Review: Three Phase Induction Motor Stator Fault Classifiers

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Abstract - *A rapidly developing technique for the online identification of developing problems is condition monitoring of induction motors. It prevents the unanticipated failure of a crucial system. Stator defects make up between 30 and 40 percent of induction motor errors. This study offers a thorough analysis of the numerous stator problems, their root causes, detection parameters/techniques, and current state-of-the-art condition monitoring technologies. Its purpose is to give induction motor researchers and application engineers a comprehensive overview of the state of stator fault monitoring. For rapid reference, a list of 10 research articles on the topic is included.*

Key Words: *Three phase induction motor, Stator faults, Fault classification*

1. INTRODUCTION

Induction motors are the main workhorse of industrial prime movers due to their extensive uses in electromechanical energy conversion, primarily because of their low cost, fairly compact size, robustness, minimal maintenance, and operation with a readily accessible power source. Even though induction machines are dependable, they are occasionally put to un-favorable conditions that result in flaws and failures [1], [10]. Numerous machine problems have been researched, including eccentricity, bearing faults, broken rotor bars, stator and rotor imbalance, and winding faults [7], [10].

Recent growth in automation and the resulting decrease in direct man-machine contact for system operation supervision has raised the necessity for condition monitoring. For the goal of identifying, analyzing, and fixing machine issues before they lead to failure, condition monitoring is the graphical trend of the machine parameters. It is employed to improve machine performance and availability, lower consequential damage, lengthen machine life, lower spare parts inventories, and lower breakdown maintenance [2]–[6], [8]. According to several studies, stator winding failure accounts for 30–40% of induction motor failures [1], [10]. An very credible research was funded by the IEEE and the Electric Power Research Institute [1].

A thorough analysis of around 7500 motors revealed that stator problems were to blame. Draft received on May 20; updated on October 28. TEC00126-2003, paper number. A. Siddique and G. S. Yadava work at the Indian Institute of Technology's Industrial Tribology, Machine Dynamics and Maintenance Engineering Centre in New Delhi, India (110016). B. Singh works at the Indian Institute of Technology's Department of Electrical Engineering in New Delhi, India (e-mail: bsingh@ee.iitd.ernet.in). Identity of the Digital Object 10.1109/TEC.2004.837304 responsible for 37% of the failures. As a result, diagnostic tests sensitive to the state of the stator winding are needed when conducting predictive maintenance on motors for stator defects.

2. THREE PHASE INDUCTION MOTOR STATOR FAULT CLASSIFIERS

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A MATLAB-based model was created and put through several fault-load combination instances for motors of various sizes. Electromechanical torque created by the motor was chosen as a defect signal. The mean, variance, max, min, and F120 time based on statistical and frequency-related properties were discovered to be quite unique for associating the acquired electromechanical torque with its corresponding proportion of shorted turns during the construction and training of the neural network. Five distinct motors—referred to as observed motors—were employed throughout the neural network's training phase. On the other hand, the electromechanical torque under various fault-load combination instances, previously unseen from the first five motors and those of two new motors (referred to as unseen), was utilized to assess the effectiveness of the proposed diagnostic tool. According to test findings, accuracy was between 88 and 99 percent.

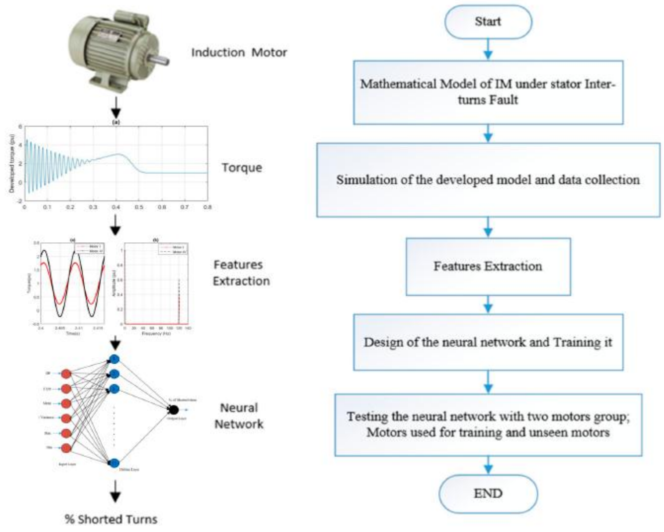

Fig-1: Three phase induction motor stator inter turn fault detection approach [1]

