research, are the current solution to the question of automatic, precise control when it comes to the operation of electric motors. Comprised of the electric motor itself, power modulator, power source, control unit, sensor unit, load and more; an electric drive is an apt practical demonstration of a closed-loop system. Due to its highly controllable nature which has proven to be reliable and efficient, the electric drive has found itself being used in numerous applications such as - industrial automation, electric vehicles, renewable energy systems, robotics and smart manufacturing. However, the number of components present within the electric drive bring up the possibility of loss of function/efficiency of drive, in case of fault in said components, leading to unexpected shutdowns and unaccounted for maintenance costs. Hence, an important aspect of the operation of electric drives is the fault detection of, and within its components, ensuring safe and timely working of the equipment. Traditional fault diagnosis techniques are largely based on signal processing, analytical models and rule- based monitoring methods; but these approaches often face limitations when put under complex operating conditions and varying load environments. This review paper attempts to address the limitations of the traditional fault diagnosis techniques, while suggesting adoption of machine learning based fault diagnosis covering different models and their effectiveness at dealing with such faults in electric drives. Various faults are specifically addressed in this review including - stator winding faults, rotor faults, bearing defects, inverter switch faults and sensor failures; discussed along with commonly used feature extraction methods such as wavelet transform, Fourier analysis and statistical indica- tors. Furthermore, supervised machine learning algorithms such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Decision Trees, Random Forest and Deep Learning models are reviewed for fault detection and classification. Finally, a comparative analysis of existing methods, advantages, and limitations is presented. The study concludes that integrating model-based approaches with machine learning techniques offers a capable manner of handling modern electric drives while providing useful predictive maintenance solutions and smart monitoring systems to maintain efficiency of any electric drive.

Index Terms—Electric Drives, Fault Diagnosis, Machine Learning, Predictive Maintenance, Inverter Faults, Induction Motor, Artificial Neural Network, Support Vector Machine, Deep Learning, Condition Monitoring

I. Introduction

Electric drives have witnessed widespread adoption across industrial and commercial sectors due to their high efficiency, accurate speed control, fast dynamic response and reliable performance [1], [2]. An average electric drive is made up of an electric motor, power electronic converter, control unit, sensor unit and mechanical load; and are frequently employed in a number of applications such as - electric vehicles, railway traction, robotics, manufacturing plants, household appliances, renewable energy systems and automated production lines.

The proper functioning of the components within an electric drive is necessary for its sustained operation and productivity. Thus, it must be remembered that such electric drive systems are frequently exposed to electrical, thermal and mechanical stresses during operation, which often lead to component degradation and faults. Common faults that arise in such conditions include stator winding short circuits, broken rotor bars, bearing damage, inverter switch failures, sensor faults, shaft misalignment and insulation deterioration [3], [4]. If these faults go undetected, they are capable of causing unexpected shutdowns, costly repairs, reduces efficiency of the drive and serious safety hazards.

Traditional fault diagnosis techniques are largely based on signal processing, mathematical modelling, vibration monitoring, thermal analysis and Motor Current Signature Analysis (MCSA) [5], [6]. While these methods are effective in many cases, they often face limitations when put under non-linear operating conditions, varying loads, noisy environments and complex fault patterns. Also, traditional approaches often require expert input for interpretation of feature trends and setting of threshold limits.

In response to the limitations of traditional fault diagnosis methods, machine learning based fault diagnosis techniques have garnered significant attention due to their ability to learn complex relationships from historical and real-time data, enabling automatic fault detection and classification with high level of accuracy. Such machine learning techniques include Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Decision Trees, Random Forest and Deep Learning models.

Beyond classical machine learning, model-based fault diagnosis has risen in popularity because it combines physical system modelling with the data-driven intelligence of machine learning algorithms. That is, digital models of electric drives are developed and simulated to generate healthy and faulty condition data for various torque-speed conditions, which is subsequently used for training classification algorithms to be used in fault analysis [7], [11]. This approach allows one to circumvent dependency on expensive datasets and observe rare fault conditions and associated features through simulation.

