System and method for condition monitoring of an induction motor

FIELD OF THE INVENTION

[0001] The present invention relates to a system and method for condition monitoring of an induction motor, more particularly, for monitoring health condition of an induction motor based on vibrational signals automatically and for instantly generating reports on the health condition of the induction motor.

BACKGROUND OF THE INVENTION

[0002] Induction motors are integral to numerous industrial and commercial applications, converting electrical energy into mechanical motion with efficiency and reliability. These motors operate on the principle of electromagnetic induction, comprising a stator and a rotor. AC power supplied to the stator windings generates a rotating magnetic field that induces currents in the rotor, leading to its rotation and mechanical output. They are widely utilized in applications such as fans, pumps, compressors, and conveyors, induction motors come in diverse designs and power ratings, serving as workhorses across industries. They have become an interest in many industries due to its robustness, reliability, and relatively low-cost compared to other types of motors. To ensure the efficiency and safe operation of induction motors, monitoring systems are often employed.

[0003] Monitoring systems for induction motors are pivotal in ensuring their optimal performance and longevity. These systems are designed to track critical parameters and conditions to facilitate smooth operation and early identification of potential issues. By adopting predictive maintenance practices, these systems may mitigate downtime and avert catastrophic failures. Monitoring can be accomplished through various means, including specialized sensors, advanced data analysis techniques, and dedicated software tools. Parameters such as vibration, temperature, current, voltage, and power factor are commonly observed to detect deviations from expected norms, which might indicate impending problems.

[0004] Detecting anomalies in induction motors is a complex undertaking fraught with numerous challenges. These challenges stem from the intricate operating environments where these motors are employed, encompassing dynamic conditions, load fluctuations, and temperature variations. A primary hurdle lies in the scarcity of labelled data that accurately represent both normal and anomalous motor behavior. This scarcity hampers the development of effective anomaly detection algorithms. Additionally, the inherent class imbalance in the data, where anomalies are infrequent compared to normal instances, can bias machine learning models towards recognizing normal behavior while struggling with anomaly identification. Feature engineering, a critical step in the process, demands the selection of pertinent motor behavior attributes that can be daunting and might not cover the full spectrum of operating nuances.

[0005] Furthermore, the non-stationarity of induction motor behavior, stemming from gradual wear, maintenance, and operational changes, poses a challenge to the performance of traditional anomaly detection methods. Transient effects during start-up, shutdown, or rapid load adjustments introduce complexities, requiring differentiation between transient deviations and genuine anomalies. The impact of noise, sensor errors, and drift in sensor measurements further muddies the waters, necessitating the disentanglement of true anomalies from data inaccuracies. Additionally, the intricate interplay of multiple simultaneous anomalies or cascading failures complicates the detection process. Model selection in striking a balance between complexity and effectiveness is another hurdle, as overly complex models risk overfitting while overly simplistic ones might miss subtle anomalies.

[0006] There are some existing products in the market i.e., a handheld portable wireless sensor that can detect anomalies based on collected vibration and temperature data using ISO standards. However, it only provides a general health condition classification based on international standards. Another monitoring system claimed to be versatile, scalable, and customizable to meet specific application needs based on vibration data. Such system provides a 24/7 visibility to assess health and protection in a single chassis and can monitor online conditions. It provides several readings related to motor health, such as RMS velocity, velocity peak, and acceleration. However, the data lack interpretability and can be difficult for users to understand. Neither system can provide anomaly diagnosis results, such as which failure modes belong to which components. If an anomaly is detected, maintenance actions must be taken. However, it is challenging for users to distinguish which failure pattern or component is causing the issue based solely on unfamiliar readings. As a result, the entire fault identification process is ineffective and prone to human error.

[0007] Another example of a monitoring and diagnostic system is disclosed by CN103995229B, wherein it monitors and diagnose motor health based on Mahalanobis distance. The said system involves collecting signals such as vibration, current and rotation speed from the motor, calculating features, selecting a feature vector, and constructing a Mahalanobis space representing normal working conditions to judge the health status of a test motor signal. Similar to the above, Jin et al. propose a health index, called Mahalanobis distance (MD), to evaluate the health of the cooling fan and induction motor using vibration signals. Both of these systems employ a statistical process control method, of which has its own set of limitations. For instance, it works best when the data is normally distributed and contains no outliers. However, in real-life situations, data can often be skewed or contain outliers, leading to inaccurate predictions and limited method applicability. Additionally, the Mahalanobis-Taguchi system relies heavily on statistical calculations and complex algorithmic models, which can pose a challenge for those without the necessary statistical expertise or resources.

[0008] Another method for detecting rotor side anomalies in an induction machine is proposed by US8473228B2, wherein it processes and rectifies a low-frequency signal of voltage and current obtained from the machine. The invention also includes a system for detecting anomalies. Such method is claimed to be possibly able to recognize that equivalents, alternatives, and modifications. However, by obtaining a low-frequency signal, the data rates may be small, and communication may be slow and therefore relaying insufficient or incorrect information of the anomalies. This may eventually lead to inaccurate or false positive detection. Additionally, it is essential to note that this method only covers the rotor side and does not encompass all components inside the induction motor.

[0009] On the other hand, WO2020180887A disclosed an integrated machine learning system for detection of anomalies in engine wherein it applies IoT and machine-learning to detect anomalies in data signals obtained by sensors installed on the machine parts. It also has an ability to adjust discriminant thresholds developed by an SVDD using Mahalanobis kernels with application to anomaly detection in a real wireless sensor network data set. Statistical models and predicting of anomalies via artificial intelligent are possible although in some cases, the inter-sample noise can be processed with subsequent stages of the algorithm. Whilst it is a sophisticated system, however, the costs to develop such system may be costly and it may not be applicable to diagnose anomalies in induction motor.

[0010] There exists a clear and pressing necessity to develop a comprehensive system or method capable of precisely pinpointing the underlying triggers behind anomalies, leveraging diverse datasets. This imperative arises from the requirement for a solution that can discern and categorize data autonomously, while minimizing its dependency on intricate statistical computations and complex algorithmic models that often demand specialized expertise in the domain. The essence of this requirement is for the proposed system to achieve rapid and automated diagnosis of failure modes in induction motors. By achieving this, the system would not only expedite the identification of anomalies but also streamline the process of determining the specific ways in which induction motors fail.

SUMMARY OF THE INVENTION

[0011] It is an objective of the present invention to provide a system that can accurately identify the root causes of anomalies based on various sets of data.

[0012] Another objective of the present invention is to provide a system that recognizes and classifies data without relying heavily on statistical calculations and complex algorithm models without an expert in said field.

[0013] It is also an objective of the present invention to provide a system that can automatically and instantaneously diagnose the failure mode of induction motors.

[0014] Accordingly, these objectives can be achieved by following the teachings of the present invention, which relates to a condition monitoring system for an induction motor, the system comprising: at least one vibrational sensor mounted on at least one surface of the induction motor for vibrational signals collection; an IoT-enabled signal conditioning module configured to receive the vibrational signals and transfer the signals to a computing device; a control platform configured to automatically determine a type of failure in the induction motor based on failure patterns; and, a storage device for storing and managing the vibrational signals and the analysed results for subsequent analysis.

[0015] Another objective achievable in the present invention relates to a method for condition monitoring of an induction motor, comprising the steps of: mounting at least one vibrational sensor on at least one surface of the induction motor to collect vibrational signals in real-time; transmitting the vibrational signals through an IoT-enabled signal conditioning module to a computing device; determining a type of failure in the induction motor by a control platform based on failure patterns automatically; alerting an operator for a corrective action if the anomaly is present or if no anomaly is detected, the online monitoring module continues scanning for an anomaly, and, storing and managing the vibrational signals and the analysed results in a storage device for subsequent analysis.

BRIEF DESCRIPTION OF THE DRAWINGS

[0016] The features of the invention will be more readily understood and appreciated from the following detailed description when read in conjunction with the accompanying drawings of the preferred embodiment of the present invention, in which:

[0017] **Figure 1** illustrates an overall view of the embodiment of the present invention;

[0018] **Figure 2** illustrates an intelligent diagnostic module **20** with other interfaces to assist in analysing vibrational signals;

[0019] **Figure 3** illustrates user interfaces in a control platform **18** in the present invention;

[0020] **Figure 4** illustrates a threshold setting interface for one of the embodiments in the present invention;

[0021] **Figure 5** illustrates a guideline table for conditions of an induction motor, extracted based on a set of pre-determined parameters, and ISO standard 10816-3;

[0022] **Figure 6** illustrates a general flow chart on the establishment of the intelligent diagnostic module **20**;

[0023] **Figures 7A-7D** illustrate vibration charts and data collected from different components of the induction motors;

[0024] **Figure 8** illustrates random forest algorithms to denoise vibrational signals;

[0025] **Figure 9** illustrates the training and validation processes for signal denoising using (RF) algorithm;

[0026] **Figure 10** illustrates a fault tree of the induction motor that corresponds failure patterns with its failure modes; and,

[0026] **Figure 11** illustrates the conditions of the induction motor in one of the embodiments of the present invention wherein "X" is a value used to determine the condition of a motor.

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENT

[0027] For the purposes of promoting and understanding the principles of the invention, reference will now be made to the embodiments illustrated in the drawings and described in the following written specification. It is understood that the present invention includes any alterations and modifications to the illustrated embodiments and includes further applications of the principles of the invention as would normally occur to one skilled in the art to which the invention pertains.

[0028] The present invention teaches a condition monitoring system **10** for an induction motor, the system comprising: at least one vibrational sensor **12** mounted on at least one surface of the induction motor for vibrational signals collection; an IoT-enabled signal conditioning module **14** configured to receive the vibrational signals and transfer the signals to a computing device **16**; a control platform **18** configured to automatically determine a type of failure in the induction motor based on failure patterns; and, a storage device for storing and managing the vibrational signals and the analysed results for subsequent analysis. An overview of an embodiment of the present invention is generally illustrated in **Figure. 1**.

[0029] In one of the embodiments, the vibrational sensor **12** is an accelerator sensor mounted on at least one surface of the induction motor to collect vibrational signals in real-time. In demonstrating the effectiveness of the present invention, the present invention has been implemented on Flue Gas Desulphurization (FGD) and train traction motors, wherein at least four accelerators have been placed in the induction motors. Whilst the said invention may work on any kind of induction motors, the number of accelerators required will be depending on the size and capacity of the induction motors.

[0030] In one of the embodiments, the accelerometers have been strategically mounted in the induction motor to collect and analyze real-time vibration signals. An IoT-enabled signal conditioning module **14**, comprising a vibration input module and a compact DAQ chassis, is used to transmit the signals to a modem and a computer device, including but not limited to a destop or a laptop and the like. A modem router serves as the network modem for remote system control via the internet, and in one of the embodiments, a laptop runs a control platform **18**, wherein the control platform **18** is guided by ISO Standard 10816-3 and a set of pre-determined parameters to provide an intelligent diagnostic module **20**. Finally, an external portable hard disk stores the collected data, which can be used for subsequent analysis and diagnosis.