The invention of a diagnostic tool based on a neural network is described in this approach [1] for determining the severity and precise proportion of stator inter-turn defects in three-phase induction motors. The benefit of adopting a steady-state electromechanical torque signature as a failure indication is demonstrated by simulation results. Variance, max, min, mean, and the F120 were discovered to be the most typical and distinguishable inter-turn fault characteristics when the acquired electromechanical torque underwent time and frequency domain analysis. Because there is just one input, one output, and one hidden layer with 11 neurons, the created neural network is simple.

Additionally, 100% unseen cases of short turns/loading conditions extracted from seen motors with an accuracy of 99% and 100% unseen cases extracted from motors never seen or used for neural network training with an accuracy of 88-96 percent were applied to the developed diagnostics tool to examine its effectiveness. Contrary to all diagnostic equipment, which may only be used on motors utilized during training, this is the case. Future research can adapt the produced diagnostic tool in this technique to detect other fault kinds, such as a confluence of inter-turn and broken bar and/or inter-turn and eccentricity. As a result, this may be utilized to create a thorough diagnosis tool. The current study may also be expanded upon by using the created technology in a laboratory setting.

An article describes an acoustic signal-based early failure diagnosis method. A single-phase induction motor was employed with the technique that was provided [2]. The following states of the motor were measured and examined by the authors: a single-phase induction motor in good condition, a single-phase induction motor with a faulty bearing, a single-phase induction motor with a faulty bearing and shorted coils of the auxiliary winding. There was discussion of a feature extraction technique known as MSAF 20-MULTIEXPANDED (Method of Selection of Amplitudes of Frequency - Multiexpanded). The feature vectors were produced by the MSAF-20-MULTIEXPANDED. The feature vectors were produced by the MSAF-20-MULTIEXPANDED. The generated vectors were categorized using the NN, NM, and GMM classifiers, respectively (Gaussian Mixture Models). The single-phase induction motors may be diagnosed using the suggested approach. It may also be used to different designs of electric rotational motors.

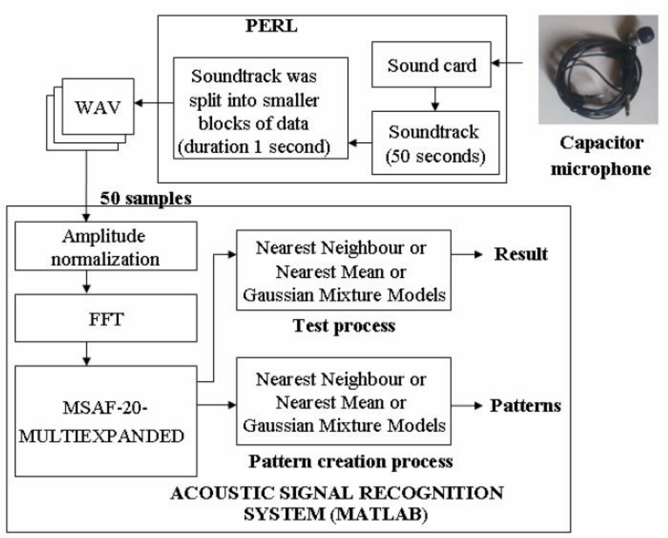

Fig-2: Block diagram of the early fault diagnostic technique based on acoustic signals [2]

The early defect diagnostic methodology based on auditory signals is presented in method [2]. The single-phase induction motor was operated using the suggested method. A single-phase induction motor in good condition, a single-phase induction motor with a defective bearing, a single-phase induction motor with a bad bearing and shorted coils of the auxiliary winding were all examined. The MSAF-20-MULTIEXPANDED feature extraction approach was utilised by the authors. In this article, the Nearest Mean classifier, Gaussian Mixture Models, and the Nearest Neighbor classifier were each examined.

