ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

DATA-DRIVEN CONDITION MONITORING AND FAULT DIAGNOSIS OF VFD-FED INDUCTION MOTORS

M.Sc. THESIS

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Department of Mechatronics Engineering

Mechatronics Engineering Programme

JUNE 2021

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

DEĞİŞKEN FREKANSLI SÜRÜCÜ İLE BESLENEN ASENKRON MOTORLARDA VERİ ODAKLI DURUM İZLEME VE ARIZA TANILAMA

YüKSEK LİSANS TEZİ

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HAZİRAN 2021

Alper SENEM, a M.Sc. student of ITU Graduate School student ID 518181003, successfully defended the thesis entitled “DATA-DRIVEN CONDITION MONITORING AND FAULT DIAGNOSIS OF VFD-FED INDUCTION MOTORS”, which he/she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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Date of Submission : 11 June 2021
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To my family,

FOREWORD

For the foreword, 1 line spacing must be set. The foreword, written as a first page of the thesis must not exceed 2 pages.

The acknowledgments must be given in this section.

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The foreword is written with 1 line spacing.

June 2021 Alper SENEM
(Mechanical Engineer)

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ABBREVIATIONS

AIC	: Akaike Information Criteria
ANN	: Artificial Neural Network
App	: Appendix
BP	: Backpropagation
CGI	: Common Gateway Interface
ESS	: Error sum-of-squares
GARCH	: Generalized Autoregressive Conditional Heteroskedasticity
GIS	: Geographic Information Systems
HCA	: Hierarchical Cluster Analysis
Mbps	: Megabits per second
St	: Station
SWAT	: Soil and Water Assessment Tool
UMN	: University of Minnesota

SYMBOLS

C	: Capacitance
H	: The amount of heat
$\mathbf{M_x}$, $\mathbf{M_y}$	: Torque Components
$\mathbf{N_x}$, $\mathbf{N_y}$, $\mathbf{N_z}$	: Normal Power Components
q	: Phase load
t	: Time
u, v	: Displacement Vector Components
w	: Angular velocity
XC	: Capacitive reactance
XL	: Inductive reactance
α	: Angle of deviation from the direction of the principal stresses
ρ	: Density
σ_x, σ_y, σ_{xy}	: Shell internal stresses

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DATA-DRIVEN CONDITION MONITORING AND FAULT DIAGNOSIS OF VFD-FED INDUCTION MOTORS

SUMMARY

1 line spacing must be set for summaries. For theses in Turkish, the summary in Turkish must have 300 words minimum and span 1 to 3 pages, whereas the extended summary in English must span 3-5 pages.

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A summary must briefly mention the subject of the thesis, the method(s) used and the conclusions derived. References, figures and tables must not be given in Summary.

Above the Summary, the thesis title in first level title format (i.e., 72 pt before and 18 pt after paragraph spacing, and 1 line spacing) must be placed. Below the title, the expression **ÖZET** (for summary in Turkish) and **SUMMARY** (for summary in English) must be written horizontally centered.

It is recommended that the summary in English is placed before the summary in Turkish.

DEĞİŞKEN FREKANSLI SÜRÜCÜ İLE BESLENEN ASENKRON MOTORLARDA VERİ ODAKLI DURUM İZLEME VE ARIZA TANILAMA

ÖZET

Özet hazırlanırken 1 satır boşluk bırakılır. Türkçe tezlerde, Türkçe özet 300 kelimeden az olmamak kaydıyla 1-3 sayfa, İngilizce genişletilmiş özet de 3-5 sayfa arasında olmalıdır.

İngilizce tezlerde ise, İngilizce özet 300 kelimeden az olmamak kaydıyla 1-3 sayfa, Türkçe genişletilmiş özet de 3-5 sayfa arasında olmalıdır.

Özetlerde tezde ele alınan konu kısaca tanıtılarak, kullanılan yöntemler ve ulaşılan sonuçlar belirtilir. Özetlerde kaynak, şekil, çizelge verilmez.

Özetlerin başında, birinci dereceden başlık formatında tezin adı (önce 72, sonra 18 punto aralık bırakılarak ve 1 satır aralıklı olarak) yazılacaktır. Başlığın altına büyük harflerle sayfa ortalanarak (Türkçe özet için) **ÖZET** ve (İngilizce özet için) SUMMARY yazılmalıdır.

Türkçe tezlerde Türkçe özetin İngilizce özetten önce olması önerilir.

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1. INTRODUCTION

1.1 Overview

Electric motors extensively employed in a system that converts electrical power into mechanical power in not only industrial applications but also residential, agricultural and transportation purposes. Taken together with systems they drive, electric motors use more than 40% of all electricity consumption and almost twice as much as the next largest user lighting [8]. Considering only industrial usage, electric motors dominate and account for close to 70% of the total electricity consumption [8, 9].

There are many different motor types available in industrial facility operations, but asynchronous alternating current (AC) induction motors are the most preferred type because of their simple, reliable and rugged design. Relatively lost cost, low maintenance, high reliability and long lifespan are the most advantageous features of AC induction motors which drive core electro-mechanical systems such as material handling, material processing, pumping, ventilation and compressed air generation [10]. Especially HVAC (Heating, ventilation and air conditioning) sector requires special attention as they have the largest share of industrial electrical consumption and reasonably high saving potentials [10].

In recent years raised awareness about global warming demands more efficient systems including electric motor-driven systems. Policymakers such as the European Parliament and the European Council implementing new requirements to increase efficiency by encouraging the usage of high-efficiency premium motors and variable frequency drives (VFD) [9, 11].

VFDs regulate the motor's output torque and speed to match the mechanical system loads and enables significant energy efficiency where variable mechanical power needed that have highly non-linear input power and output torque and speed such as pumps, fans and compressors. Previously Direct Current (DC) motors have been dominant for variable motor speed control, yet developments in semiconductor technology became the driving force behind the prevalence usage of VFDs with AC motors [12]. Motor speed control is advantageous in terms of lower system energy costs, increased system reliability and less maintenance.

Considering 20-year in service, the power consumption of an electric motor depicts 90% of the total cost of ownership and followed by downtime costs as 5% and rebuild costs as 4% [8]. The initial purchase price represents only 1% of the total cost and it can be concluded that savings can be achieved by actions taken during operation of motor [8].

Industry 4.0 shaping industrial operations through automation and efficiency. Condition monitoring paves the way to Industry 4.0 through evaluating the state of the plant and/or equipment throughout its service life [3]. Maintenance can be defined as actions to retain or restore equipment in order to maintain its designed functions within the entire lifespan [3]. Traditional maintenance relies on periodically health checks to provide operability, but researches show that even if maintenance is done on time and correctly the vast majority of failures arises during operation state [13]. Condition monitoring and diagnostics can help to schedule maintenance to prevent such situations whilst avoiding unintended downtime and financial losses. Also, condition monitoring has the opportunity to build a database to understand better via trend analysis of the equipment or plant that leads more reliable system in the long run.

There are many condition monitoring methods available such as vibration, temperature, and current monitoring that can be used to assess insights into the health of equipment varying from bearings to electric motors and pumps. Current monitoring distinguishes itself from other methods since it is readily measured to control induction motor operation. VFDs are presenting a great potential to not only controlling the motor operation but also can be utilised as a connection to the Internet of Things structure to serve Industry 4.0.

1.2 Objectives of Research

This study aims to diagnose and identify mechanical and electrical faults of VFD-fed induction motors under various loads and speeds via monitoring only motor current.