The objective of this review paper is to present a comprehensive overview of model-based fault diagnosis in electric drives using machine learning techniques. As well as discussing various fault types, methods of feature extraction, machine learning algorithms, comparative studies, challenges faced and future research opportunities in the field. This review aims to aid future researchers and engineers in designing a reliable and cost-effective fault diagnosis system to be used in electric drive applications.

II. Classification of Faults in Electric Drives

Faults commonly observed in electric drive systems are generally classified into one of the following categories – electrical, mechanical, power electronic, sensor/control and thermal/insulation. It is important to correctly classify these faults, so that suitable techniques of monitoring and diagnosis can be chosen afterwards [3], [4].

A. Electrical Faults

Electrical faults are noticed often in motor windings and rotor circuits of the drive system. In induction motors, failure of the stator winding insulation can cascade into inter-turn short circuits, phase-to-ground faults or phase-to-phase faults. Meanwhile, rotor faults are responsible for broken rotor bars, unbalanced rotor conditions and cracking of end rings. Overall, these faults result in issues such as abnormal current harmonics, reduced efficiency, overheating and torque pulsations [9], [10].

B. Mechanical Faults

Mechanical faults cover faults that occur due to the moving/mechanical parts of the drive system such as shaft misalignment, looseness, gearbox wear, rotor eccentricity and more. A common mechanical defect that can also occur is bearing faults, which may arise in inner race, outer race, cage or any of the rolling elements. Faults like these generate abnormal amounts of vibration, acoustic noise and result in increased losses from friction [4], [12].

C. Power Electronic Faults

Power electronics-based converters/modulators such as inverters are integral components in the structure of an average electric drive. Faults that can occur in inverters include gate driver failures, short circuit faults, open circuit switch faults, DC link capacitor degradation and failure of diodes. Such faults introduce distortion in output voltage and current waveforms, causing poor motor performance and may result in shutdown of the entire drive system [5], [7], [11].

D. Sensor and Control Faults

Sensors are the primary source of current, voltage, speed, position and temperature measurements used within an electric drive system. Thus, faults in them could result in biased, delayed and noise-filled signals which leads to improper controller action. Control faults may also arise from software errors, mismatch of parameters, delay in communication or controller instability [1], [2].

E. Thermal and Insulation Faults

Sustained overloading, improper ventilation and high surrounding temperature may cause overheating in motors and converters. This introduction of excessive temperature tends to accelerate the aging of insulation and reduces the expected lifetime of components, thus increasing the probability of a catastrophic failure condition. Making thermal monitoring a must for predictive maintenance of an electric drive-based system [3].

Hence, faults can be caused by multiple sources at once and often interact with each other making accurate identification necessary for improving reliability of the system, reducing downtime and enabling maintenance on the basis of diagnosed condition.

III. Conventional Fault Diagnosis Techniques

Conventional fault diagnosis techniques have been used since before the advent of modern computing facilities due to their practicality and simplicity of implementation; mostly reliant on analytical models, signal measurements and expert diagnosis in order to identify abnormal operating conditions [3], [4].

One of the most common methods of fault diagnosis is Motor Current Signature Analysis (MCSA), in which stator current signals are analysed by the means of frequency-domain transformations such as the Fast Fourier Transform (FFT). Several faults such as broken rotor bars, bearing failures and eccentricity produce a characteristic harmonic in the current spectrum that can be picked up during Motor Current Signature Analysis (MCSA) [3]. This method is non-invasive in nature as it does not require additional sensors in the drive system, and is thus also far more economical by extension.

Another means of fault diagnosis is vibration analysis for suspected mechanical faults in the system such as looseness, bearing damage, shaft misalignment and rotor imbalance. Vibration signal data is captured through the use of accelerometers, and fault patterns are studied using time-domain or spectral analysis. While effective, this method can be costly due to the added expenses of the additional sensor hardware [4].