The findings of all the chosen classifiers were as follows: Gaussian Mixture Models (ET = 65.7-88.8%), Nearest Mean classifier (ET = 89.7-95.3%), and Nearest Neighbor classifier (ET = 84.1-91.6%). The single-phase induction motors can be protected using the fault diagnostic approach. The proposed approach may also be used to diagnose other types of spinning equipment. The suggested method is non-intrusive and reasonably priced. However, the suggested method was susceptible to influence from outside disturbances.

The approach [3] presents a three-phase asynchronous motor's stator short circuit fault detection technique that is based on current vector coordinate transformation. Statistics show that inter-turn short circuits, which are caused by the breakdown of turn insulation, account for 78% of stator problems. It frequently results in motor shutdown. It demonstrates the fundamentals of developing a stator winding diagnostic system using current measurements. The simulation results supported the efficacy of the suggested methods for detecting stator short circuit failures. With the use of a lab test bench, a motor with an inter-turn short circuit was also evaluated.

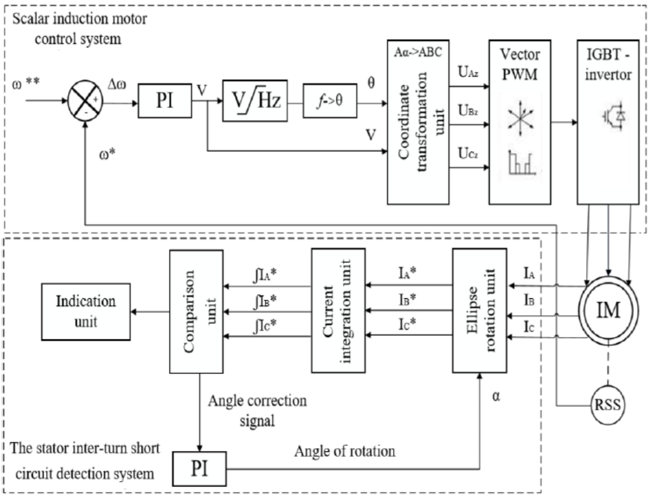

Fig-3: Three phase induction motor stator inter-turn short circuit fault detection approach [3]

Even with inexpensive current sensors, the devised diagnostic system is usable and offers a wide range of measurement accuracy. The suggested system's use is not just restricted to a lab bench. This technique can be utilised in industries where the motor is installed in an inaccessible location (crane electric drive, air conditioning systems, electric centrifugal pump installations, etc.), or when installations are remotely placed (in sucker rod pump and water supply units). The aforementioned techniques are all more computationally intensive or need for test-based settings.

The key benefit of the suggested approach is that it requires little data array processing in the built diagnostic system's algorithm. However, a comparison of the discussed and suggested diagnostic procedures for detecting stator inter-turn short circuits can produce high-quality relative analysis data that are highly helpful for verifying the method's applicability.

A potential approach for describing fault states is deep learning architecture, which uses several hidden layers to automatically build hierarchical representations from large input data sets. This technique [4] provides a deep learning-based multi-signal defect diagnostic approach that takes advantage of convolutional neural networks' (CNNs') potent feature learning capabilities in pictures. The suggested deep model has the capacity to concurrently learn from several types of sensor signals, enabling accurate induction motor defect identification and robust performance. First, a wavelet transform is used to transform the obtained sensor signals into a time-frequency distribution (TFD). Then, using the TFD pictures as a starting point, a deep convolutional neural network is used to learn discriminative representations. A fully linked layer in a deep architecture then provides a forecast of the state of the induction motor based on features that have been learnt. Experiments are conducted on a machine failure simulator where both vibration and current data are evaluated to determine the efficacy of the developed deep model. The suggested method works better than conventional fault diagnostic techniques, according to experiment data, proving its efficacy in induction motor applications. The suggested deep model is able to automatically learn and choose relevant characteristics that contribute to effective defect diagnosis in contrast to existing approaches that rely on delicate features retrieved by skilled professionals.