As an outcome of this research comparative results among time-domain versus frequency-domain analysis and classical machine learning algorithms versus deep learning algorithms are presented. Also, these analyses investigated under single-fault and multiple-fault approaches.

The achievement of this study was facilitated by the following specific objectives:

- Analyse motor faults under VFD controlled motor current
- Investigate effects of various loads and speeds
- Build different feature engineering methods
- Benchmark Classical ML and Deep Learning algorithms
- Investigate single-fault scenarios and multiple-fault scenario

1.3 Organization of Thesis

Thesis organised in five chapters to achieve aforementioned objectives;

- Chapter-2 provides an in-depth background to condition monitoring and fault diagnosis of AC induction motors including general information about induction motors, fault types, condition monitoring and signal processing techniques followed by fault diagnosis methods.
- Chapter-3 presents the experimental testing system and used methodology.
- Chapter-4 discusses the diagnostics of faults via two different approaches: component-based and motor-based condition monitoring.
- Chapter-5 remarks obtained results with different approaches and concludes with future recommendations.

2. CONDITION MONITORING OF INDUCTION MOTORS: BACKGROUND

2.1 Introduction of Induction Motors

2.1.1 Principle of operation

Electric motors are divided into two classes depending on their power supply type: direct current (DC) or alternating current (AC). The latter can be broken into two classes as synchronous or induction according to their operating speed. Induction motors, which operates slightly lower than synchronous speed, are also sub-divided as wounded and squirrel-cage motors. In this study, squirrel-cage induction motors have been investigated by means of induction motors, since the squirrel-cage type is predominantly used in industrial applications.

Induction motors run at a speed slightly lower than synchronous speed at the point where motor torque and load torque are equal [14]. The difference between the actual speed and synchronous speed is known as slip [12].

$$\text{Synchronous Speed} = \frac{120 \cdot \text{Frequency (Hz)}}{\text{number of poles}} \tag{2.1}$$

$$\text{Slip} = \frac{\text{Synchronous Speed - Rotor's Mechanical Speed}}{\text{Synchronous Speed}} \tag{2.2}$$

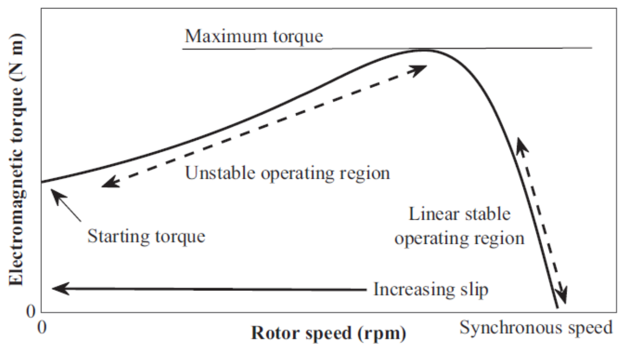

Figure 2.1 : Steady-state torque-speed curve of an induction motor, adapted from [2].

In Principle, induction motors transfer electrical energy into mechanical energy by interlinking two electrical components: stator as stationary part and rotor as rotational part. Electrical energy transmitted from stator to rotor via electromagnetic induction, then a mechanical component bearing guides rotor to provide mechanical power [5,15].

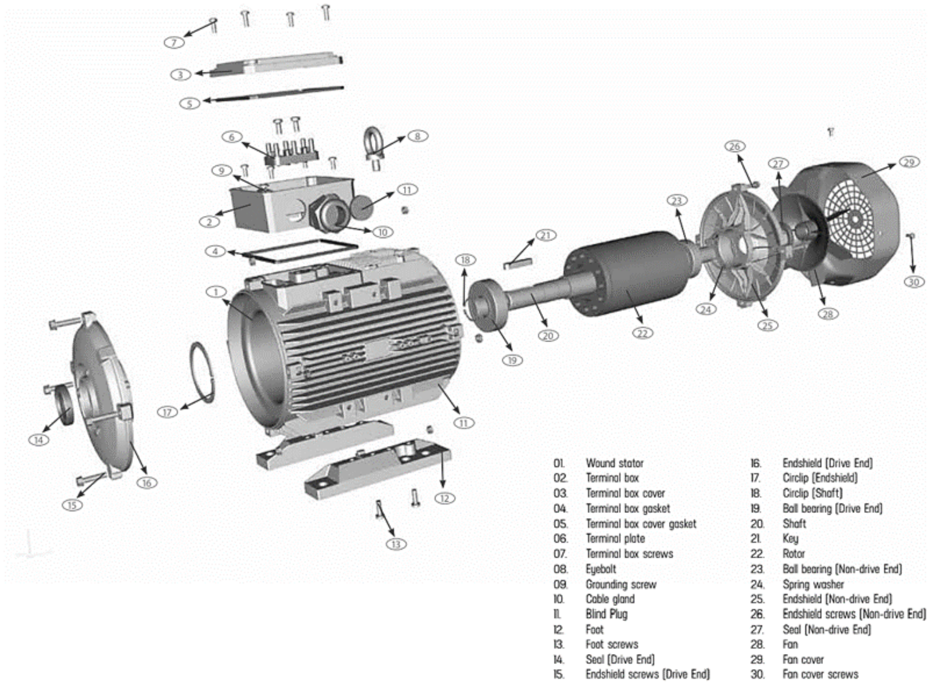

Figure 2.2 : Squirrel cage induction motor structure, courtesy of WAT Motor Co.

2.1.2 VFD-fed induction motors

A variable frequency drive, also called as adjustable-frequency drive (AFD), variable-speed drive (VSD) or inverter, fed motor system controls the rotation speed of the induction motor by controlling the supply frequency and voltage of the motor. The main difference between line-start and VFD-fed induction motors is that while in line-start mode supply voltage is the only controllable parameter, on the other hand, VFD-fed has the ability to control torque and speed easily [2].

From a historical point of view, DC motors have been utilised in speed control applications. However, as a result of advances in power semiconductor technology used in inverters, the performance of AC motors in terms of precision, response, and speed range began to exceed that of DC motors [11,12]. As a driving force behind the induction motor control dominance today, VFDs generally have the following control strategies regarding speed and torque regulation [16,17]:

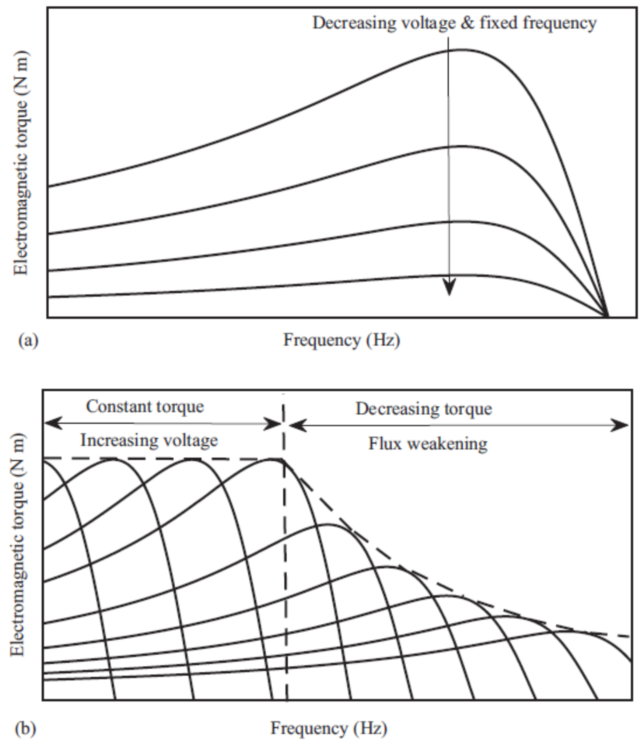

Figure 2.3 : (a) Torque–speed curves for different voltages in line-start operation and (b) Torque–speed curves for different voltages and frequencies in VFD-fed operation, adapted from [2].