Thermal conditions can also be monitored in order to detect overheating that may have underlying causes such as overloading, friction losses, poor cooling and insulation failure. Temperature sensors and infrared devices are integrated to observe possible heat anomalies in motors and converters [2]. It should be noted however that thermal anomalies are typically a lagging indicator, manifesting only after the fault has already developed and thus it is not suitable when discussing possibilities for predictive maintenance.

Similar to current analysis, analysis of voltage and current waveforms are applied when searching for inverter and converter faults. Open switch and short circuit faults in such conditions create detectable distortion in the waveforms, cause imbalance and present as harmonic changes that can all be measured and analysed [5], [11].

Electric drive condition can also be judged on the basis of comparison with mathematical models of healthy drives, also known as residual analysis. Where the difference between the expected values from the model and the measured values, known as the residuals, is analysed for detection of faults [7]. Their usefulness aside, most conventional methods fail to perform adequately under modern operating conditions of – variable speed operation, non-linear systems, multiple fault occurrences and noisy environments; resulting in diminishing accuracy. These methods also require interpretation by skilled experts for appropriate diagnosis. Such limitations have encouraged further development of smart fault diagnosis systems such as those that use machine learning for the fault diagnosis [12].

IV. Machine Learning Based Fault Diagnosis

Machine learning has garnered interest in possible applications for fault diagnosis in electric drives due to its ability to understand and distinguish patterns from a dataset, which can allow it to accurately classify healthy and faulty operating conditions. Compared to conventional techniques that are still dependent on the expert knowledge for its feature interpretation and final diagnosis, machine learning models can process large-scale datasets to identify complex non-linear relationships without any such external interpretation [7], [14]. Machine learning models for fault diagnosis purposes are trained by – data acquisition, signal preprocessing, feature extraction, training of model and then classification of fault. Data is generally collected for current, voltage, vibration, temperature, speed and torque through the means of sensors. Needed features are then extracted using time-domain, frequency-domain or time-frequency signals to further train intelligent classifiers.

Artificial Neural Networks (ANNs) are one of the most commonly used machine learning technique employed for fault diagnosis purposes, capable of learning hidden patterns from fault data, it can classify multiple categories of faults with high level of accuracy. It is usually trained for bearing faults, inverter switch faults and stator winding faults [4], [7].

Support Vector Machines (SVMs) is a class of supervised machine learning algorithm used in binary multi-class fault classification. Support Vector Machines (SVMs) perform well even with limited training dataset and provide strong generalization capability. They are currently best applied to motor current and vibration-based diagnosis problems.

Decision Trees and Random Forest are simple learning algorithms known for quick computation times and easy interpretability, they are used to determine important features and provide decision rules for use of maintenance engineers. In addition to these, deep learning techniques like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have gained attention as they are capable of automatic feature extraction from raw sensor signals without the need of manual engineering to often achieve what is superior performance in complex fault environments [8], [14].

Major advantages of the machine learning based fault diagnosis techniques is their high diagnosis accuracy, adaptability in varying operating conditions, ability to detect multiple faults and its support for predictive maintenance capabilities. However, such models are often held back by their requirement for quality training data, proper feature selection, high computational resources and susceptibility to overfitting.

Machine learning at large has brought electric drive fault diagnosis from rule-based monitoring to automated decision-making systems, suitable for smart and digital industry applications.

V. Model-Based Fault Diagnosis Using Machine Learning

Model-based fault diagnosis systems can be described as solutions that combine system modelling with integrated machine learning techniques to improve general fault detection approach in electric drives. In this method, mathematical or simulated versions of the drive system are developed to represent numerous instances of operating conditions – healthy and faulty. The generated data from these instances is then used as the training dataset for the classifier machine learning algorithms used in automatic fault detection [7].

A typical electric drive and now its model, as discussed earlier, includes the motor, inverter, controller, sensors and a mechanical load. Different fault scenarios are then simulated on this model by changing parameters like torque, speed, resistance, fault location or switching characteristics, allowing generation of large datasets without causing harm to physical, expensive equipment.