With its use on induction motors, this technique [4] presents a DCNN-based multi-signal defect detection framework that uses time-frequency distributions of sensor signals as the input pictures. The multi-signal model, which uses CNN as its foundation, demonstrates the capacity to automatically learn discriminative features from TFD pictures and deliver precise fault classification. In order to evaluate the effectiveness of the proposed framework, both vibration and current signals are employed. Through trials, the performances of two distinct DCNN-based multi-signal architectures are compared, with the merged model showing the best results. On the basis of statistical analysis, the impact of measurement uncertainty is also examined.

The detection of electrical motor deterioration is a crucial field of research nowadays. A motor's diagnostic information is typically contained in vibration signal signals. The authors offered a method for evaluating the vibration signals from three-phase induction motors. This technique provides ways for diagnosing rotor defects in three-phase induction motors (TPIM) [5]. The methods disclosed made use of vibration signals and signal processing methods. The authors looked at the success rate of identifying vibration signal readings for three different TPIM states: a healthy TPIM, a TPIM with one broken bar, and a TPIM with two damaged bars. The authors proposed a method for extracting information from vibration signals called Method of Selection of Amplitudes of Frequencies (MSAF-12). The feature vectors were obtained using the FFT, MSAF-12, and the vector sum's mean. The three classification methods that were examined were nearest neighbour (NN), linear discriminant analysis (LDA), and linear support vector machines (LSVM). The performance of the tested classifiers varied from 97.61% to 100%.

This method [5] discusses rotor of the TPIM diagnostic methods. The suggested methods relied on vibrational cues. Three different TPIM states' vibration signals were examined by the authors. The researchers examined three motors: one without a broken bar, one with one broken bar, and one with two broken bars (3 motors in total). The MSAF-12 approach was created and employed by the authors. MSAF-12, FFT, and the mean of the vector sum were used to produce the feature vectors.

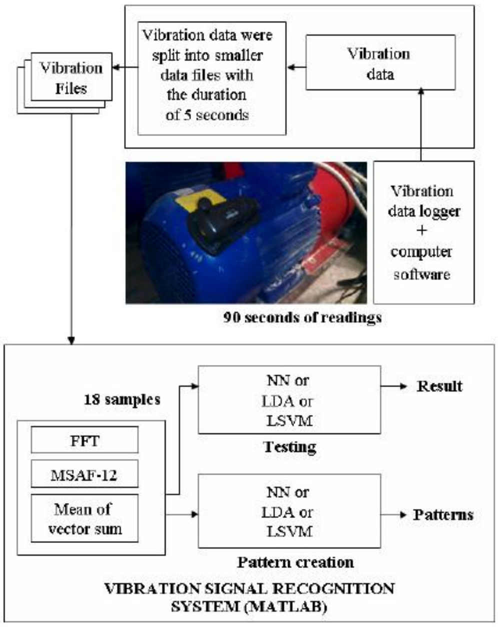

Fig-4: Vibration based three phase induction motor fault diagnostic technique [5]

The following three classification techniques were used: NN, LDA, and LSVM. The calculated outcomes of the aforementioned classifiers were equivalent to outcomes attained by further diagnostic techniques (TEVSR was equal to 100 percent for the MSAF-12). The described diagnostic methods cost little money. Costs for acceleration and vibration data recorders are around $100. The price of a PC is between $250 and $300. The given strategies are effective in detecting degradation, as shown in the results section. The study demonstrated that vibration signals include diagnostic data. The suggested methods can also be used to identify bearing problems, broken gears, and broken sprocket teeth in spinning electrical motors.