- Voltage per Frequency Control (V/f)
- Field Oriented Control (FOC)
- Direct Torque Control (DTC)

The common idea behind these methods is based on controlling the torque and flux references applied to the motor separately, as in DC motor control [2]. In the scope of this thesis, only the V/f control strategy emphasized due to the widespread adoption of the control method in pump, compressor and fan applications.

V/f control can be employed in both open-loop and closed-loop modes. Open-loop V/f control, which is by far the most popular control due to its simplicity, as the name implies, creates a constant air-gap flux by keeping the ratio between the voltage and frequency applied to the induction motor constant, and as a result, it provides the opportunity to work at operating frequencies from zero to nominal frequency [18].

VFDs come with benefits such that energy savings, reliability and product quality, yet in concern of fault diagnosis they introduce a number of factors, which will be discussed later on, that increase the complexity.

2.1.3 Need for condition monitoring

Condition monitoring defined as measuring activities concerning characteristics and parameters of physical equipment at predetermined intervals either manually or automatically [3]. Leveraging rapid technological advancements in data storage, data process and network structure, condition monitoring became one of the driving force behind the industry 4.0 paradigm. The key goal behind this paradigm is to acquisition, transmission and analysis of data in order to predict future behaviours of machinery, or plant on a larger scale, to boost efficiency and reliability [19, 20].

Researchers from both academia and industry have devoted significant attention to condition monitoring of induction motors over decades. Even though induction motors renowned for robustness, environmental, electrical and mechanical effects may lead induction motors to failure. As a result, industrial processes subjected to potential losses in a manner of time and capital, so the desire to minimize or even prevent these losses emerges the need for condition monitoring.

2.1.4 Maintenance strategies

Maintenance can be defined as the combination of all technical and administrative actions taken to maintain or restore an item throughout its life cycle in a condition where it can fulfil its designed function [3]. A motor maintenance program should effectively address reliability, cost, and scheduling issues, as well as the causes of the most common motor failures. Essentially, there are two types of maintenance strategies: corrective and preventive.

Corrective maintenance is a type of maintenance performed after the induction motor failure to detect the fault and restore it to operational condition [3]. The main purpose of this type of maintenance is to get the equipment up and running as soon as possible by repairing or replacing the defective equipment. However, corrective maintenance as a failure-driven method contains a high-risk potential as faults may occur at unexpected times, can disrupt the operation. Since this type of maintenance approach does not take

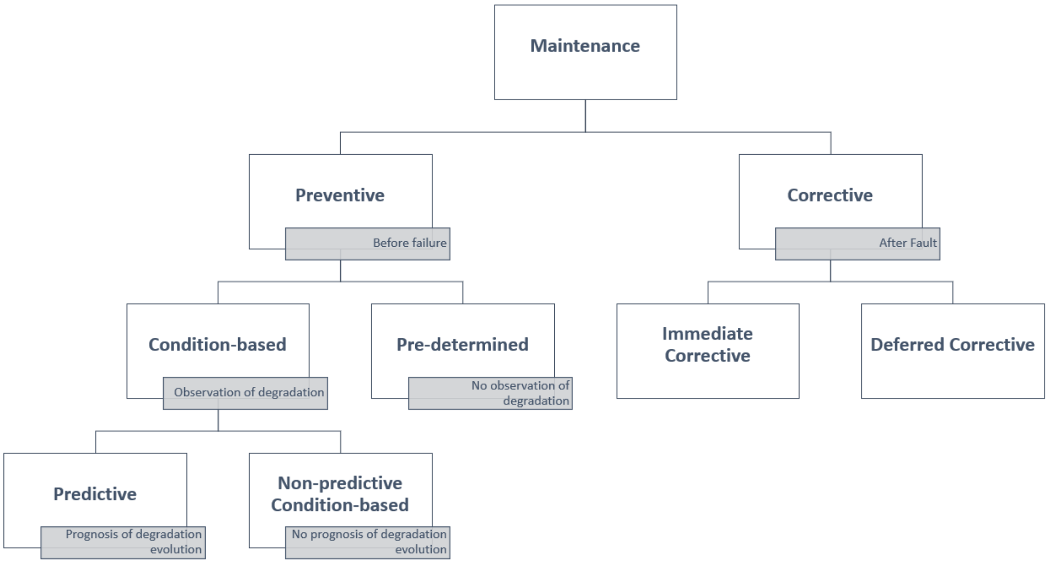

Figure 2.4 : Maintenance types, adapted from [3].

into account the damages that may occur, it may be suitable for equipment that is not critical to the business that does not pose a safety risk.

Preventive maintenance, on the other hand, aims to detect faults at an early stage and correct them before they introduce risk to operation [3]. Preventive maintenance employed to increase efficiency and reliability by taking into account the probability of failure or the ageing of the equipment, at certain intervals or according to pre-planned scheduling. Although this approach is beneficial in cases where the wear-out characteristics are evident, it has disadvantages, especially in terms of not being able to use equipment lifespan efficiently and increasing the maintenance cost compared to the corrective maintenance approach [21].

Predictive maintenance is a condition-based approach to maintenance that is used to evaluate the parameters and characteristics of the equipment or to make predictions based on repeated analysis [3]. Compared to preventive maintenance, predictive maintenance maximizes equipment service-life whilst minimizing unnecessary maintenance. In 99% of machine failures, it is possible to observe indications that malfunctions will occur, in other words, the necessary measures can be taken before 99% of the faults occur by continuously monitoring the machine [21].

Under the predictive maintenance approach, decision-making can be divided into two: diagnosis, which is the analysis of the current situation, and prognosis, which is the assessment of conditions measured over time [4]. A P-F curve can be used to better understand diagnostic and prognostic monitoring systems.

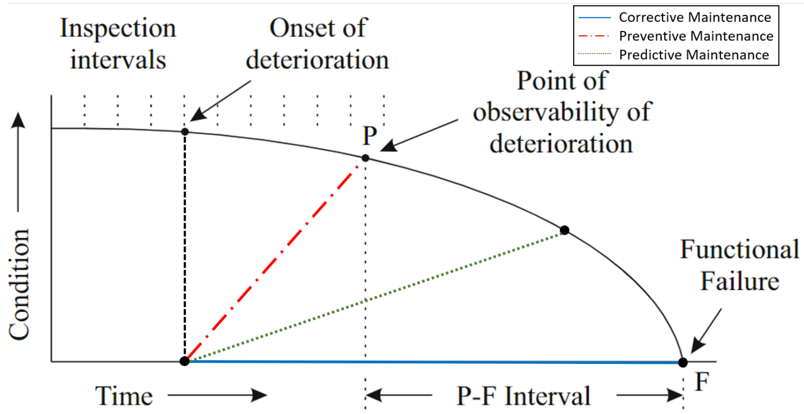

Figure 2.5 : The P-F curve shows the point where the fault started, became observable and the fault occurred, adapted from [4].

The downside of predictive maintenance is that it requires additional equipment and relatively high investment costs. But the advantage of VFDs also comes out here. As they currently monitor motor parameters in control applications, they have a high potential for predictive maintenance applications without the need for additional sensors and investments.

2.2 Induction Motor Fault Types

From a mechanical perspective, induction machines basically consist of three components: stator, rotor and bearing. Electrical, mechanical, and environmental disturbances constantly affect asynchronous motor components and cause most malfunctions [22]. Table 2.1 exhibits various surveys that studied and categorized the most common failures [1, 13, 23–25].