[0031] In another embodiment of the present invention, the intelligent diagnostic module **20** generates failure modes **21** that automatically correspond to anomalies in the vibration signal and their corresponding failure patterns. **Figure 2** illustrates the user interface for the intelligent diagnostic module **20**, coupled with other displays i.e., Fast Fourier transform (FFT) of vibration velocity at a sampling rate of 4,000 Hz and a continuous short-time Fourier transform (STFT) of vibration velocity. The purpose of this feature is to automatically identify failure modes based on a set of pre-determined parameters and instantly inform operators or users of the failure modes.

[0032] In another embodiment, the system further comprises an online user interface providing automatic anomaly diagnosis information including but not limited to instantaneous risk conditions with vibration velocity root-mean-square (RMS) values **30**, an ISO-compliant risk summary table as a reference **32**, real-time visualization of vibration velocity signals **36a** and trend **36b**, the failure modes **21** and a threshold setting **22**. The user interface further provides information including but not limited to data storage **40** and file merging settings **42** for the subsequent analysis wherein the subsequent analysis can be done offline for further diagnosis. This is further illustrated in **Figure 3** and **Figure 4**.

[0033] In one of the embodiments of the present invention, there is a threshold setting **22** (in

Figure 4) that allows customization by incorporating manual setting of a failure pattern **44**, store data for historical backups in the storage device, and merge files for historical trend analysis. More specifically, the threshold setting **22** is one of the interfaces that customizes failure patterns thresholds. It includes four components: manual failure pattern setting, FFT visualization to assist with failure pattern setting, data storage **40**, and file merging for offline trend analysis. The interface sets failure patterns and thresholds through visualization for intelligent diagnostic module **20**, stores data for historical backups, and merges files for historical trend analysis.

[0034] The present invention also teaches a method for condition monitoring of an induction motor, comprising the steps of: mounting at least one vibrational sensor **12** on at least one surface of the induction motor to collect vibrational signals in real-time; transmitting the vibrational signals through an IoT-enabled signal conditioning module **14** to a computing device **16**; determining a type of failure in the induction motor by a control platform **18** based on failure patterns automatically; alerting an operator for a corrective action if the anomaly is present or if no anomaly is detected, the online monitoring module continues scanning for an anomaly, and, storing and managing the vibrational signals and the analysed results in a storage device for subsequent analysis.

[0035] In addition to the above, the storage device is an external hard disk.

[0036] In another embodiment, in determining the type of failure in the control platform **18**, the step further comprising establishing an intelligent diagnostic module **20**. The steps of establishing the intelligent diagnostic module **20** comprising preparing standard failure modes and its corresponding standard failure patterns guided by ISO Standard 10816-3 (**Figure 5**) and a set of pre-determined parameters; benchmarking failure patterns based on historical data and collected data containing anomalies; extracting the failure patterns from the historical data and the collected data guided by the standard failure patterns and modes; and, analysing the historical data and the collected data statistically to obtain root-mean-square (RMS) values **30** to assist in deciding a threshold for the intelligent diagnostic module **20**.

[0037] Referring to **Figure 6**, data filtering, benchmarking with historical data, extraction of feature modes or health indicators guided by a set of pre-determined parameters and statistical analysis based on failure patterns. Data filtering removes abnormal cyber data, while benchmarking guides the design of optimal filters or algorithms using historical data. Feature modes extraction identifies features based on a set of pre-determined parameters that reflect the induction motor's health condition or failure modes. Statistical analysis determines the distribution, mean, or maximum values of each health indicator to assist in deciding the rule threshold for the control platform **18**.

[0038] Vibrational charts and data collected from different components of the induction motors (**Figures 7A-D**) are also provided to help with the extraction process. More specifically, **Figure 7A** illustrates a failure model for "mass unbalance" of the induction motor, wherein (A) illustrates force unbalance wherein 1X RPM dominates the spectrum and approximately 0-degree phase difference between unload-side and load-side horizontals; (B) illustrates couple unbalance wherein 1X RPM dominates the spectrum and approximately 180-degree phase difference between unload-side and load-side horizontals; (C) illustrates dynamic unbalance wherein it is a combination of both force and couple unbalance and 1X RPM dominates the spectrum and the phase difference between unload-side and load-side bearings can range from 0 to 180-degrees and (D) illustrates overhung rotor unbalance wherein high 1X RPM in both axial and radial directions. Axial readings are in-phase, whereas radial phase readings might be unsteady.

[0039] Another embodiment of the present invention is depicted in **Figure 7B,** wherein said figure shows results of failure models for rotor rub and journal bearing. The rotor rub usually generates a series of frequencies, often exciting one or more resonances and integer fraction subharmonics of running speed (1/2, 1/3, 1/4, 1/5, ...) and journal bearing wear/clearance problem is evidenced by the presence of whole senses of running speed harmonics up to 10 or 20 (see A). and oil instability (see B) occurs at 0.4-0.48X RPM and is considered severe.

[0040] Another embodiment of the present invention is depicted in **Figure 7C** wherein said figure shows failure spectra of rolling element bearings related to their specifications. The failure modes of rolling element bearings can be determined via the following formulas:

$$BPFI = \frac{N_b}{2}(1 + \frac{B_d}{P_d} cos\theta) \times RPM$$

$$BPFO = \frac{N_b}{2}(1 - \frac{B_d}{P_d} cos\theta) \times RPM$$

$$BSF = \frac{P_d}{2B_d}(1 - (\frac{B_d}{P_d})^2 (cos\theta)^2) \times RPM$$

$$FTF = \frac{1}{2}(1 - \frac{B_d}{P_d} cos\theta) \times RPM$$

[0041] Another embodiment of the present invention is depicted in **Figure 7D** wherein said figure illustrates failure models in AC induction motor. In said figure, (A) describes the stator eccentricity wherein, the stator problem will generate high vibration at 2X line frequency ($2F_L$); (B) describes eccentric rotor that produces a rotating variable air gap between the rotor and stator, which induces pulsating vibration; (C) describes a rotor problem, wherein the broken rotor bar will generate sidebands around the second, third, fourth, and fifth running speed harmonics and (D) describes phasing problems due to broken connectors which can cause excessive vibration at 2X line frequency, with sidebands around it spaced at 1/3 line frequency levels at $2F_L$.

[0042] In an embodiment of the present invention, the collected data undergoes a denoising step by a pre-trained artificial intelligence module by filtering interference using random forests (RF) algorithms with a predetermined hyperparameter value (**Figure 8**). More specifically, to accurately monitor the health of induction motor signals, peaks caused by other electromagnetic interference must be filtered out. In this approach, anomalous data can be filtered using random forests (RF) algorithms with a set hyperparameter value. Raw vibration acceleration signals from the channels are used as input. The dataset is divided into training, validation, and test sets using an 8:1:1 ratio. The training set determines model parameters, while the validation set selects hyperparameters. **Figure 9** illustrates the training and validation processes for signal denoising using (RF) algorithm.

[0043] Another embodiment of the present invention is in filtering interference using RF algorithms, raw vibration signals are divided into training, validation, and test sets with training setting model parameters and validation fine-tuning hyperparameters.

[0044] In another embodiment, the subsequent analysis conducted offline further comprising the steps of: analysing the historical data containing the anomalies with medium and high-risk conditions for failure patterns; analysing trend-related information including but not limited to change rate of RMS values **30**, first harmonic order, second harmonic order, third harmonic order and manually selecting frequency of a Fast Fourier Transform (FTT) spectrum; and generating an offline report for historical event backup.

[0045] In another embodiment of the present invention wherein a fault tree of the induction motor is summarised is shown in **Figure 10**. After summarising the failure modes of the induction motor in the form of a fault tree, it is necessary to understand the corresponding failure patterns of each mode. Based on the illustrated vibration diagnostic chart and the motor specifications, the failure patterns of each mode are summarised in **Table 1**. Different failure patterns can be added when necessary.

Table 1

Failure mode		Pattern																				
		Order amplitude																		Phase		Raised floor
		0.4-0.48	0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	6	7	8	9	10	$2F_l$	F_p	Relationship between two sides of bearings	Relationship between horizontal and vertical readings on each side	
Shaft-related	Force unbalance			√																0 degree	90 degrees	
	Couple unbalance			√																180 degrees	90 degrees	
	Dynamic unbalance			√																Horizontal phase difference closely matches vertical phase difference	90 degrees	
Journal bearing-related	Wear/Clearance problem		√	√		√		√		√		√	√	√								√
	Oil whirl instability	√		√																		
	Oil whip instability	Decided by the first rotor critical speed																				
Rolling bearing-related	Train	5 Hz																				
	Ball spin	29.75 Hz																				
	Ball pass inner race	90.5 Hz																				
	Ball pass outer race	120.5 Hz																				
Stator-related	Stator eccentricity			√		√												√				
	Phasing problem			√		√												√				
Rotor-related	Rotor rub		√	√	√	√	√	√	√	√	√	√										
	Eccentric rotor			√		√												√	√			
	Broken rotor bar			√		√		√		√		√	√						√			

[0046] In another embodiment, the "X" in **Figure 11** refers to the value used to determine the feature modes (or health conditions) of a motor. This value can be defined according to ISO standard 10816-3, which considers the induction motor's foundation type and rated power. For example, by using an induction fan motor used in a Flue Gas Desulphurization (FGD), the "X" value in **Figure 11** equals 2.3, which is rigid in the foundation type and 300kW Up in the rated power. Corresponding characteristic frequencies of the critical failure modes can be determined, and the rule-based expert inference system with the initial threshold can be formulated in **Table 2.**

Table 2

Failure modes	Rule boundaries (mm/sec)									
	$T_{1^{st}}$	$T_{2^{nd}}$	$T_{3^{rd}}$	$T_{4^{th}}$	$T_{5^{th}}$	$T_{6^{th}}$	T_{F_p}	T_{2F_s}	T_{BPIR}	T_{BPOR}
Stator eccentricity	1.35	3.28						0.097		
Eccentric rotor	1.35	3.28					0.68	0.097		
Broken rotor bar	1.35	3.28	0.22	1.02	0.06	0.22	0.68			
Ball pass inner race									0.18	
Ball pass outer race										0.017

[0047] In another embodiment, a threshold setting interface in the control platform **18** is customizable corresponding to at least one failure mode wherein in updating the setting of the threshold in the control platform **18**, the updating comprises the steps of: determining the at least one failure mode; extracting its corresponding failure patterns from the historical data and the collected data in real-time; conducting statistical analysis of failure-pattern related features; and, determining filter frequencies based on the standard failure modes to determine the condition of the induction motor. When future failure patterns match the preset rules, fault identification (diagnostic) can be performed automatically. After consulting with experts, filter frequencies are determined based on a set of pre-determined parameters for fault detection and identification of the induction motor.