A two-stage fault detection and classification strategy particularly created for spinning electrical devices is presented by this method [6]. The strategy makes use of brand-new, frequency-domain-specific condition indicators.

The approach [6] suggests two separate features: one based on peak extraction using the prominence measure, a method taken from the morphology of mountains, and another based on the computation of the occupied band power ratio for particular distinctive fault frequencies. Principal component analysis (PCA), a feature reduction approach with a linear foundation, has been used to represent all the data. The three-phase current signals online were then detected and classified using shallow neural networks. Using signals collected from grid- and inverter-fed induction motors, the efficacy of the suggested approach has been experimentally verified.

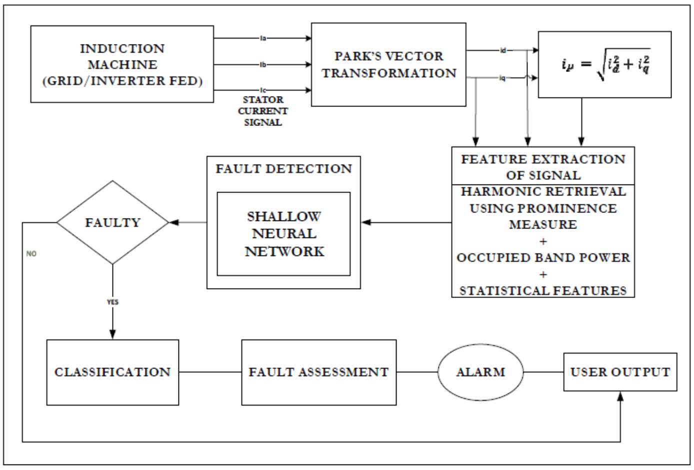

Fig-5: FD and classification scheme using Non-Parametric, Statistical-Frequency Features and Shallow Neural Networks [6]

Using two-stage NNs, a defect detection and classification technique has been developed with accuracy levels exceeding 95%. The selection of characteristics that generalize the data in many different ways and are able to differentiate classes in the event of anomalies is a key factor in improving the system accuracy. Thus, the following features are the key focus of this method's [6] contribution:

First, the usage and improvement of the prominence measure-based peak extraction approach, which has not yet been suggested or used in the field of FD and CM. The frequency spectrum elaboration in the suggested technique allows for fault analysis customization. Although it is not required, previous knowledge of the model order is necessary to properly extract significant peaks. The method of prominence is more time-efficient than classical and parametric-based strategies for harmonic retrieval, performs as well for short time intervals, and doesn't require any pre-processing.

The second is the usage of the occupied BPR ratio in relation to the frequency spectrum's CFFs. In order to combat external noise produced by the inverter, these characteristics also incorporate statistical frequency aspects.

Creating this technique [7] aims to offer a novel method for identifying and diagnosing electrical problems in three-phase induction motors, especially those that occur in the stator winding. The stator winding usually breaks down when an induction motor fails. To better comprehend internal winding fault in induction motor, four case studies of distinct three-phase induction motors (TPIM) were analyzed under two conditions: normal winding condition and windings shorted between two phases. This strategy is outlined in the frequency response analysis (FRA) measurement on the stator winding with the inter-phase short [7]. It is also advised to classify and quantify the problem using the Frequency Response Analysis (FRA) interpretive technique. To comprehend the FRA, a statistical indicator known as the NCEPRI technique is used to compare the measured responses.