Table 2.1 : Distribution of induction motor faults by component (%).

Component	IEEE	EPRI	Thorsen-Dalva	Bonnett-Yung
Bering	44	41	51	69
Stator	26	37	16	21
Rotor	8	10	5	7
Other	22	12	28	3

Considering the actual distribution of the faults, in total 80% of the faulty motors have only one fault, while this rate reaches 90% especially in low voltage supply motors [1].

Table 2.2 : Actual distribution of multiple failures (%)) [1].

Exact Failure	Motor Supply Voltage			Total
	Low	Middle	High	
1 Fault	91.1	79.6	77.1	79.9
2 Faults	8.0	11.8	13.1	11.9
3 Faults	0.9	3.3	5.5	4.0
4 Faults	0.0	2.2	0.8	1.3
>4 Faults	0.0	3.0	3.5	2.9

As can be seen in Table 2.1, most of the faults associated with bearings followed by stator related faults. It also should be noted that these surveys do not include the effects of power electronics. A motor controlled by VFD is subjected to short and high voltage pulses called PWM (Pulse Width Modulation), which are sent at a very high frequency, which can have a detrimental effect on the wire insulation and cause a burn on the stator [14]. Although this problem can be solved with high-quality insulation, PWM signals also create non-continuous electrical discharges on the bearings, causing wear which reduces bearing lifespan [26]. Therefore, it would not be wrong to conclude that bearing and stator failures will also have a high rate in VFD-fed induction motors.

2.2.1 Bearing related faults

In all kinds of electrical machines, the mechanical element positioned between the frame that initiates the movement and the rotating axis shaft is called a bearing. These mechanical elements, which help the rotational movement of the electric motor, are exposed to many internal and external destructive effects during their operation and failures arise as a result. Major sources of bearing failures are given below [22,27–31]:

Mechanical stresses: Fatigue, which mostly begins on the surface, turns into small-sized material ruptures at the beginning and later dimensional surface indentations and protrusions. Loose motor connection, misalignment where the motor shaft and load shaft are connected without aligning on the same axis, angular misalignment where the motor shaft and load shaft axes are connected at a certain angle, and unbalanced load connection, which is an unbalance condition where the centre of gravity of the load connected to the motor shaft is not on the rotation axis are other mechanical disturbances on the bearing.

Environmental stresses: Corrosion occurs on the bearing surfaces used in high humidity working environments. Especially the moisture absorbed in the bearing oil initiates this process and the rust that occurs due to corrosion causes deterioration that turns into indentation and protrusion on the surface of the bearing element, and cracks in the later stages.

Thermal stresses: Insufficient lubrication generally causes problems with bearing components. Normally, there is a layer of oil in the bearing that prevents direct contact between the rotating elements so that their surfaces do not wear out quickly. In case of insufficient lubrication, excessive wear and subsequent material deterioration occur as a result of increased friction due to direct contact between metal surfaces.

Electrical stresses: the electrical discharge current effect occurs with a fault current flowing through the bearings from the motor frame to the ground in motors that do not have a suitable ground connection. Asymmetry of stator windings, permanent magnetism effect developing in the motor over time, electrostatic charge accumulation in the motor frame and application of voltage to the motor shaft from the outside, or common end voltages generated due to the high switching frequency of semiconductor power electronics (VFDs using PWM) are the factors that cause this malfunction. The irregular current will cause wear and tear on the bearing metal surface, and as a result, the degree of material rupture and surface deterioration increases.

Vibration in the motor causes the rotor to rotate irregularly or axially unbalanced in the motor air gap. Any axial misalignment that occurs in the motor air gap adversely affects the air gap flux density and causes the formation of harmonic components [2, 30, 31]. Consequently, this can induce harmonic components in the current drawn by the motor with frequencies given by formula [30]:

$$f_{bng} = f_e \pm m \cdot f_{\mathrm{v}} \qquad \textbf{(2.3)}$$

where,

f_e is the electrical supply frequency;

f_{v} is the rotational speed frequency of the rotor;

m is the harmonic number $1, 2, 3 \ldots$..;

f_{bng} is the current component frequency due to air gap changes.

2.2.2 Stator related faults

As researches have shown, stator faults occupy an important place among asynchronous motor faults after bearing [1, 13, 23–25]. Mechanical, electrical, thermal and environmental factors cause malfunctions in the stator windings, as well as their laminations [5, 32]. Winding faults, as the most common stator faults, are winding short-circuit faults that are mostly the result of the aforementioned effects of the winding insulation. Types of winding faults are as follows [5, 32, 33]:

- Short-circuit between two turns in the same phase, (turn-turn failure)
- Short-circuit between two coils side by side in the same phase (coil-coil failure),
- Short-circuit between the turns of two phases (phase-phase failure),
- Short circuit consisting of all three-phase turns,
- Short-circuit between the conductor of the winding and the stator core (phase-ground short circuit),
- Open-circuit fault when winding gets break.

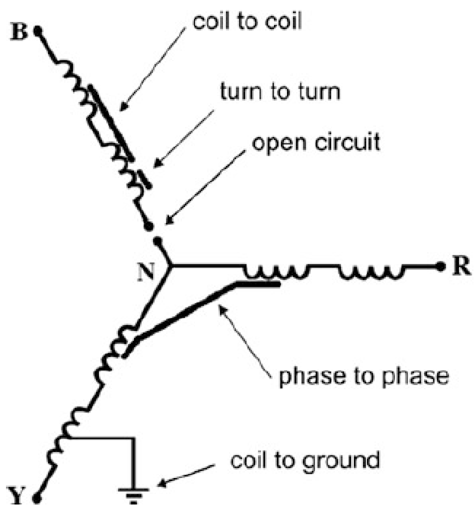

Figure 2.6 : Star-connected stator winding faults, adapted from [5].

The factors that cause the motor winding insulation to deteriorate are explained below [2, 5, 32, 34]:

Mechanical stresses: While the motor is running, the rotor may rub or hit the inner surface of the stator due to motor shaft deterioration, bearing failures and misalignment. This force creates a turn-to-turn or a phase-to-earth short-circuit, causing the stator coil and the stator winding insulation to break down. On the other hand, winding breakage may occur due to vibration during operation and therefore the motor produces the open-circuit fault.

Environmental stresses: The environment in which the motor is running can be very hot, cold or humid. On the other hand, substances in the external environment can contaminate the windings, causing the heat dissipation to deteriorate and the insulation to be damaged. In addition, the airflow can be blocked and cannot absorb the air required for cooling. Therefore, it causes the motor windings to heat and consequently the insulation to deteriorate.

Thermal stresses: Thermal effects occur as a result of overloading or a motor failure. With motor overload, the motor temperature rises above the limit value of the insulation class and the insulation deteriorates. At this point, every 3.5% unbalance in the motor supply voltage increases the temperature of the motor by 10°C. In addition, every 10°C temperature increase above the limit temperature value of the insulation halves the life of the insulation.

Electrical stresses: The main reason for this is sudden changes in supply voltage. Transients during commissioning and decommissioning and voltage fluctuations frequently occur, especially in asynchronous motors powered by variable frequency drives. Winding insulations deteriorate due to these voltage variations.

Under the inter-turn short-circuit condition, a significant deviation in rotor slot harmonics components, called as principle slot harmonics (PSH), occurs and can be obtained by given formula [35];

$$f_{st} = f_e \cdot \left[n \cdot \frac{(1-s)}{p} \pm k \right] \tag{2.4}$$

where,

f_e is the electrical supply frequency ;

p is the number of pole pairs of the motor ;

n $= 1, 2, 3 \ldots (2p-1)$;

s is the slip ;

k is the harmonic number $1,2,3\ldots..$;

f_{st} is the principle slot harmonic frequencies.