[0048] In view of the above, the present invention represents a significant breakthrough in induction motors, particularly for systems such as Flue Gas Desulphurization (FGD) and train traction motors. All embodiments disclosed in the present invention are unique features that distinguish the present invention from existing solutions or patents by providing a system and method guided by ISO standard and a set of pre-determined parameters for anomaly diagnosis function capable of automatically and instantaneously diagnosing the failure mode of induction motors. This automatic anomaly diagnosis function is more effective and instantaneous and eliminates the possibility of human error.

[0049] Moreover, the present invention is integrated with expertise from the induction motor, ensures that the system's response to diagnosing failure modes is accurate and reliable and that the anomaly diagnosis system is more accessible, straightforward, and accurate for the specific application and capable of covering all components inside the induction motor.

[0050] Furthermore, establishing failure pattern thresholds is critical to the present invention. It enables users to customize failure pattern thresholds based on data analysis results, which helps to ensure that the system is optimized for their specific application needs. By customizing these thresholds, users can achieve optimal performance and minimize failures, which is essential for maintaining the integrity of their systems. Additionally, the ability to customize these thresholds gives users greater control and flexibility, allowing them to adapt the system as their needs evolve over time.

[0051] AI algorithms that are specifically designed for signal denoising in induction motors dramatically contributes to the high accuracy of the present invention's anomaly detection function, making it an even more reliable and effective solution for systems that use induction motors.

[0052] Furthermore, vibration analysis is a method used to detect motor faults by revealing discrepancies in the vibration spectrum. This technique can identify bearing defects, unbalance, misalignment, gear faults, and lubrication issues. Additionally, it can also detect structural problems and weaknesses in the motor. By monitoring the vibration signals, potential issues can be detected early on, allowing corrective action to be taken before they become significant.

[0053] The present invention uses only one type of sensor, the accelerometer, which measures proper acceleration. Accelerometers can detect machinery and bearing faults by reporting vibration and changes in shaft time, and users can detect machine faults before equipment fails by monitoring accelerometer vibration data. This single data type for diagnosis is more practical and cost-effective than multiple sensors.

[0054] The fact that the present invention collects data outside the motor, it offers a non-invasive way to detect anomalies.

[0055] The present invention explained above is not limited to the aforementioned embodiment and drawings, and it will be obvious to those having an ordinary skill in the art of the prevent invention that various replacements, deformations, and changes may be made without departing from the scope of the invention.

CLAIMS

WHAT IS CLAIMED:

1. A condition monitoring system (10) for an induction motor, the system comprising:

at least one vibrational sensor (12) mounted on at least one surface of the induction motor for vibrational signals collection;

an IoT-enabled signal conditioning module (14) configured to receive the vibrational signals and transfer the signals to a computing device (16);

a control platform (18) configured to automatically determine a type of failure in the induction motor based on failure patterns; and,

a storage device for storing and managing the vibrational signals and the analysed results for subsequent analysis.

2. The system according to claim 1, wherein the vibrational sensor (12) is an accelerator sensor mounted on at least one surface of the induction motor to collect vibrational signals in real-time.

3. The system according to claim 1, wherein the IoT-enabled signal conditioning module (14) further comprising a vibration input module and a compact DAQ chassis.

4. The system according to claim 1, wherein the control platform (18) is guided by ISO Standard 10816-3 and a set of pre-determined parameters to provide an intelligent diagnostic module (20).

5. The system according to claim 4, wherein the intelligent diagnostic module (20) generates failure modes (21) that automatically correspond to anomalies in the vibration signal and their corresponding failure patterns.

6. The system according to claim 1 or 4, wherein the system further comprises an online user interface providing automatic anomaly diagnosis information including but not limited to instantaneous risk conditions with vibration velocity root-mean-square (RMS) values (30), an ISO-compliant risk summary table as a reference (32), real-time

visualization of vibration velocity signals (36a) and trend (36b), the failure modes (21) and a threshold setting (22).

7. The system according to claim 6, wherein the user interface further provides information including but not limited to data storage (40) and file merging settings (42) for the subsequent analysis.

8. The system according to claim 6 or 7, wherein the threshold setting (22) is customizable to incorporate manual setting of a failure pattern (44), store data for historical backups in the storage device, and merge files for historical trend analysis.

9. The system according to claim 1 or 7, wherein the subsequent analysis is conducted offline.

10. The system according to claim 1, wherein the storage device is an external hard disk.

11. A method for condition monitoring of an induction motor, comprising the steps of:

mounting at least one vibrational sensor (12) on at least one surface of the induction motor to collect vibrational signals in real-time;

transmitting the vibrational signals through an IoT-enabled signal conditioning module (14) to a computing device (16);

determining a type of failure in the induction motor by a control platform (18) based on failure patterns automatically;

alerting an operator for a corrective action if the anomaly is present or if no anomaly is detected, the online monitoring module continues scanning for an anomaly, and,

storing and managing the vibrational signals and the analysed results in a storage device for subsequent analysis.

12. The method according to claim 11, wherein in determining the type of failure in the control platform (18), the step further comprising establishing an intelligent diagnostic module (20).

13. The method according to claim 12, wherein the steps of establishing the intelligent diagnostic module (20) further comprising of:

preparing standard failure modes and its corresponding standard failure patterns guided by ISO Standard 10816-3 and a set of pre-determined parameters;

benchmarking failure patterns based on historical data and collected data containing anomalies;

extracting the failure patterns from the historical data and the collected data guided by the standard failure patterns and modes; and,

analysing the historical data and the collected data statistically to obtain root-mean-square (RMS) values (30) to assist in deciding a threshold for the intelligent diagnostic module (20).

14. The method according to claim 13, wherein the collected data undergoes a denoising step by a pre-trained artificial intelligence module by filtering interference using random forests (RF) algorithms with a predetermined hyperparameter value.

15. The method according to claim 11, wherein a threshold setting interface in the control platform (18) is customizable corresponding to at least one failure mode.

16. The method according to claim 15, wherein in updating the setting of the threshold in the control platform (18), the updating comprises the steps of:

determining the at least one critical failure mode;

extracting its corresponding failure patterns from the historical data and the collected data in real-time;

conducting statistical analysis of failure-pattern related features; and,

determining filter frequencies based on the standard failure modes to determine the condition of the induction motor.

17. The method according to claim 14, wherein in filtering interference using RF algorithms, raw vibration signals are divided into training, validation, and test sets with training setting model parameters and validation fine-tuning hyperparameters.

18. The method according to claim 11, wherein the subsequent analysis conducted offline further comprising the steps of:

analysing the historical data containing the anomalies with medium and high-risk conditions for failure patterns;

analysing trend-related information including but not limited to change rate of RMS values (30), first harmonic order, second harmonic order, third harmonic order and manually selecting frequency of a Fast Fourier Transform (FTT) spectrum; and,

generating an offline report for historical event backup.

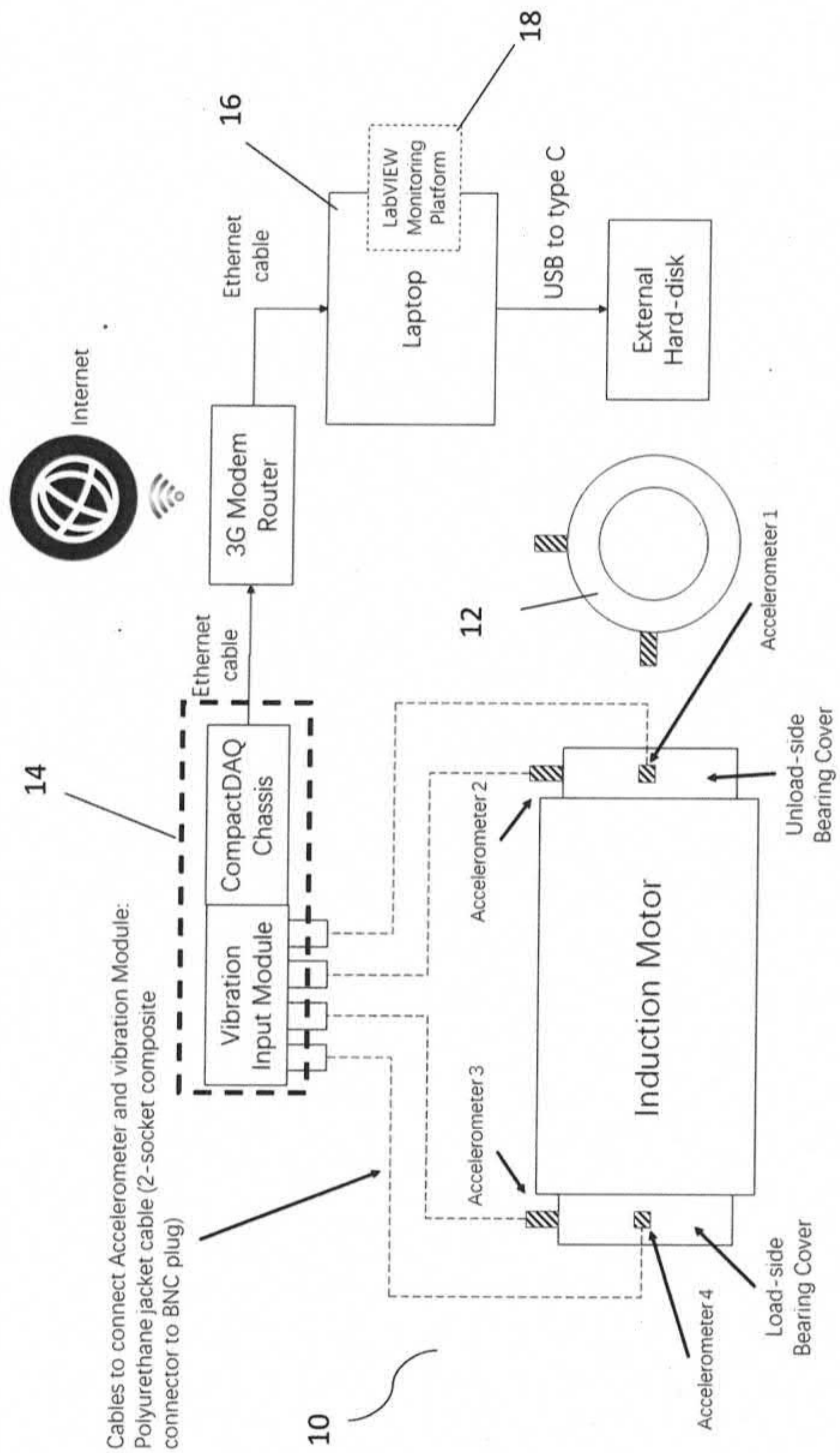
Internet
3G Modem Router
Ethernet cable
Laptop
LabVIEW Monitoring Platform
USB to type C
External Hard-disk
16
18
14
12
10
CompactDAQ Chassis
Vibration Input Module
Ethernet cable
Cables to connect Accelerometer and vibration Module: Polyurethane jacket cable (2-socket composite connector to BNC plug)
Induction Motor
Accelerometer 1
Accelerometer 2
Accelerometer 3
Accelerometer 4
Unload-side Bearing Cover
Load-side Bearing Cover