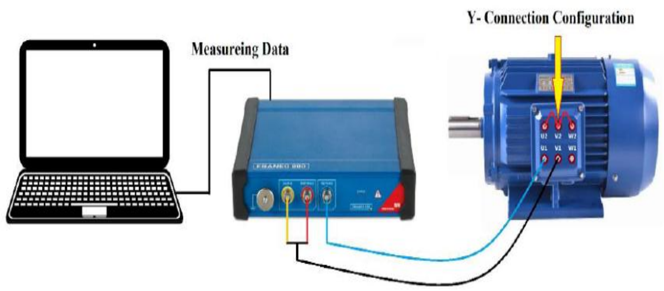

Fig-6: Equipment connection to measured FRA for motor windings [7]

This approach had a phase to phase turns (PPT) error in the TPIM winding [7]. The PPT defect in the TPIM winding causes some fluctuation in the FRA response, according to the comparison of frequency responses (FR). In part 4, the changes in FRA signatures for windings were understood and examined. According to a discovery of this approach [7], it has been demonstrated that the fluctuation in the FRA response in phases while measuring the frequency response may be used to diagnose and identify a defect that was caused by a PPT problem. Additionally, this technique [7] offered the FRA validation at the PPT fault situation utilizing one of the NCEPRI algorithm's recognized statistical indicators. Where, according to the assessment factor's computation (E12), the frequency regions with the highest levels of distortion are those with low and medium frequency ranges. Additionally, the distortion level will be minimal in the high frequency region. The suggested technique had an advantageous outcome; it may be regarded as a novel technique for locating and diagnosing the PPT defect in a three-phase induction motor. Additionally, the established method's applications may be utilized to diagnose and find different kinds of TPIM defects.

Asynchronous motors are widely used in a variety of sectors. Induction motors are strong and dependable, but they can develop a variety of problems. Induction motor malfunctions can result in awful things like operational accidents, manufacturing disruptions, and raw material losses. Identification of defect has therefore become increasingly crucial in Induction motor maintenance. Bearing failure is one of the many problems that may develop in a motor and, if ignored at an early stage, can cause catastrophic damage to the machine. Therefore, it is necessary to continually check the condition of the bearings in induction machines. A unique method [8] is put forward that makes use of the discrete cosine transform (DCT) to analyses speed and the probabilistic neural network (PNN) to pinpoint bearing errors. When the motor is used under various loading situations with both good and bad bearings, the stator currents of the induction motor are examined and categorized. The experimental results validate the value of the created technique, and the suggested PNN classifier has the capacity to classify the various forms of defect in bearing. When compared to traditional SVM and ANN classifiers, PNN-based motor bearing defect identification and diagnosis performs better.

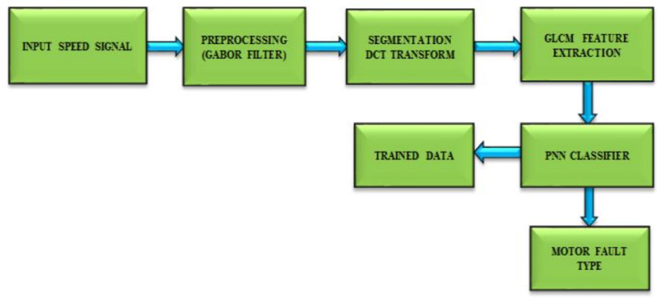

Fig-7: Probabilistic neural network-based Fault classifier for Induction Motor [8]

SVM and ANN-based classifiers are compared to the PNN classifier's effectiveness. PNN is not only useful for analysing the situation in which a defect occurred, but it also speeds up calculation and produces a perceptive conclusion regarding the reason for speed exaggeration. The performance indices taken into account for evaluating the performance of the suggested PNN classifier are accuracy, specificity, and sensitivity. The results show that PNN classifiers outperform ANN and SVM-based classifiers in terms of accuracy, sensitivity, and specificity, regardless of the number of pictures. as Q-learning is used to train PNN. It is regarded as one of the key models in the categorization issue. PNN classifier can therefore be utilised to solve future bearing defect detection issues. This suggested approach is highly useful and keeps the speed in a stable condition. It is also crucial for the power system.