2.2.3 Rotor related faults

There are several reasons why rotor bar faults can occur in an induction motor. In caged motors, breaking one cage bar does not significantly change the operating behaviour of the machine. However, due to the fracture that occurs, the current distribution, air gap flux, force balance and temperature distribution in the rotor deteriorate, and heating and strains increase [36]. If the rotor continues to run in this state, damage can also spread to the sidebars, causing multiple bars of the rotor to break. In this respect, it is very important to diagnose the condition when a rotor bar broken.

The main reasons of rotor broken bar of an induction motor can be mentioned as follows [32, 34, 36, 37];

Mechanical stresses: In cases that cause structural asymmetry such as rotor misalignment or bearing failure, the resultant of the normal direction forces in the air gap is not equal to zero and the force acting on the bars increases. In addition, dynamic effects such as impact forces due to sudden load change, centrifugal forces due to excessive acceleration also cause failure.

Environmental stresses: Dusty, wet and/or oily environment in which the electric motor operates negatively affects the engine and increases the possibility of malfunction.

Thermal stresses: Thermal stresses may occur during take-off and/or operation. The temperature limit values of the motor and rotor are different. In terms of the safe operation of the motor, the rotor temperature at start-up and the stator temperature during operation are decisive. Thermal stresses are generally caused by frequent starting, locking of the motor shaft, bearing failure, insufficient cooling, skin effect and current accumulation. It takes the form of partial warming in machines fed by power electronics.

Electrical stresses: The flux created by the current flowing through the rotor bars creates an electrodynamic force $(F \propto I^2)$ acting from the rotor surface towards the shaft in quadratic proportion to the current. The bar vibrates at $2 \cdot s \cdot f_e$ and $4 \cdot s \cdot f_e$

frequencies and can therefore cause breakage in the rotor bars. In addition, since the rotor current at motor start-up is very high, the rotor bar is again exposed to high stresses.

Cracked or broken bar in the rotor cage produces a series of sideband frequencies in the stator current given by [5];

$$f_{brb} = f_e \cdot [1 \pm 2 \cdot k \cdot s] \tag{2.5}$$

where,

f_e is the electrical supply frequency ;

s is the slip ;

k is the harmonic number $1, 2, 3 \ldots$..;

f_{brb} is the broken rotor bar sideband frequencies.

2.3 Condition Monitoring Techniques

Condition monitoring is applied to the motor continuously or periodically, as a diagnostic tool for fault detection and as one of the fundamentals of maintenance planning. Sudden or unexpected changes in monitored parameters provide important information about the condition of the motor. Although the parameters to be monitored vary depending on the end-user, temperature, vibration and current magnitudes are widely used in the industry [38].

2.3.1 Temperature monitoring

One of the parameters that can be followed in order for electric motors to work safely and without failure for a long time is the motor temperature. By installing sensors such as Resistance Temperature Detectors, thermistors, thermocouples and thermostats, electrical or mechanical faults can be detected [38]. These sensors are usually placed in the stator windings, bearings and frame [39]. In addition, temperature monitoring can be performed by parameter estimation over the stator supply current without using any temperature sensor [40].

As mentioned before, thermal stresses resulting from effects such as overloading and bearing lubrication problems may damage various components of the motor. While bearing temperatures provide useful information about possible friction problems, the coolant bulk outlet temperature is frequently monitored, especially when the machine is forced beyond its nominal values, and winding temperature monitoring is also useful in the event of overheating due to overload [41]. Continuously monitoring of temperature will give an indication of potential failures to avoid catastrophic incidents.

2.3.2 Vibration monitoring

Due to their working principles, rotating gears, electric fields and shafts periodically generate vibrations [42]. Since the produced vibration signals contain information about the condition of the machine and can be followed without interfering with the operation of the motor, it is mostly preferred in condition monitoring studies. Vibration monitoring has the ability to track sudden changes in the machine condition that enables monitor the condition of the equipment continuously or intermittently.

Vibration can be measured in units of displacement, velocity, and acceleration. The displacement type is generally used in the measurement of rotor vibration, while the velocity type is used in motor housing vibration measurements associated with machine fatigue [38]. With the most commonly used acceleration type, the vibration condition is monitored by positioning it close to a bearing on the motor frame at high frequencies [38, 43].

Vibration analysis is used in many studies on mechanical failures also occurring in induction motors. Imbalance, misalignment, looseness, and bearing failures are specific signs in the vibration spectrum [41]. A condition monitoring strategy can be established by correlating certain fault types with specific frequencies, or by trend analysis with acceleration data. Depending on the application and user requirements, with vibration condition monitoring, a cost-effective maintenance plan can diagnose and take action before the machine and its components fail or cause performance loss.

2.3.3 Motor current monitoring

Condition monitoring via supply current signals provide useful information on not only for motor itself but also the mechanical system that motor drive [44]. An important aspect of the maintenance strategy is the inclusion of a mechanical system that motor drive. Especially with VFD-fed systems, where current is already sensed to control motor operation, both electrical and mechanical faults can be diagnosed without additional sensor need [31, 44–46].

In industrial applications where ambient conditions are not suitable for vibration signal measurement, current monitoring may be preferred due to its robustness to ambient conditions, especially when disturbances are high. Therefore, current-based condition monitoring, which proven in industrial applications, has benefits such as economical, versatile and reliable over other monitoring techniques.

Although many studies have been done to diagnose fault using current signals, studies on VFD-fed motors are limited. It should be noted that the PWM signals used in VFDs can mask the characteristics of a fault in the motor current signal, making diagnosis difficult [47]. In this study, electrical and mechanical fault detection is emphasized in different load and frequency scenarios over the single-phase stator supply current of the VFD-fed three-phased induction motor.

2.4 Signal Processing Techniques

Signal processing, also named feature generation, can be defined as the extraction and interpretation of the characteristics of the sensor data received from the machine whose status is to be monitored [48]. In a sense, it is the transfer of expert knowledge to the system and its use in monitoring the motor condition. Signals such as vibration, temperature and current are carried out to reach the information that is not always easily visible in the data, which is often required to be revealed [49]. Signals are generally studied in two different domains: time and frequency.

2.4.1 Time domain based signal analysis

Time-domain features may be beneficial to monitor the state of continuous dynamical systems [50]. The performance of the diagnosis is strictly dependent on the selection of features that represent the characteristics of the system. The selection of appropriate features, on the other hand, is based on expert knowledge to obtain a reliable and accurate diagnosis [51]. In practice, there exists a large range of indicators to reveal the system's state, but in this study statistical features such as Root Mean Square (RMS), Mean, Median, Standard Deviation, Kurtosis and Skewness are employed [52].

2.4.2 Statistical analysis

The main idea behind statistical analysis is to understand the location, which is the typical or central value of a data set, and variability, which is the spread of a data set according to centre and tails [53]. The mean and median values are used to find the location, while standard deviation indicates the spread. Skewness and kurtosis criteria can also be examined to better understand the data.