Figure 1

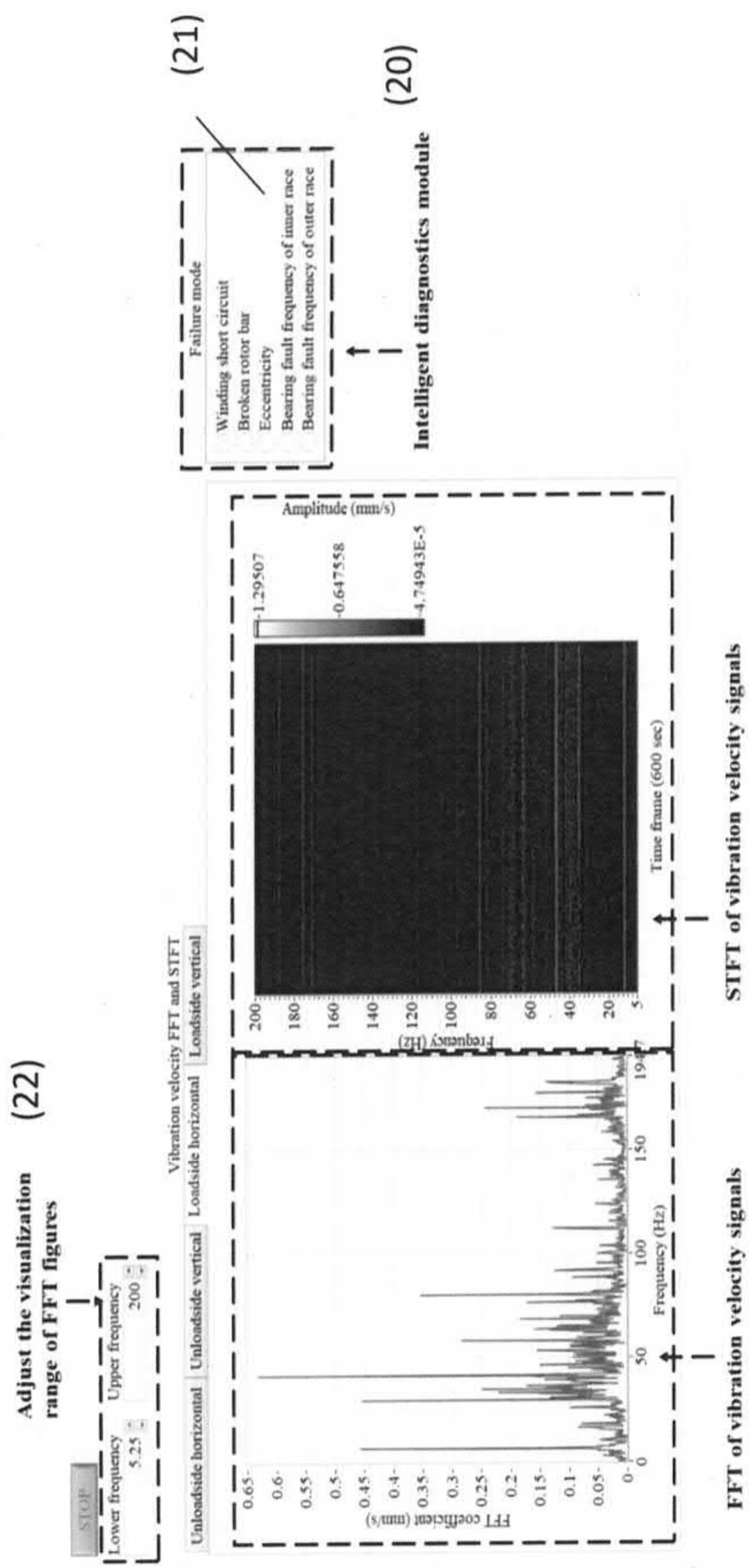
(21)
(20)
Failure mode
Winding short circuit
Broken rotor bar
Eccentricity
Bearing fault frequency of inner race
Bearing fault frequency of outer race
Intelligent diagnostics module
(22)
Adjust the visualization range of FFT figures
STOP
Lower frequency
5.25
Upper frequency
200
Vibration velocity FFT and STFT
Unloadside horizontal
Unloadside vertical
Loadside horizontal
Loadside vertical
Amplitude (mm/s)
1.29507
0.647558
4.74943E-5
Frequency (Hz)
Time frame (600 sec)
FFT coefficient (mm/s)
FFT of vibration velocity signals
STFT of vibration velocity signals

Figure 2

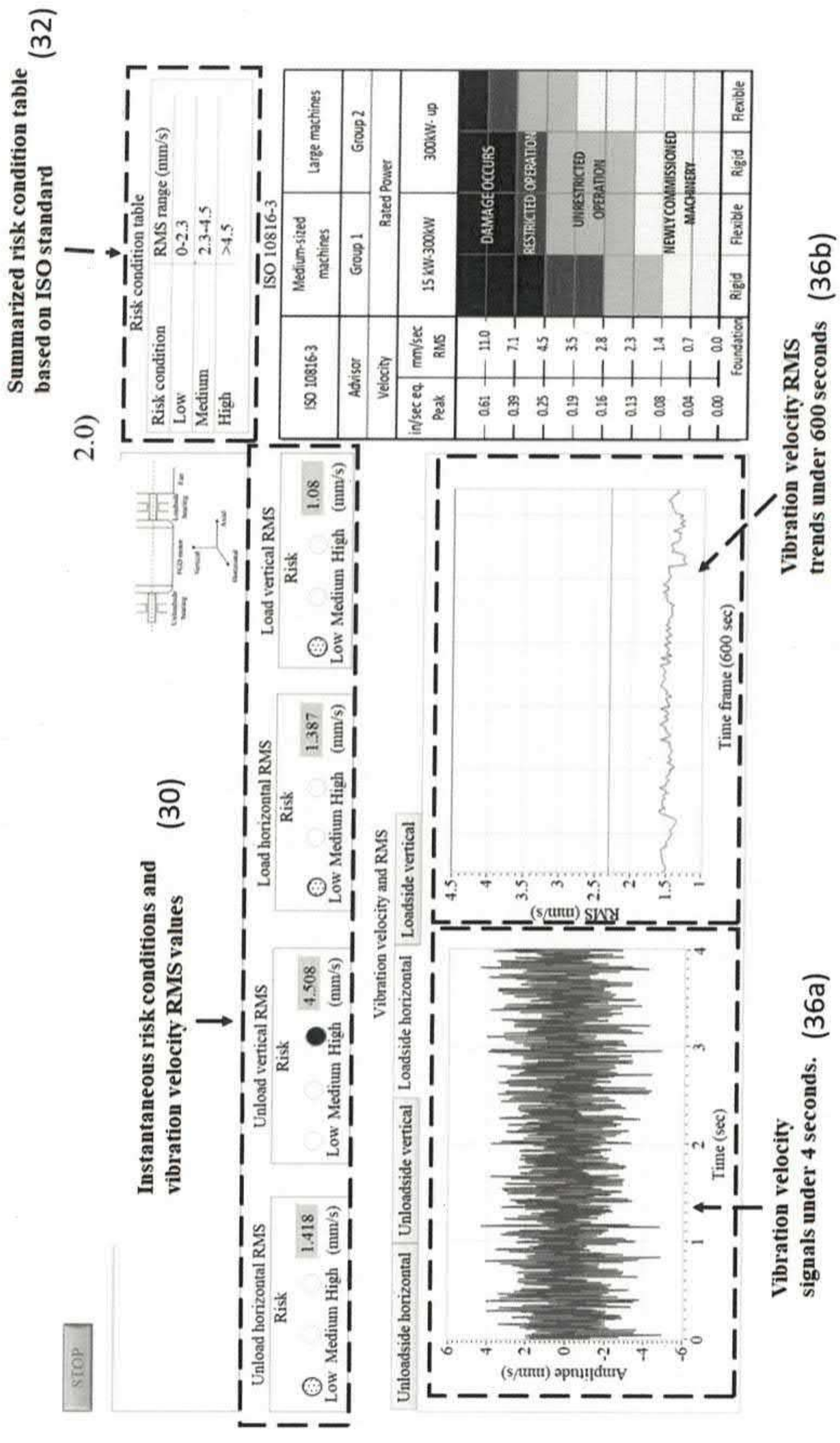
Summarized risk condition table based on ISO standard
(32)
Risk condition table
Risk condition
RMS range (mm/s)
Low
0-2.3
Medium
2.3-4.5
High
>4.5
ISO 10816-3
2.0)
Instantaneous risk conditions and vibration velocity RMS values
(30)
STOP
Unload horizontal RMS
Risk
Low Medium High
1.418
(mm/s)
Unload vertical RMS
Risk
Low Medium High
4.508
(mm/s)
Load horizontal RMS
Risk
Low Medium High
1.387
(mm/s)
Load vertical RMS
Risk
Low Medium High
1.08
(mm/s)
Vibration velocity and RMS
Unloadside horizontal
Unloadside vertical
Loadside horizontal
Loadside vertical
Amplitude (mm/s)
Time (sec)
RMS (mm/s)
Time frame (600 sec)
Vibration velocity signals under 4 seconds.
(36a)
Vibration velocity RMS trends under 600 seconds
(36b)
DAMAGE OCCURS
RESTRICTED OPERATION
UNRESTRICTED OPERATION
NEWLY COMMISSIONED MACHINERY
Medium-sized machines
Large machines
Group 1
Group 2
Rated Power
15 kW-300kW
300kW- up
Foundation
Rigid
Flexible