The main advantage experienced with model-based simulation is the ability to simulate and study rare and possibly dangerous faults without damage to real equipment. Some examples of such faults include – inverter short circuit faults, open switch faults, sensor faults and stator winding failures which can be reproduced under controlled conditions through simulations. These simulated signals are later processed for feature extraction that are to be used in the training of the machine learning model [5], [11].

The model generated data is then used to train machine learning classifier models such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs) and decision trees. After training, the model is capable of classifying real-time measured signals into healthy and faulty categories. Thereby, reducing dependency on expensive fault databases.

Electric drives are also known to work under varying speeds and load conditions, so simulation data can be generated for a wide torque-speed range helping the trained classifier to perform accurately in real practical environments demonstrating robustness of model when under different operating points [7].

However, model-based approaches may show poor diagnosis performance when the simulation model is not an accurate representation of the real system. Similarly, parameter uncertainties, aging effects and sensor noise can create significant difference between the simulated and actual signals.

In spite of such limitations, model-based learning methods prove to be a cost effective and intelligent means of fault diagnosis that is especially useful when real faulty data is inaccessible due to being limited, expensive or unsafe to obtain. Making model-based fault diagnosis highly suitable for predictive maintenance and smart drive systems.

VI. Feature Extraction and Signal Processing Techniques

Feature extraction describes the stage of machine learning algorithms where useful features are extracted from a dataset to accurately and effectively represent a system. Feature extraction is important in fault diagnosis as raw sensor signals can often carry noise, redundant information and increase data size significantly. For example - useful features can be extracted from a dataset containing current, voltage, vibration, temperature and speed signals to more specifically and effectively represent the condition of an electric drive system [4], [12].

Time-domain features is a method of feature extraction commonly used for its simplicity and low computational costs, these include – mean, root mean square (RMS), standard deviation, variance, skewness, kurtosis, crest factor and peak value. Time-domain features are effective for identifying abnormal changes in signal magnitude and waveform shape.

Similar to time-domain analysis, frequency-domain analysis is used for periodic and harmonic fault detection. Fast Fourier Transform (FFT) is used in such cases to convert signals from time domain to frequency domain, when harmonics and sideband frequencies are to be observed for fault possibility. This method is employed in Motor Current Signature Analysis when testing for broken rotor bars and eccentricity faults [3].

For non-stationary signals, time-frequency techniques provide better results. Wavelet transform is commonly used, as it is capable of analysing both time and frequency simultaneously. It is noted to be highly effective when testing for transient faults, switching faults and varying speed operation. Short Time Fourier Transform (STFT) is also used for similar conditions.

Signal preprocessing refers to steps undertaken to improve quality of dataset required before feature extraction, which in turn increases performance and signal quality of machine learning classifiers. Common preprocessing steps include filtering, normalization, denoising, sampling and segmentation.

While deep learning models are capable of learning features directly from raw data, conventional feature extraction methods are still preferred in many systems due to their lower computational requirements and easy to interpret nature [14].

Hence, feature extraction and signal processing are integral parts of the training process that significantly improve diagnosis accuracy, reduce training complexity and enable reliable monitoring of conditions for an electric drive system.

VII. Comparative Analysis of Machine Learning Techniques

Of the various machine learning algorithms studied for fault diagnosis applications in electric drives, each one has its own strengths and limitations. Thus, selection of suitable algorithm is a viable concern judged on the basis of factors like – dataset size, computational resources, feature quality and required diagnosis accuracy [7], [14].

Artificial Neural Networks (ANNs) are used because of their capability to map complex non-linear relationships between features and faults. They are known for providing high accuracy but require proper training, sufficient datasets and parameter tuning [4].