2.4.2.1 Mean

Commonly called as average, is the sum of the samples in the dataset divided by the total number of samples [52]. The mean is one of the best indicators if the underlying distribution is normal, but lacks the robustness of validity [53]. That is, if the underlying distribution is not normal, mean-based confidence intervals tend to be imprecise.

$$\bar{Y} = \sum_{i=1}^{N} Y_i/N \tag{2.6}$$

where,

$\bar{Y}$ is the mean;

N is the number of data points;

2.4.2.2 Median

The median, which is the point in a dataset that is greater than half the numbers and less than the other half, tends to have a robustness of validity but not a robustness of efficiency [52, 53].

$$\tilde{Y} = Y_{(N+1)/2} \quad \text{if } N \text{ is odd} \tag{2.7}$$

$$\tilde{Y} = \left(Y_{N/2} + Y_{(N/2)+1}\right)/2 \quad \text{if } N \text{ is even} \tag{2.8}$$

where,

$\tilde{Y}$ is the mean;

2.4.2.3 Root Mean Square (RMS)

RMS is also known as quadratic mean and represents tha magnitude of a varying signal [52, 54]. As one of the most applied feature for rotating machinery, especially in AC electric motors, it is used for roughly estimating motor load and detecting general noise level.

$$\text{RMS} = \sqrt{\frac{1}{N}\left[\sum_{i=1}^{N}(Y_i)^2\right]} \quad \textbf{(2.9)}$$

2.4.2.4 Standard Deviation

Standard deviation is the square-root of the variance which is aritmetic average of the squared distance from the mean [52]. Similar to mean, standard deviation is also one of the best estimator, but also suffers the same lack of precision in case of distribution is not normal [53].

$$s = \sqrt{\sum_{i=1}^{N}(Y_i - \bar{Y})^2/(N-1)} \quad \textbf{(2.10)}$$

where,

s is the standard deviation;

2.4.2.5 Kurtosis

Kurtosis a measure that is to be used to understand if the data peaked or flat relative to a normal distribution [52]. High kurtosis indicates that the dataset tends to have a prominent peak close to the mean, while the dataset with low kurtosis tends to have a flat peak close to the mean rather than a sharp peak [53].

$$\text{kurtosis} = \frac{\sum_{i=1}^{N}(Y_i - \bar{Y})^4}{(N-1)s^4} \quad \textbf{(2.11)}$$

2.4.2.6 Skewness

Skewness represents a lack of symmetry in a data set. The dataset is symmetrical if it looks the same to the left and right of the centre point [52]. The left skew represents a negative value while showing that it is taller on the left than on the right [53]. The right skew indicates the opposite situation. The skewness of a symmetric dataset converges to zero, and it is zero for a normal distribution [53].

$$\text{skewness} = \frac{\sum_{i=1}^{N}(Y_i - \bar{Y})^3}{(N-1)s^3} \quad \textbf{(2.12)}$$

2.4.3 Frequency based signal analysis

The frequency domain is needed to reveal properties of a signal that are not easy to see in the time domain. This need actually has different motivations. One of them, considering the operating conditions, industrial machines are quite susceptible to noise and disturbances [48, 55]. To suppress or eliminate these effects, frequency domain transformations are less expensive in terms of computational requirements than time-domain methods [48, 56]. Another motivation is that the fault characteristics can be seen better in the frequency spectrum, as it is widely applied in the literature [56].

Frequency domain analysis has different techniques including the Fourier transform of time-domain waveforms, but Fast Fourier Transform and Power Spectral Density methods will be examined in the thesis.

2.4.3.1 Shannon-Nyquist sampling theory

Hardware-wise, it is not possible to transfer an analogue signal to the digital environment as it is in the physical world. For this reason, sampling of the analogue signal is necessary in order to represent a signal digitally. The Shannon-Nyquist Sampling Theorem specifies conditions that must be satisfied in order for an analogue signal to be converted to a digital signal [57].

When an analog signal $x(t)$ is sampled with the period T_s, the resulting signal is the discrete signal $x_s(n \cdot T_s)$ with $n = 0, 1, 2, \ldots$.

Two condition must be satisfied for accurate representation of $x(t)$ [57]:

1. The frequency spectrum of $x(t)$ must be limited by some maximum frequency, such that f_{max}
2. The sampling rate f_s, must be at least twice the maximum frequency $f_{\max}$

$$f_s \geq 2 \cdot f_{\max}$$

where, $f_s = \dfrac{1}{T_s}$

2.4.3.2 Fast Fourier transform

After an analogue signal is sampled and the shape of the signal is obtained, this signal is now in a form that can be processed and analyzed in the digital environment. As an example, in order to find the output expression of a linear and time-invariant system, the input function of this system in the time domain is multiplied by the pulse input response of this system and the resulting signal is integrated. This computationally cumbersome convolution operation becomes an algebraic multiplication in the frequency space [48]. Therefore, in signal processing studies, some transformation methods have been developed to find the equivalent of the signal in the frequency space. One of these methods is the Fourier Transform.

In practice, to calculate the frequency spectrum (frequency-amplitude expression of the Fourier Transform) of a signal, the Discrete Fourier Transform of the signal is calculated. The mathematical expression of DFT is as follows [55]:

$$X(k) = \sum_{n=0}^{N-1} x(n) \cdot exp\left(\frac{-j2\pi nk}{N}\right) \tag{2.13}$$

where, $0 \leq k \leq N-1$ and N is the number of samples in discrete signal.

Since the form of the Discrete Fourier Transform given by the equation 2.13 requires N^2 complex multiplication and $N \cdot (N-1)$ addition in the computer environment, the computational load is quite high especially for large N [42, 55, 57, 58]. For this reason, some Fast Fourier Transform (FFT) algorithms have been developed for faster computation of DFT. Some practical aspects of FFT to be used in condition monitoring [49];

- Motor supply current sampling is usually done at 5 kHz. Therefore, the bandwidth of the sensor should be at least 10 kHz.
- Shannon-Nyquist theorem indicates that sampling frequency must be twice the maximum frequency, but in practice 10 times increases accuracy.
- Spectral resolution, $\Delta f = \frac{f_s}{N}$

2.4.3.3 Power spectral density estimation

The harmonics seen in the current spectrum as a result of the faults depend on the motor load and hence the slip. When the signal is processed with the FFT, it introduces errors as it averages the spectrum amplitudes over the sampling period [59, 60]. PSD, on the other hand, is more resistant to slip variations due to its ability to monitor different frequency bands. PSD estimation can be categorized into two technique: parametric and non-parametric [61, 62]. In the scope of the thesis, a non-parametric method, Welch's approach is investigated.

In Welch's method, the time domain signal is divided into segments of a certain length with overlaps between its segments, and a time-domain window is applied to the individual data segments, then estimate PSD by computing DFT for each segment and finally, the calculated PSDs are averaged [6, 63, 64].

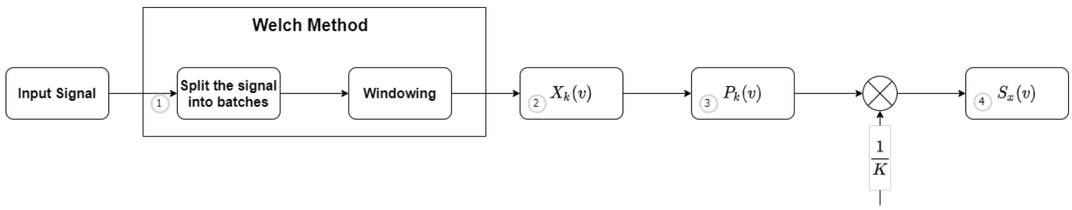

Figure 2.7 : Flowchart of Power Spectral Density estimation via Welch's method [6].