Figure 3

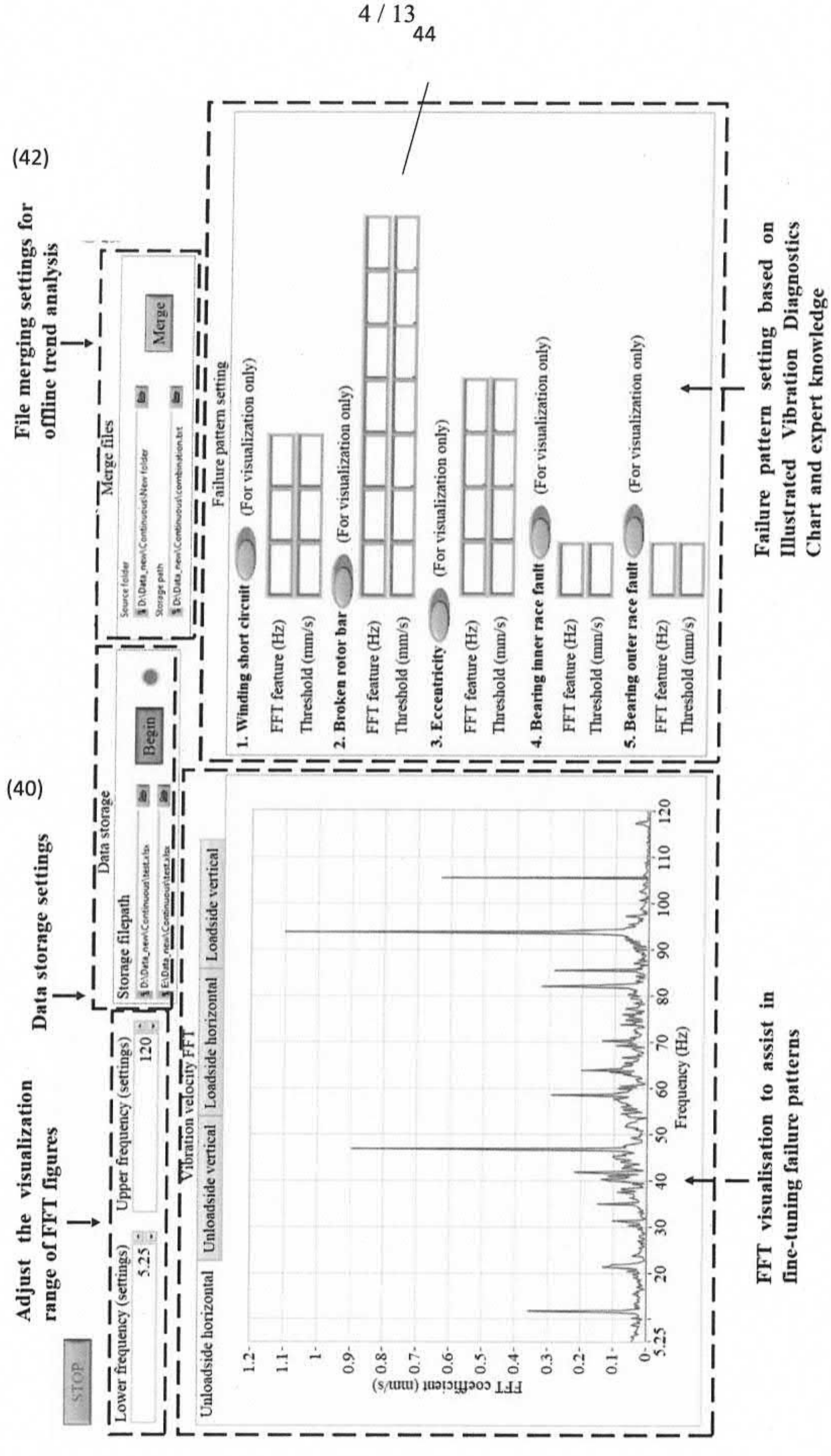
44
(42)
(40)
Adjust the visualization range of FFT figures
Data storage settings
File merging settings for offline trend analysis
FFT visualisation to assist in fine-tuning failure patterns
Failure pattern setting based on Illustrated Vibration Diagnostics Chart and expert knowledge
STOP
Lower frequency (settings)
5.25
Upper frequency (settings)
120
Data storage
Storage filepath
Begin
Merge files
Source folder
Storage path
Merge
Vibration velocity FFT
Unloadside horizontal
Unloadside vertical
Loadside horizontal
Loadside vertical
FFT coefficient (mm/s)
Frequency (Hz)
Failure pattern setting
1. Winding short circuit
2. Broken rotor bar
3. Eccentricity
4. Bearing inner race fault
5. Bearing outer race fault
(For visualization only)
FFT feature (Hz)
Threshold (mm/s)

Figure 4

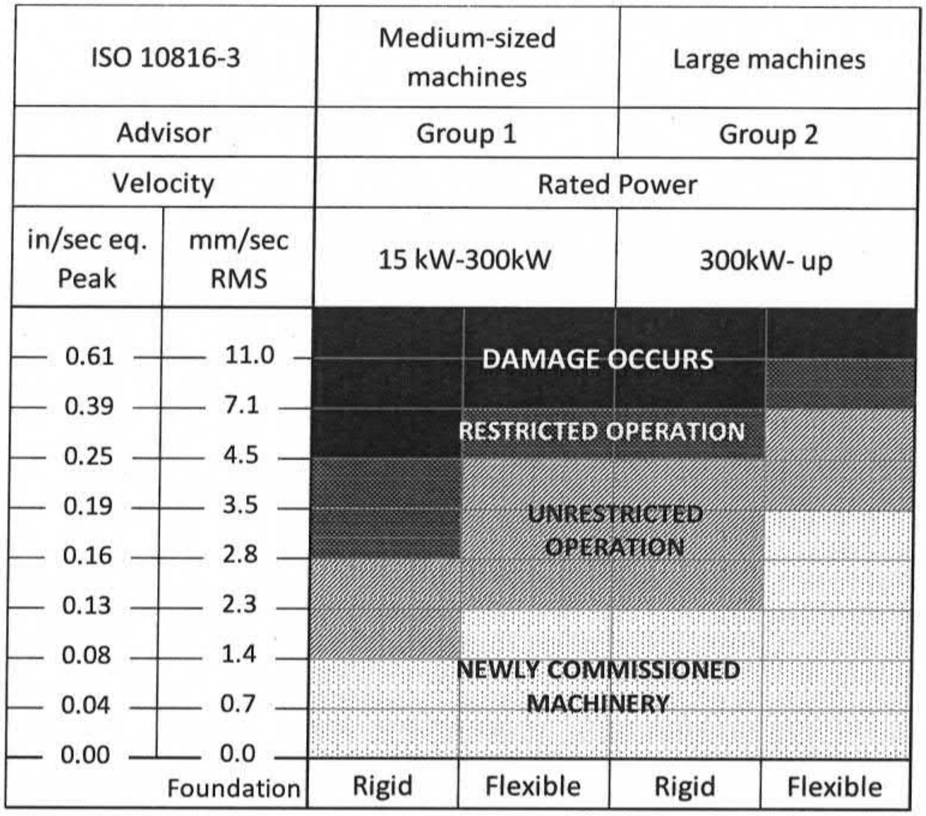

Figure 5

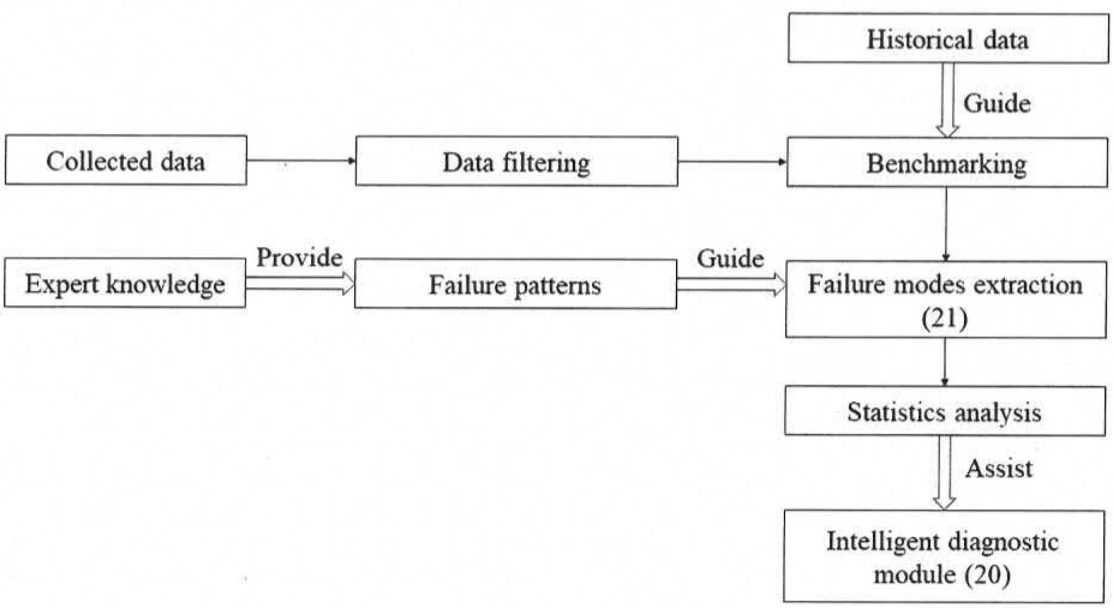

Figure 6

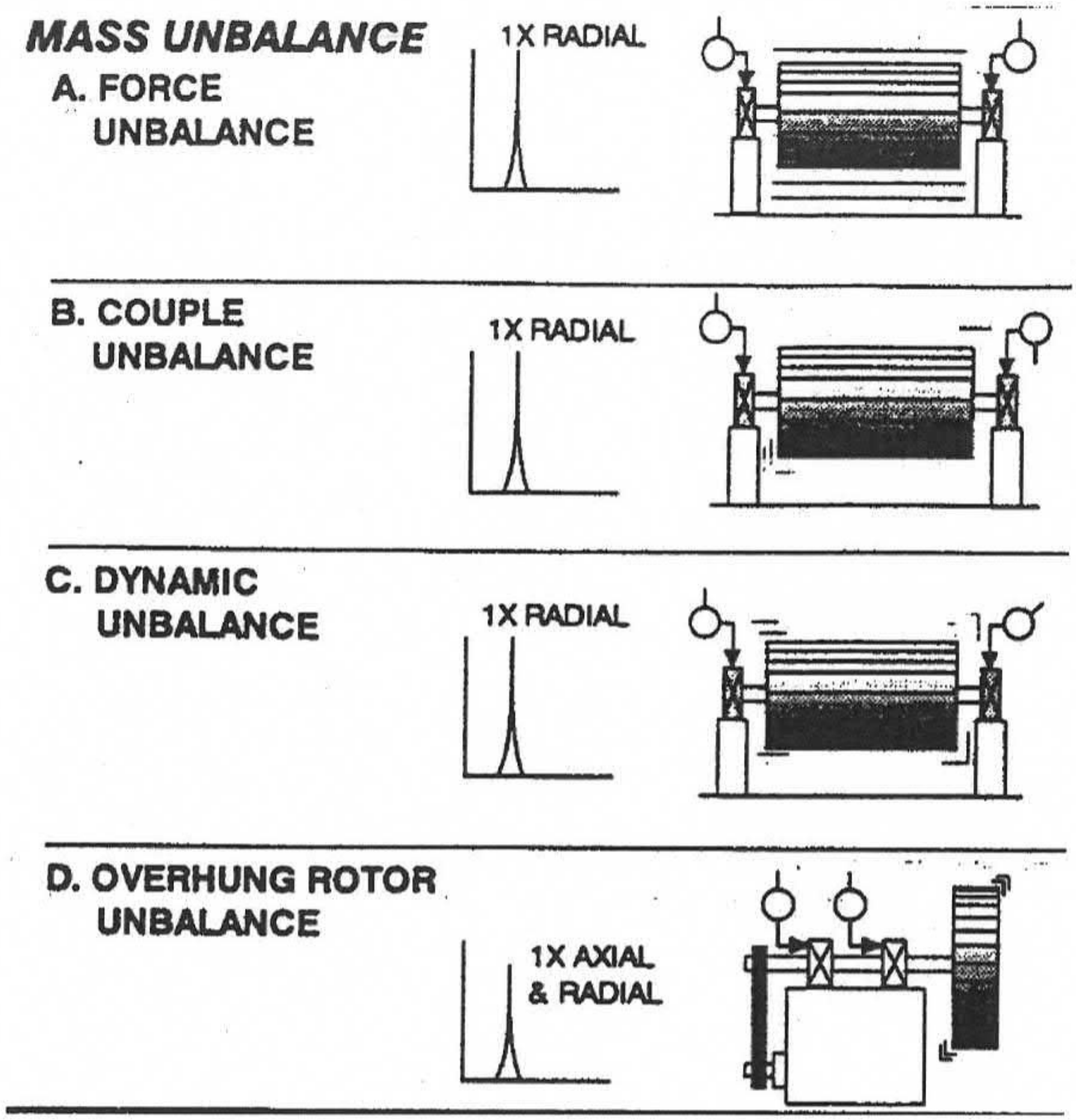
MASS UNBALANCE
A. FORCE
UNBALANCE
1X RADIAL
B. COUPLE
UNBALANCE
1X RADIAL
C. DYNAMIC
UNBALANCE
1X RADIAL
D. OVERHUNG ROTOR
UNBALANCE
1X AXIAL
& RADIAL