TABLE I
Comparative Analysis of ML Techniques for Fault Diagnosis

Technique	Advantages	Limitations	Applications
ANN	High accuracy, nonlinear modeling	Needs tuning, overfitting risk	Motor, inverter, bearing faults
SVM	Strong generalization, good for small data	Slow for large datasets	Signal-based fault classification
DT	Easy to understand, fast training	Overfitting, less stable	Basic industrial diagnosis
RF	Robust, accurate, reduces overfitting	Higher memory usage	Real-time monitoring
KNN	Simple, no explicit training phase	Slow prediction, scaling sensitive	Small dataset problems
CNN	Auto feature extraction, high accuracy	High computation cost	Raw signal/image diagnosis
RNN/LSTM	Good for time-series data	Complex training	Dynamic fault prediction

Support Vector Machines (SVMs) are effective when used for small and medium sized datasets, offering strong generalization capabilities and ability to perform well when in multi-dimensional feature spaces. It unfortunately faces large training time with increasing dataset size and when trained for multiclass problems.

Decision Trees are simple, fast and easy to interpret and their tendency to provide clear decision rules prove useful in industrial applications. However, single trees are known to suffer from overfitting issues and lower stability.

Random Forest improve upon Decision Trees by combining multiple trees, providing better accuracy, robustness and resistance to overfitting issues. They are widely used for practical classification tasks.

K-Nearest Neighbours (KNN) is a simple to implement algorithm that works well for datasets that are smaller in size. However, prediction time increases with data size and therefore performance depends strongly on scaling of features.

Deep learning methods like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are also capable of automatically learning features from raw signals and often achieve superior results in complex environments.

Their main limitation is the high computational cost and requirement of a large, labelled dataset [8], [14].

Generally, ANNs and SVMs are opted for medium scale fault diagnosis; Random Forest serving as a balanced practical solution; and Deep Learning being the most suitable algorithm for large scale monitoring systems. No single method is treated or believed to be best and so, algorithm selection should be based on the requirements of the application.

VIII. Challenges and Future Research Directions

Machine learning based fault diagnosis has brought about significant improvements in electric drive monitoring systems, even still several challenges persist – Availability of high-quality labelled fault data is still incredibly rare as in real industries, faults occur rarely and collecting such data can be expensive, time consuming and possibly unsafe [7].

Another challenge it faces is the variation of operating conditions such as speed, load, torque, temperature and supply voltage variation in different practical environments; as such models trained on one condition may not perform adequately in said practical environments. Therefore, robustness and adaptiveness are expected of algorithms during real world implementation.

Proper preprocessing and fault tolerant sensing techniques should be highlighted as – noise and sensor errors affect diagnosis accuracy; measured signals contain disturbances, missing values and communication delay which impact classifier performance. Proper preprocessing is required to overcome these issues.

Deep learning methods provide high accuracy but are held back by their requirements of large datasets, powerful hardware and long training times. Thus, in industrial systems lightweight and embedded solutions are preferred. Hence, development of efficient models for real-time edge devices is a significant research direction [14].

Interpretability of diagnosis made is another important concern, as advanced models tend to behave like black-box systems, making it difficult to understand reasons behind a decision. Implementation of Explainable Artificial Intelligence (XAI) is suggested, as to improve trust and industrial acceptance of the machine learning systems.

Future research in this field is expected to have an increased focus on hybrid diagnosis methods that combine physical modelling, signal processing and intelligent learning algorithms. Digital models of electric drives can generate real-time simulated data in tandem for predictive maintenance of drive. Transfer Learning and Federated Learning can be employed across multiple machines to help train models while retaining sensitive industrial data.

Integration with Industrial Internet of Things (IIoT), cloud monitoring and smart sensors will allow remote condition monitoring and automated maintenance systems making future electric drives more reliable, maintenance free and self-diagnosing.

IX. Conclusion

It is understood that fault diagnosis in electric drives is essential for improving a system's reliability, reducing maintenance cost, preventing unexpected failures and ensuring safe operation when put to industrial use. Traditional diagnosis techniques such as current analysis, thermal inspection, vibration monitoring and model-based residual methods have been widely used, but their performance is limited when tested under complex and varying operating conditions.

Machine learning thus provides an enticing alternative by providing automatic feature learning, fault classification and predictive maintenance capabilities. Techniques such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Decision Tree, Random Forest and Deep Learning models demonstrate a strong ability in detecting electrical, mechanical and converter related faults with high level of accuracy.