By segmenting the data and adding window overlaps to the data, the Welch method can increase the resolution and also effectively reduce both the variance and bias of the spectral estimation [61, 63, 65]. The mechanism of adding window overlaps on the signal, which is similar to noise removal with the recursion algorithms, results a better Signal-to-Noise Ratio (SNR) in high noise data [6, 60, 66]. Welch's PSD estimation with Hamming window for fault diagnosis in induction motors outperforms FFT and periodogram methods in terms of robustness and accuracy due to reduced bias and variance [67].

1. Partition the data sequence:

$$x[0], x[1], \ldots, x[N-1]$$

into K segments or batches:

Segment 1: $x[0], x[1], \ldots, x[M-1]$

Segment 2: $x[S], x[S+1], \ldots, x[M+S-1]$

Segment K: $x[N-M], x[N-M+1], \ldots, x[N-1]$

where

$M =$ Number of points in each segment or batch size

$S =$ Number of points to shift between segments

$K =$ Number of segments or batches

2. For each segment ($k = 1$ to K), compute a windowed discrete Fourier transform (DFT) at some frequency $\nu = i/M$ with $-(M/2-1) \leq i \leq M/2$:

$$X_k(\nu) = \sum_m x[m]w[m]\exp(-j2\pi\nu m)$$

where

$$m = (k-1)S, \ldots, M + (k-1)S - 1$$

$$w[m] = \text{the window function}$$

3. For each segment ($k = 1$ to K), form the modified periodogram value, $P_k(f)$, from the discrete Fourier transform:

$$P_k(\nu) = \frac{1}{W}|X_k(\nu)|^2$$

where

$$W = \sum_{m=0}^{M} w^2[m]$$

4. Average the periodogram values to obtain Welch's estimate of the PSD:

$$S_x(\nu) = \frac{1}{K}\sum_{k=1}^{K} P_k(\nu)$$

Figure 2.8 : Algorithm of Power Spectral Density estimation via Welch's method [7].

2.5 Data-driven fault diagnosis techniques

Model and signal-based approaches have been applied successfully for many years in condition monitoring and fault diagnosis studies in induction motors. Although these approaches have their own advantages, they require a certain level of field expertise. With the establishment of the Industry 4.0 phenomenon, the increasing data size in industrial applications in recent years and the developments in the technologies of the hardware that will store and process this data form the infrastructure for data-oriented approaches. The fact that there has been vast academic interest in machine learning techniques, which are also defined as artificial intelligence, especially in the last ten years, causes an increase in industrial applications.

Increasing data-driven studies in the induction motors will be examined under classical machine learning and deep learning methods in this study. The state information of the motor contained in the current signal usually requires processing of the signal. Fault diagnosis can be made with classical machine learning methods by processing the signal with statistical approaches in the time and frequency domains and approaches to extract characteristics at certain frequencies in the frequency domain. On the other hand, in deep learning methods, since there is no need for signal processing in a manner of feature extraction, fault diagnosis can be performed over raw current data.

2.5.1 Classical machine learning methods

2.5.1.1 Support Vector Machines

2.5.1.2 Naive Bayes

2.5.1.3 Random Forest

2.5.1.4 Multi Layer Perceptron

2.5.1.5 Ensemble Learning

2.5.2 Deep learning methods

2.5.2.1 1D-Convolutional Neural Networks

2.5.2.2 Long-Short Term Memory Networks

2.6 Performance evaluation

Various metrics, which can be aggregated under binary or multi-class classification, are used to compare the performance of algorithms to be used in fault diagnosis [68,69]. In the diagnosis of asynchronous machine or their components, binary classification can be made as healthy or faulty condition, while multiple classification metrics should be used when separating two or more fault types. Although there is no definite consensus for the metrics used in the comparison between the classification methods, the most frequently used metrics for multi-class classification will be examined in this section.

In order to create metrics, certain measures must be introduced. The confusion matrix shows the actual and predicted classification using certain measures. In the motor diagnostics specific, these four metrics can be defined as follows:

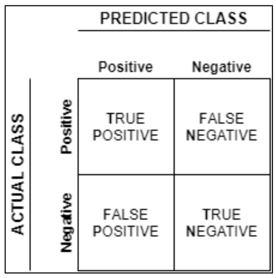

Figure 2.9 : An example of Confusion Matrix.

True Positive (TP), the state where both the actual and predicted values are healthy,
False Positive (FP), the classification of the actually faulty condition as faulty,
False Negative (FN), the classification of the actually healthy motor as faulty,
True Negative (TN), the state where both the actual and predicted values are faulty.

2.6.1 Precision & Recall

Precision refers to the ratio of samples that the classification method predicts as healthy to actually healthy samples, and shows how reliable the healthy motor prediction can be. Recall, on the other hand, expresses how many of the healthy motor samples were labelled correctly as a result of the classification and shows the model's ability to find the healthy motor.

$$\begin{aligned}\text{Precision} &= \frac{TP}{TP+FP} \quad (2.14)\\ \text{Recall} &= \frac{TP}{TP+FN} \quad (2.15)\end{aligned}$$

2.6.2 Accuracy

Accuracy, one of the most common model performance metrics, is an indicator of how well it can distinguish between healthy and faulty motors in the entire data set [70]. Generally, the number of healthy state data is naturally higher in diagnostic applications that result unbalanced data set. In such a case, evaluating only with the accuracy metric may lead to catastrophic situations.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} \quad (2.16)$$

2.6.3 F-measure

As a metric based on Recall and Precision, F-Measure allows better inference than accuracy on classification performance, especially on unbalanced datasets [71].

$$\text{F-measure} = 2 \cdot \frac{Recall \cdot Precision}{Recall + Precision} \quad (2.17)$$

Especially in condition monitoring applications, fault alarms even though there is no fault increase the maintenance cost and at the same time, it can disrupt the operation. On the other hand, missing a fault condition can also damage equipment and disrupt the operation. The performance of the classification method is important in terms of optimizing both cases. F-measure can respond to this optimization as it contains components for these two states [69, 72].

2.6.4 Cohen's Kappa

Another metric that works well with unbalanced data, Cohen's Kappa correlates the estimated and actual values, taking into account the imbalance in the class distribution [73]. By removing the random dependency between the predicted and actual classification, enables to compare different classifiers [70].

$$\text{Cohen's Kappa} = \frac{c \cdot s - \sum_{k}^{K} p_k \cdot t_k}{s^2 - \sum_{k}^{K} p_k \cdot t_k} \tag{2.18}$$

where:

K is the total number classes

$c = \sum_{k}^{K} C_{kk}$ the total number of samples that correctly predicted

$s = \sum_{i}^{K} \sum_{j}^{K} C_{ij}$ the total number of samples

$p_k = \sum_{i}^{K} C_{ki}$ the number of times that class k was predicted (column total)

$t_k = \sum_{i}^{K} C_{ik}$ the number of times that class k actually presents (row total)

2.6.5 Area Under the Curve

Receiver operating characteristic (ROC) curve, which is another method widely used in binary classification performance measurement, shows the performance of classification methods in two dimensions [74]. To reduce this metric to one dimension, the area under the ROC curve (AUC) is calculated.

In multiclass classification problems, AUC values now transform into multiple binary classification values. The specified formula is used to reduce to a single numerical value [74]:

$$AUC_{total} = \sum_{c_i \in C} AUC(c_i) \cdot p(c_i) \tag{2.19}$$

where:

c_i is the reference class

C is the total number of classes

$p(c_i)$ is the prevalence of the reference class in the dataset

$AUC(c_i)$ is the area under the class reference *ROC* curve for c_i

According to this formula, AUC values are calculated by creating a ROC curve for each reference class, and the AUC_{total} value is obtained by weighting it with the prevalence of the reference class [71, 74]. The advantage of this method is that it is easily computable and is derived directly from reference class ROCs [74].