Figure 7A

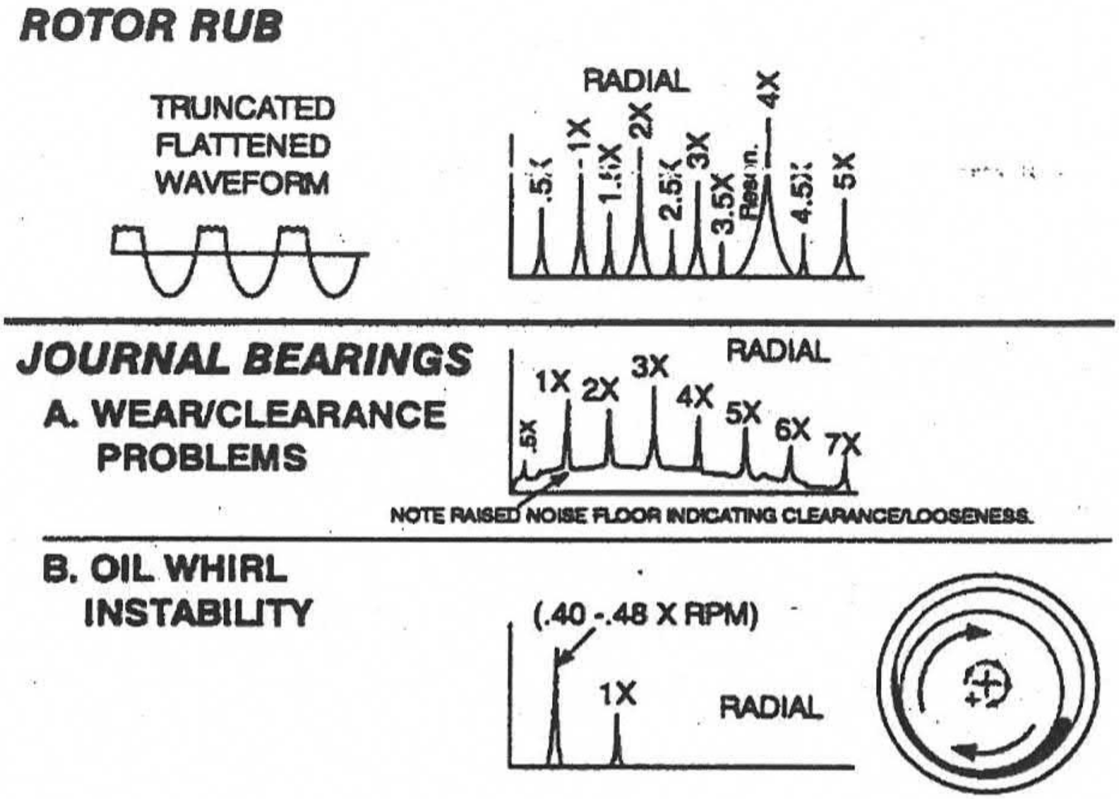
ROTOR RUB
TRUNCATED
FLATTENED
WAVEFORM
RADIAL
.5X
1X
1.5X
2X
2.5X
3X
3.5X
Reson.
4X
4.5X
5X
JOURNAL BEARINGS
A. WEAR/CLEARANCE
PROBLEMS
RADIAL
.5X
1X
2X
3X
4X
5X
6X
7X
NOTE RAISED NOISE FLOOR INDICATING CLEARANCE/LOOSENESS.
B. OIL WHIRL
INSTABILITY
(.40 -.48 X RPM)
1X
RADIAL

Figure 7B

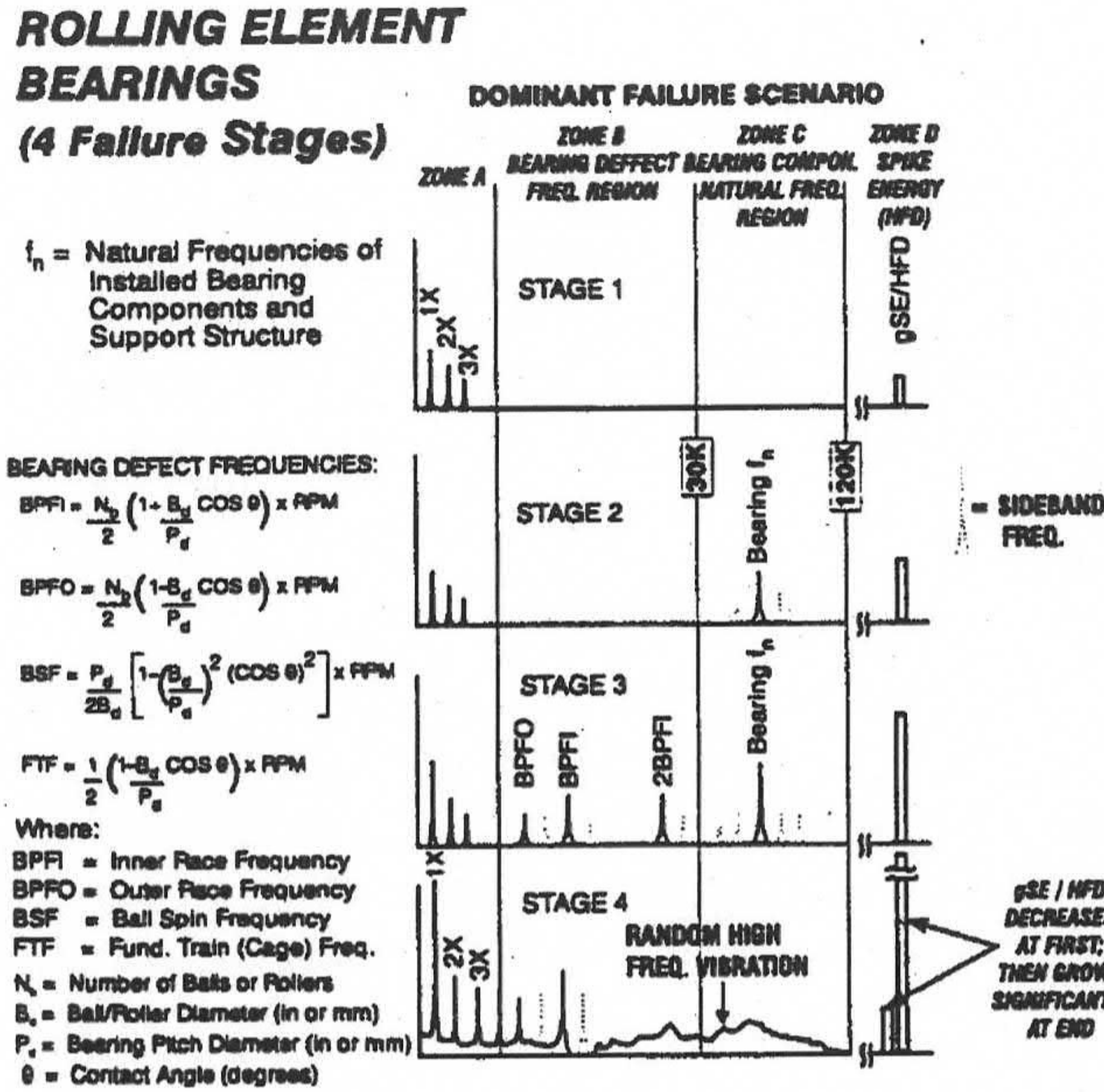
ROLLING ELEMENT BEARINGS
(4 Failure Stages)
DOMINANT FAILURE SCENARIO
ZONE A
ZONE B
BEARING DEFFECT FREQ. REGION
ZONE C
BEARING COMPON. NATURAL FREQ. REGION
ZONE D
SPIKE ENERGY (HFD)
fn = Natural Frequencies of Installed Bearing Components and Support Structure
STAGE 1
1X
2X
3X
gSE/HFD
BEARING DEFECT FREQUENCIES:
BPFI = Nb/2 (1+ Bd/Pd COS θ) x RPM
BPFO = Nb/2 (1-Bd/Pd COS θ) x RPM
BSF = Pd/2Bd [1-(Bd/Pd)^2 (COS θ)^2] x RPM
FTF = 1/2 (1-Bd/Pd COS θ) x RPM
STAGE 2
30K
120K
Bearing fn
= SIDEBAND FREQ.
STAGE 3
BPFO
BPFI
2BPFI
Bearing fn
Where:
BPFI = Inner Race Frequency
BPFO = Outer Race Frequency
BSF = Ball Spin Frequency
FTF = Fund. Train (Cage) Freq.
Nb = Number of Balls or Rollers
Bd = Ball/Roller Diameter (in or mm)
Pd = Bearing Pitch Diameter (in or mm)
θ = Contact Angle (degrees)
STAGE 4
1X
2X
3X
RANDOM HIGH FREQ. VIBRATION
gSE / HFD DECREASES AT FIRST; THEN GROWS SIGNIFICANTLY AT END