It is crucial to predict an induction motor's unknown problem in order to avoid an unplanned shutdown. Using a multiclass support vector machine (SVM) and a decision-directed acyclic graph, an unknown induction motor defect has been identified and authenticated from other types of failures in this case (DDAG). Induction motors with various types of known fault states and one induction motor with an unknown type of fault condition are used to acquire three phase current data samples. In order to distinguish the kind of unidentified fault from the mixture of several types of faults, an experiment using motor fault current signature analysis (MFCSA) has been conducted.

Two eigenvalues of stator currents, referred to as principal components, are useful fault features of the motors that are captured with the aid of PCA transformation. Principal component analysis (PCA) is a feature extraction and dimensions reduction process that is used to extract information from fault current signature of each faulty motor. One versus. one (OVO) SVM technique is used to nonlinearly separate each pair of classes out of the six classes by allocating the unknown test sample to the class using an RBF type kernel. Each defective induction motor's numerous PC values for each phase are grouped together into one class. For each phase's n-class issue, the OVO-SVM builds n (n-1)/2 classifiers, and the DDAG approach is used to build a directed acyclic graph utilizing the classifiers to make an accurate determination regarding the classification of the unknown defect. According to the maximum membership count produced by classifiers, the unknown fault is categorized for each phase among several types of faults, and the fault is also validated using the DDAG findings from the three stages.

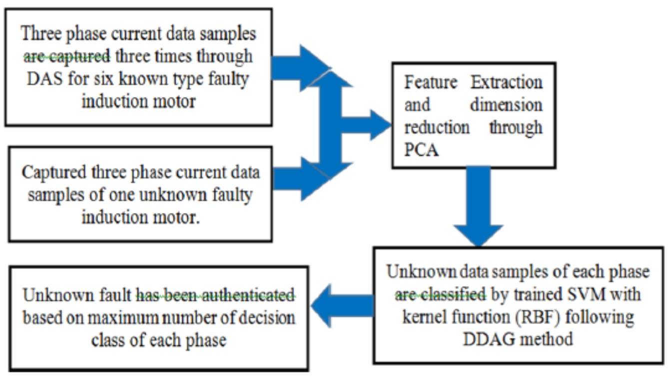

Fig-8: Block diagram of Induction motor fault monitoring and fault classification using deep learning probabilistic neural network

In contemporary industry, determining the type of unknown fault is a difficult process. The purpose of this job is to categories and validate the kind of unidentified defect that happened in the machine, together with the location of the issue. The defect is categorized as a combination of many fault types, including both electrical and mechanical failures. Six separate defective induction motors' current signals were selected for the investigation because current signature analysis may be used to quickly and cheaply identify both mechanical and electrical defects. Six distinct types of malfunctioning induction motors' current signal characteristics are grouped into six different types of classes, and one unknown kind is categorized among the six types phase-wise.

Depending on the (n-1) number of membership classes of the DDAG for each of the three phases independently, the unknown type fault is categorized for each phase if there are n classes, and the unknown fault is authenticated. The DDAG approach speeds up pairwise categorization while maintaining training accuracy. This idea has never been used before to identify an induction motor defect of an unknown nature. Any sort of defect, not just one specific kind, can be categorized among the classifications that are already well-established. This study uses six different types of malfunctioning induction motors, although any issue may be identified and validated if there are more recognized classes than six. There are several restrictions on how faults are classified using linear separating hyperplanes. The classes are separated using a kernel function that is RBF-based to get rid of this. Since of the dispersed data, linear separation is challenging because it presents a significant classification challenge. The SVM kernel function converts data from a high dimensional space into the original feature space.