Machine Learning based diagnosis is further improved by introducing model-based fault diagnosis, combining physical system knowledge with intelligent data driven mechanics. Simulation models allow generation of healthy and faulty datasets under various working conditions, reducing dependency on need for expensive real world fault experiments' dataset.

This review paper discusses classification of faults, conventional methods of classification, approaching classification with machine learning techniques, introduction of model-based fault classification, feature extraction and data preprocessing, a comparative analysis of machine learning algorithms discussed and finally future challenges in this field – design and exploration of efficient hybrid model-based machine learning systems that offer practical solutions for the next generation of electrical drives.

In the future, integration of digital twins, XAI, IIoT and edge computing methods is expected to make electric drive systems faster, smarter, autonomous and highly reliable for adoption in Industry 4.0 applications.

References

[1] D. W. Novotny and T. A. Lipo, *Vector Control and Dynamics of AC Drives*. Oxford, U.K.: Clarendon Press, 1996.
[2] N. Mohan, T. M. Undeland, and W. P. Robbins, *Power Electronics: Converters, Applications, and Design*. New York, NY, USA: Wiley, 1995.
[3] M. E. H. Benbouzid, "Bibliography on induction motor faults detection and diagnosis," *IEEE Trans. Energy Conversion*, vol. 14, no. 4, pp. 1065–1074, Dec. 1999.
[4] F. Filippetti, G. Franceschini, C. Tassoni, and P. Vas, "Recent developments of induction motor drives fault diagnosis using AI techniques," *IEEE Trans. Industrial Electronics*, vol. 47, no. 5, pp. 994–1004, Oct. 2000.
[5] D. Kastha and B. K. Bose, "Investigation of fault modes of voltage-fed inverter system for induction motor drive," *IEEE Trans. Industry Applications*, vol. 30, no. 4, pp. 1028–1038, Jul./Aug. 1994.
[6] J. Holtz, "Pulsewidth modulation—A survey," *IEEE Trans. Industrial Electronics*, vol. 39, no. 5, pp. 410–420, Dec. 1992.
[7] Y. L. Murphey, M. A. Masrur, Z. Chen, and B. Zhang, "Model-based fault diagnosis in electric drives using machine learning," *IEEE Trans. Industrial Electronics*, 2005.
[8] L. Wen, X. Li, L. Gao, and Y. Zhang, "A new convolutional neural network-based data-driven fault diagnosis method," IEEE Trans. Industrial Electronics, vol. 65, no. 7, pp. 5990–5998, Jul. 2018.

[9] K. Kim and A. G. Parlos, "Induction motor fault diagnosis based on neural networks and wavelet signal processing," *IEEE/ASME Trans. Mechatronics*, vol. 7, no. 2, pp. 201–219, Jun. 2002.
[10] F. Zidani, M. E. H. Benbouzid, D. Diallo, and M. S. Nait-Said, "Induction motor stator faults diagnosis by a current Concordia pattern-based fuzzy decision system," *IEEE Trans. Energy Conversion*, vol. 18, no. 4, pp. 469–475, Dec. 2003.
[11] R. L. A. Ribeiro, C. B. Jacobina, E. R. C. da Silva, and A. M. N. Lima, "Fault detection of open-switch damage in voltage-fed PWM motor drive systems," *IEEE Trans. Power Electronics*, vol. 18, no. 2, pp. 587–593, Mar. 2003.
[12] W. Fenton, T. McGinnity, and L. Maguire, "Fault diagnosis of electronic systems using intelligent techniques: A review," *IEEE Trans. Systems, Man, and Cybernetics*, vol. 31, no. 3, pp. 269–281, Aug. 2001.
[13] E. L. Allwein, R. E. Schapire, and Y. Singer, "Reducing multiclass to binary: A unifying approach for margin classifiers," *J. Machine Learning Research*, vol. 1, pp. 113–141, 2000.
[14] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2016.
[15] F. Chollet, *Deep Learning with Python*. Shelter Island, NY, USA: Manning Publications, 2018.