Figure 7C

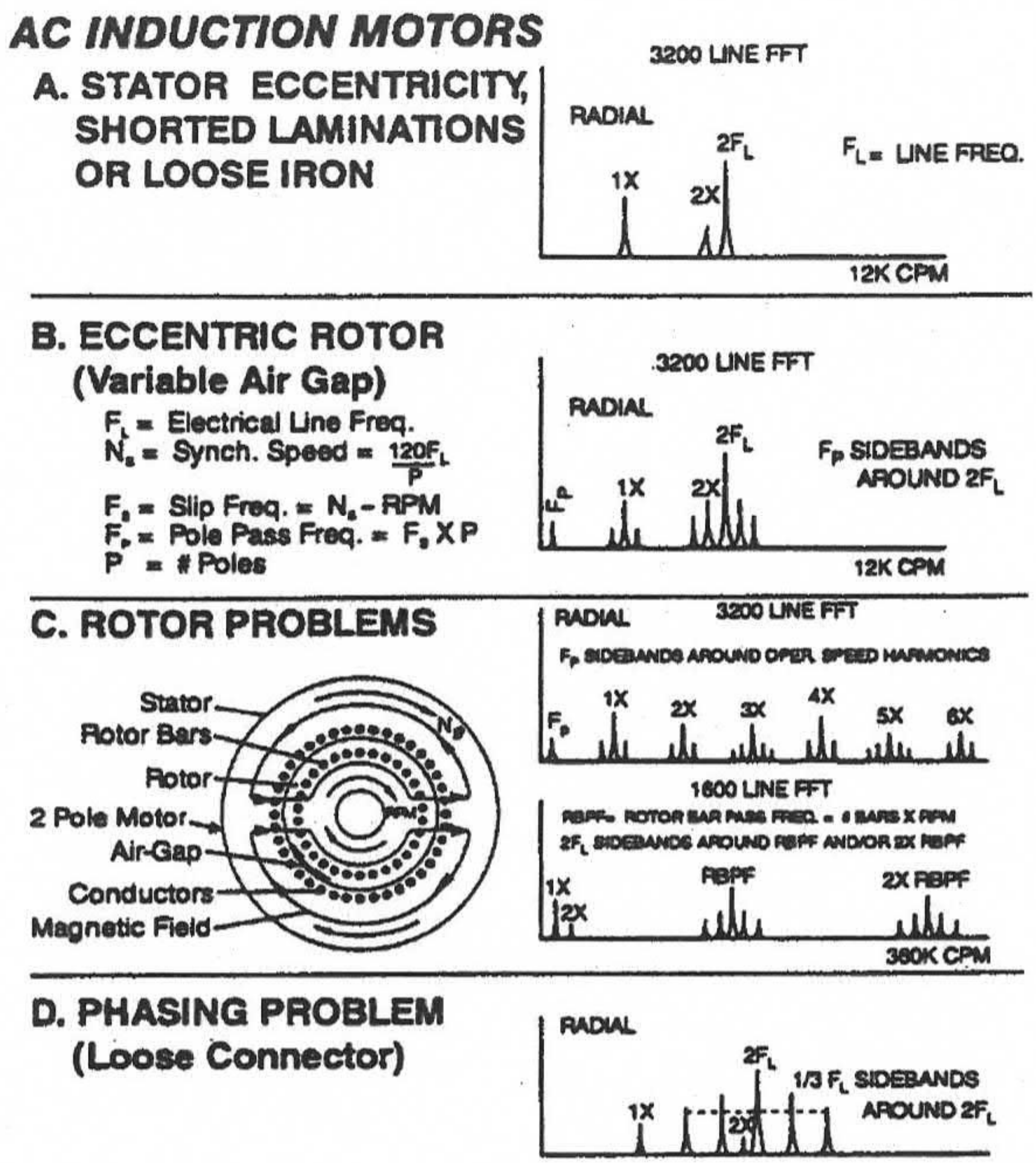
AC INDUCTION MOTORS
A. STATOR ECCENTRICITY, SHORTED LAMINATIONS OR LOOSE IRON
3200 LINE FFT
RADIAL
2F_L
F_L = LINE FREQ.
1X
2X
12K CPM
B. ECCENTRIC ROTOR (Variable Air Gap)
F_L = Electrical Line Freq.
N_s = Synch. Speed = 120F_L / P
F_s = Slip Freq. = N_s - RPM
F_p = Pole Pass Freq. = F_s X P
P = # Poles
3200 LINE FFT
RADIAL
2F_L
F_p SIDEBANDS AROUND 2F_L
F_p
1X
2X
12K CPM
C. ROTOR PROBLEMS
Stator
Rotor Bars
Rotor
2 Pole Motor
Air-Gap
Conductors
Magnetic Field
RPM
RADIAL
3200 LINE FFT
F_p SIDEBANDS AROUND OPER. SPEED HARMONICS
F_p
1X
2X
3X
4X
5X
6X
1600 LINE FFT
RBPF= ROTOR BAR PASS FREQ. = # BARS X RPM
2F_L SIDEBANDS AROUND RBPF AND/OR 2X RBPF
1X
2X
RBPF
2X RBPF
360K CPM
D. PHASING PROBLEM (Loose Connector)
RADIAL
2F_L
1/3 F_L SIDEBANDS AROUND 2F_L
1X
2X

Figure 7D

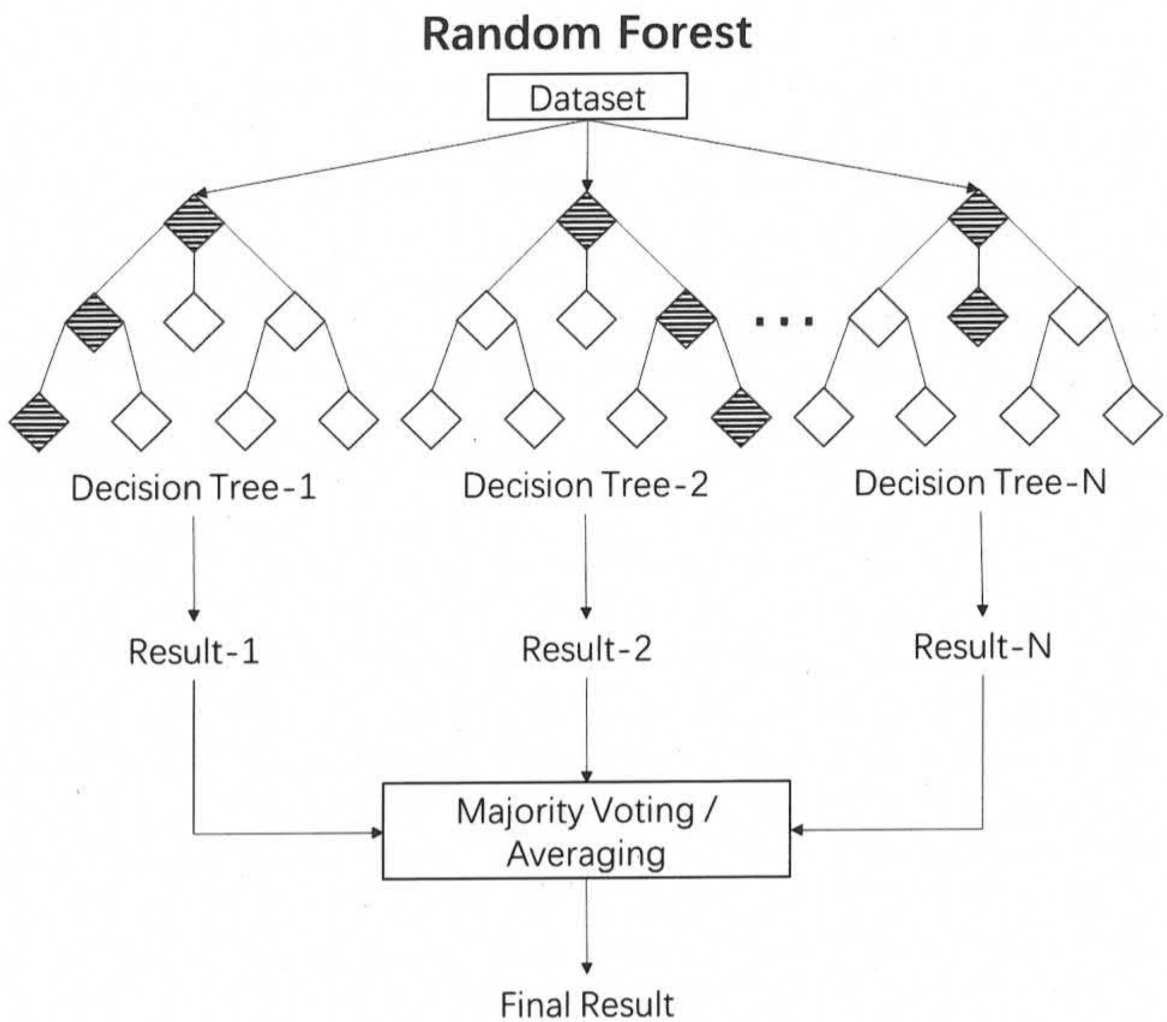
Random Forest
Dataset
Decision Tree-1
Decision Tree-2
Decision Tree-N
Result-1
Result-2
Result-N
Majority Voting / Averaging
Final Result