This approach [10] describes a Wavelet Packet Transform-based fault detection method for three-phase induction motors (WPT). The suggested approach uses a frame of samples from an induction motor's three-phase supply current. By calculating the Root Mean Square (RMS) value of the three phase current samples at each time stamp, the three phase current samples are then merged to produce a single current signal. The final step is to partition the obtained current samples into windows of 64 samples. The samples in the resultant window are then processed independently. Non-overlapping window samples and moving/overlapping window samples are the two strategies used by the suggested algorithm to construct window samples. Non-overlapping window samples are produced by simply splitting the current data into 64-sample windows, whereas moving window samples are produced by taking the first 64 current samples and then repeatedly moving the window one sample at a time across the current samples.

The final 63 samples from the previous window plus one additional sample make up the current window of samples. The defect detection time is decreased to a single sample accuracy by using the overlapping approach. However, it uses much more computer memory and is computationally more expensive than the non-overlapping technique. The subsequent window samples are handled individually as follows: Each sample from the resultant window is subjected to a two-level WPT operation by the suggested technique, which divides its coefficients into four wavelet sub-bands. The trip signal is then activated to disconnect the motor from the power source using information from wavelet high frequency sub-bands for fault detection. The Entropy power Energy (EE) of the high frequency WPT sub-bands' coefficients was utilized to assess the motor's condition after the suggested technique was initially implemented in the MATLAB environment. The programmed then determines what kind of defect there is if the induction motor has a problem. The suggested algorithm condition was then evaluated in a real-world setting where various failures were artificially created in the induction motor. The proposed system was then put into an empirical configuration.

The suggested system may identify a malfunction, cut off the induction motor from the power source, and then activate a trip signal to safeguard the motor from more electrical harm. It was also demonstrated that, while having a larger computational cost and memory utilization than the nonoverlapping technique, a one-sample moving window could detect the error significantly more quickly.

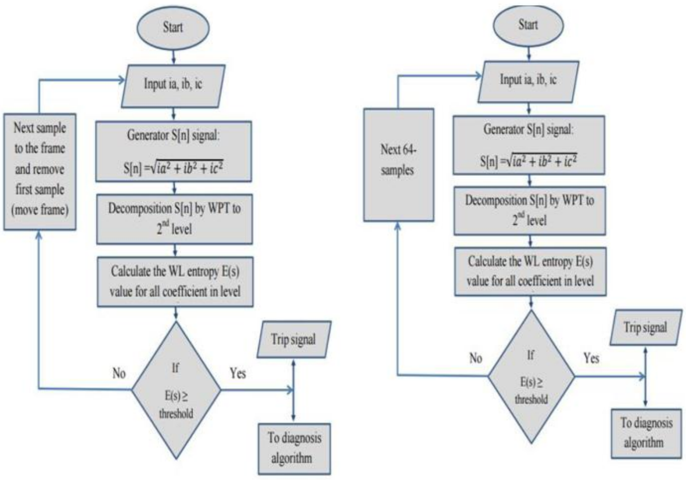

Fig-9: Three phase induction motor fault detection using moving frame algorithm and non-overlapping window frame method

The suggested procedure was first tested using an actual motor and testing apparatus, then it was implemented. The computer results and the experimental findings on a variety of motors were in agreement. To the authors' knowledge, transmission line fault detection has made extensive use of the Stockwell and Hilbert transforms together. However, as a future improvement to the suggested technique, their applications for defect detection and classification in induction motors can be researched.

3. CONCLUSION

Here is a quick overview of the most common electrical issues that affect induction motors, particularly stator failures, along with the most recent developments in their detection and diagnosis. To keep up with the most recent developments, more precise and effective modelling and simulation techniques of stator faults are urgently required. These techniques must take into account nonlinear ties, saturation effects, etc. of magnetic substances and supply anomalies in order to clearly distinguish the relevant frequency components from other components caused by time harmonics, machine saturation, etc. The newest AI approaches for stator fault monitoring and modeling/simulation of defective motors have their own sections. Future developments in the diagnosis of stator faults have also been explored.

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