Figure 8

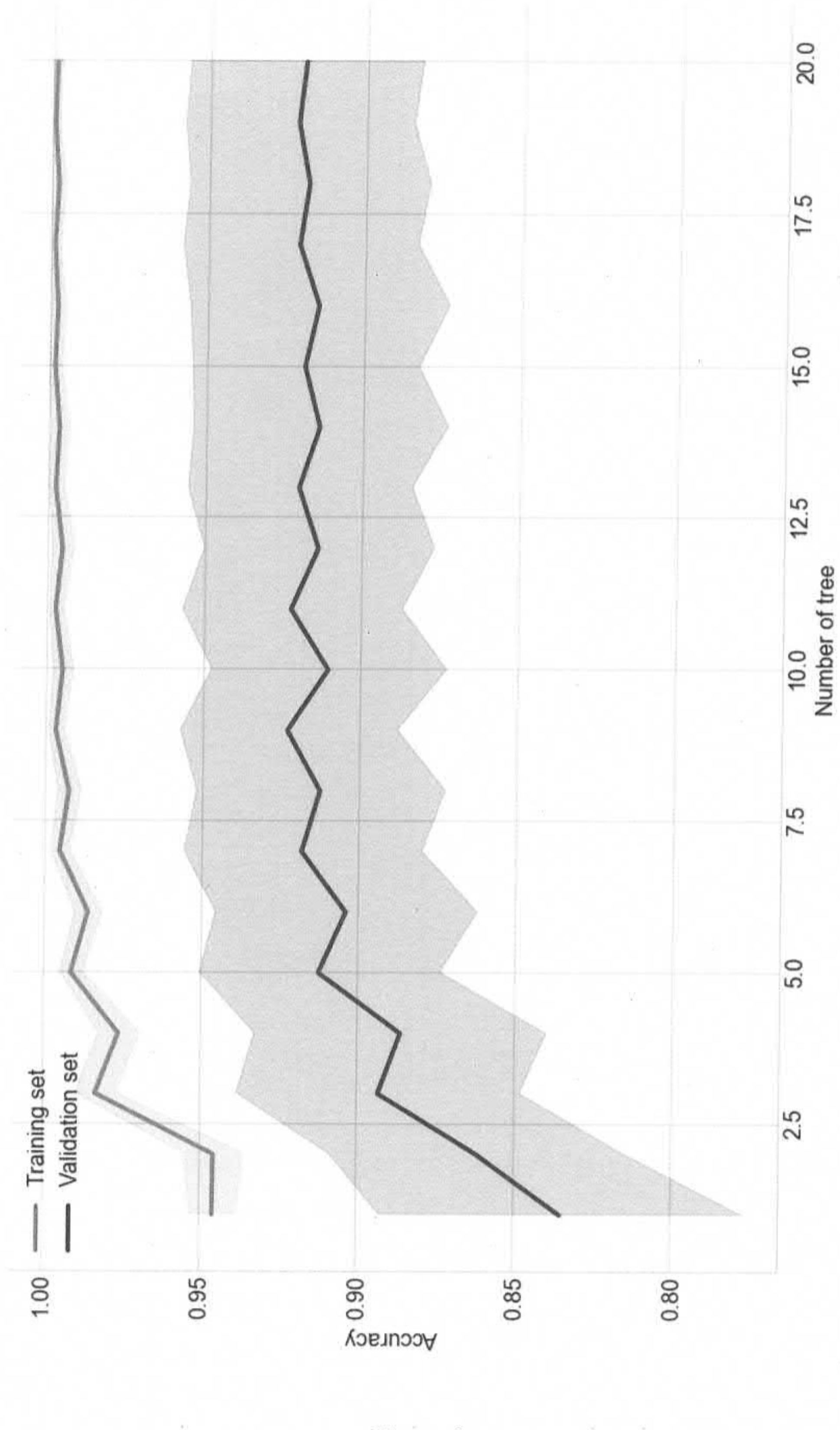
Training set
Validation set
Accuracy
1.00
0.95
0.90
0.85
0.80
Number of tree
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

Figure 9

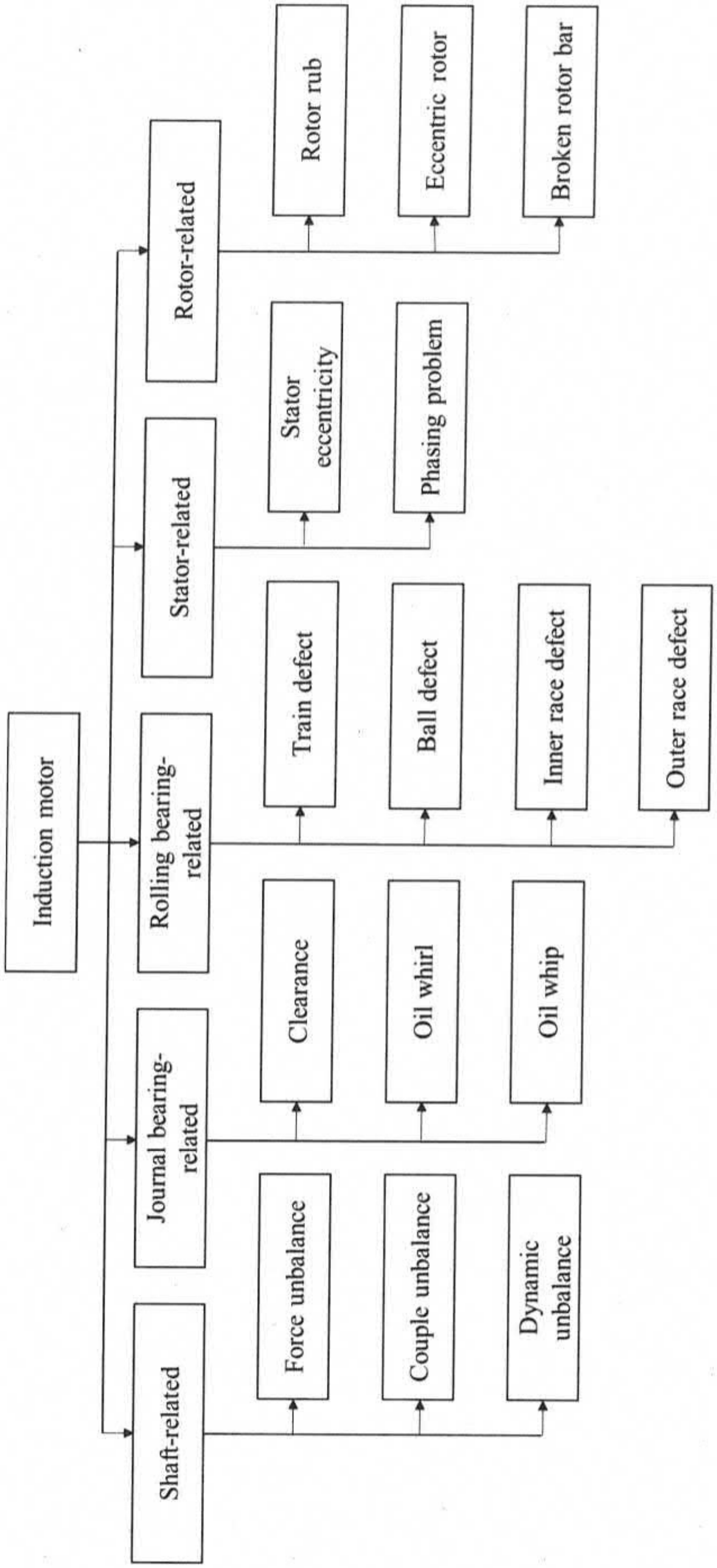
Induction motor
Shaft-related
Journal bearing-related
Rolling bearing-related
Stator-related
Rotor-related
Force unbalance
Couple unbalance
Dynamic unbalance
Clearance
Oil whirl
Oil whip
Train defect
Ball defect
Inner race defect
Outer race defect
Stator eccentricity
Phasing problem
Rotor rub
Eccentric rotor
Broken rotor bar

Figure 10

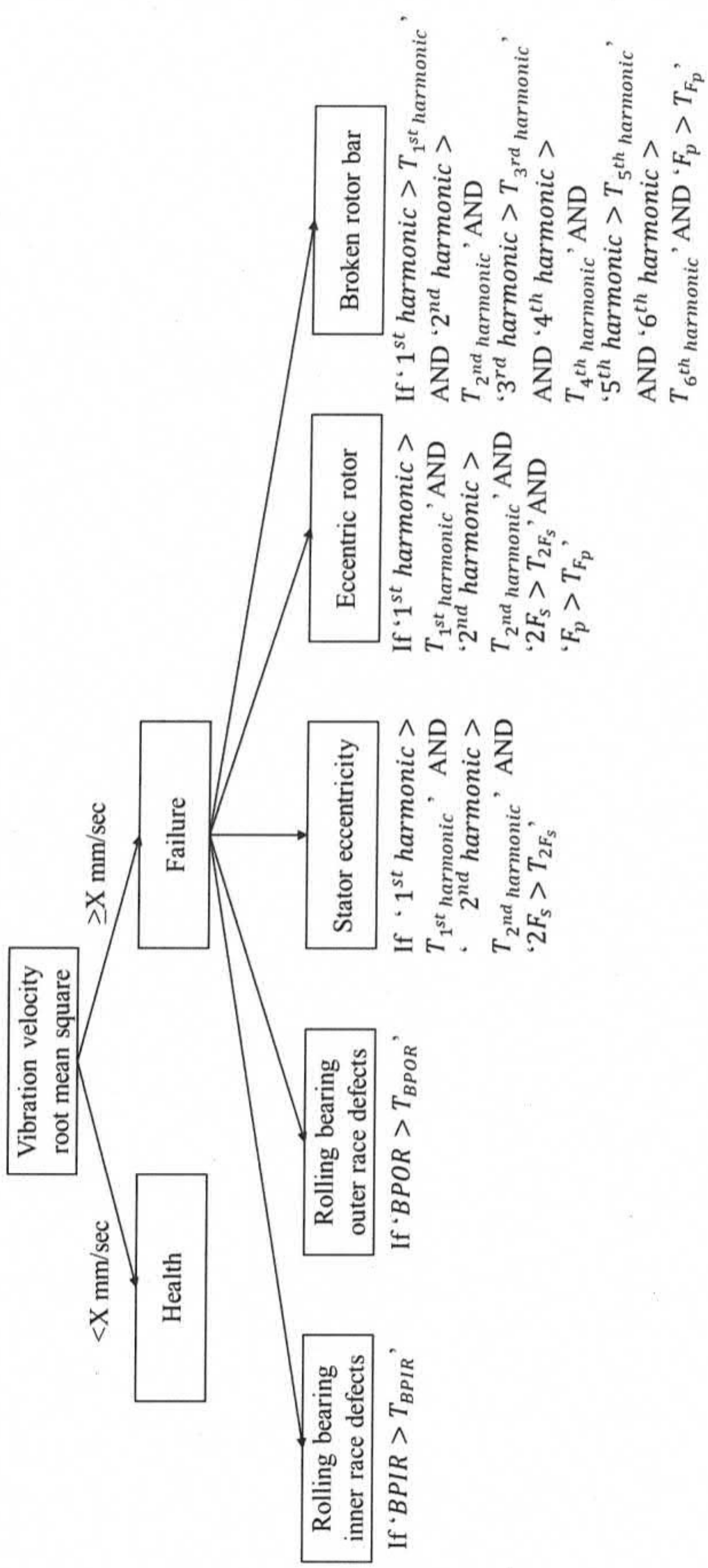
Vibration velocity root mean square
<X mm/sec
≥X mm/sec
Health
Failure
Rolling bearing inner race defects
If 'BPIR > T_BPIR'
Rolling bearing outer race defects
If 'BPOR > T_BPOR'
Stator eccentricity
If '1st harmonic > T_1st harmonic' AND '2nd harmonic > T_2nd harmonic' AND '2F_s > T_2F_s'
Eccentric rotor
If '1st harmonic > T_1st harmonic' AND '2nd harmonic > T_2nd harmonic' AND '2F_s > T_2F_s' AND 'F_p > T_F_p'
Broken rotor bar
If '1st harmonic > T_1st harmonic' AND '2nd harmonic > T_2nd harmonic' AND '3rd harmonic > T_3rd harmonic' AND '4th harmonic > T_4th harmonic' AND '5th harmonic > T_5th harmonic' AND '6th harmonic > T_6th harmonic' AND 'F_p > T_F_p'

Figure 11