REFERENCES

[1] **Albrecht, P., Appiarius, J., Cornell, E., Houghtaling, D., McCoy, R., Owen, E. and Sharma, D.** (1987). Assessment of the reliability of motors in utility applications, *IEEE transactions on energy conversion*, (3), 396–406.

[2] **Faiz, J., Joksimović, G. and Ghorbanian, V.** (2017). *Fault diagnosis of induction motors*, Institution of Engineering & Technology.

[3] **EN, B.** (2017). 13306:2017: Maintenance—Maintenance terminology, *BSI Standards Publication*.

[4] **Tinga, T. and Loendersloot, R.**, (2019). Physical model-based prognostics and health monitoring to enable predictive maintenance, Predictive Maintenance in Dynamic Systems, Springer, pp.313–353.

[5] **Karmakar, S., Chattopadhyay, S., Mitra, M. and Sengupta, S.** *Induction motor fault diagnosis*, volume 25, Springer.

[6] **Jwo, D.J., Chang, W.Y. and Wu, I.H.** (2021). Windowing Techniques, the Welch Method for Improvement of Power Spectrum Estimation, *CMC-COMPUTERS MATERIALS & CONTINUA*, *67*(3), 3983–4003.

[7] **Solomon Jr, O.** (1991). PSD computations using Welch's method, *NASA STI/Recon Technical Report N*, *92*, 23584.

[8] **Waide, P. and Brunner, C.U.** (2011). Energy-efficiency policy opportunities for electric motor-driven systems.

[9] **Kulterer, K., Werle, R., Lackner, P., Brunner, C. and Ellis, M.** (2014). Policy Guidelines for Electric Motor Systems–Part 2: Toolkit for Policy Makers, *4E Electric Motor Systems EMSA, 4E Energy Efficient Enduse Equipment, International Energy Agency*.

[10] **Fleiter, T. and Eichhammer, W.** (2012). Energy efficiency in electric motor systems : Technology , saving potentials and policy options for developing countries.

[11] **Mikami, H., Ide, K., Shimizu, Y., Senoo, M. and Seki, H.** (2011). Historical evolution of motor technology, *Hitachi Review*, *60*(1), 39.

[12] (2014). Improving Motor and Drive System Performance – A Sourcebook for Industry, `https://www.osti.gov/biblio/1220836`.

[13] (1985). Report of Large Motor Reliability Survey of Industrial and Commercial Installations, Part I, *IEEE Transactions on Industry Applications*, *IA-21*(4), 853–864.

[14] **Hovstadius, G. and Bolles, S.** (2016). Manual for Industrial Pump Systems Assessment and Optimization, **Technical Report**, United Nations Industrial Development Organization.

[15] **Oliver, J.** (1992). Electric motor predictive and preventive maintenance guide, **Technical Report**, Electric Power Research Inst.

[16] **Motors, W.E.** (2018). Induction motors fed by PWM frequency inverters, **Technical Report**, `https://www.weg.net/institutional/US/en/search/downloadcenter`.

[17] **Drives, D.** (2019). Facts Worth Knowing about AC Drives, **Technical Report**, `https://danfoss.ipapercms.dk/Drives/DD/Global/SalesPromotion/FWK`.

[18] **Bose, B.** (2002). *Modern Power Electronics and AC Drives*, Eastern Economy Edition, Prentice Hall PTR.

[19] **Lughofer, E. and Sayed-Mouchaweh, M.**, (2019). Prologue: Predictive maintenance in dynamic systems, Predictive Maintenance in Dynamic Systems, Springer, pp.1–23.

[20] **Ruiz-Sarmiento, J.R.**, **Monroy, J.**, **Moreno, F.A.**, **Galindo, C.**, **Bonelo, J.M. and Gonzalez-Jimenez, J.** (2020). A predictive model for the maintenance of industrial machinery in the context of industry 4.0, *Engineering Applications of Artificial Intelligence*, *87*, 103289.

[21] **Ahmad, R. and Kamaruddin, S.** (2012). An overview of time-based and condition-based maintenance in industrial application, *Computers & Industrial Engineering*, *63*(1), 135–149.

[22] **Bonnett, A.H.** (2010). Root cause failure analysis for AC Induction Motors in the petroleum and chemical industry, *2010 Record of Conference Papers Industry Applications Society 57th Annual Petroleum and Chemical Industry Conference (PCIC)*, pp.1–13.

[23] **Albrecht, P.**, **Appiarius, J.**, **McCoy, R.**, **Owen, E. and Sharma, D.** (1986). Assessment of the reliability of motors in utility applications-Updated, *IEEE Transactions on Energy conversion*, (1), 39–46.

[24] **Thorsen, O.V. and Dalva, M.** (1995). A survey of faults on induction motors in offshore oil industry, petrochemical industry, gas terminals, and oil refineries, *IEEE transactions on industry applications*, *31*(5), 1186–1196.

[25] **Bonnett, A.H. and Yung, C.** (2008). Increased efficiency versus increased reliability, *IEEE Industry Applications Magazine*, *14*(1), 29–36.

[26] **Trigeassou, J.C.** (2013). *Electrical machines diagnosis*, John Wiley & Sons.

[27] **Zhang, P.**, **Du, Y.**, **Habetler, T.G. and Lu, B.** (2010). A survey of condition monitoring and protection methods for medium-voltage induction motors, *IEEE Transactions on Industry Applications*, *47*(1), 34–46.

[28] **Bonnet, A.H.** (2012). The Cause and Analysis of Bearing and Shaft Failures in Electric Motors, **Technical Manual 27**, EASA Technology & Education Consultant.

[29] (2017). Bearing damage and failure analysis, **Technical Manual PUB BU/I3 14219/2 EN**, SKF Group.

[30] **Schoen, R.R.**, **Habetler, T.G.**, **Kamran, F. and Bartfield, R.** (1995). Motor bearing damage detection using stator current monitoring, *IEEE transactions on industry applications*, *31*(6), 1274–1279.

[31] **EN, B.** (2013). 20958:2013: Condition monitoring and diagnostics of machine systems — Electrical signature analysis of three-phase induction motors, *BSI Standards Publication*.

[32] **Siddique, A.**, **Yadava, G. and Singh, B.** (2005). A review of stator fault monitoring techniques of induction motors, *IEEE Transactions on Energy Conversion*, *20*(1), 106–114.

[33] **Lipo, T.A.** (2017). *Introduction to AC Machine Design*, John Wiley & Sons, Ltd.

[34] **Bonnett, A.H.** (1999). Root cause AC motor failure analysis, *Industry Applications Society 46th Annual Petroleum and Chemical Technical Conference (Cat. No. 99CH37000)*, IEEE, pp.85–97.

[35] **Penman, J.**, **Sedding, H.**, **Lloyd, B. and Fink, W.** (1994). Detection and location of interturn short circuits in the stator windings of operating motors, *IEEE Transactions on Energy Conversion*, *9*(4), 652–658.

[36] **İmeryüz, M.** (2009). Asenkron Makinede Kafes Kırılmasının İncelenmesi, *Ph.D. Dissertation*, Fen Bilimleri Enstitüsü.

[37] **Filippetti, F.**, **Bellini, A. and Capolino, G.A.** (2013). Condition monitoring and diagnosis of rotor faults in induction machines: State of art and future perspectives, *2013 IEEE Workshop on Electrical Machines Design, Control and Diagnosis (WEMDCD)*, IEEE, pp.196–209.

[38] **Mistry, R.**, **Finley, W.R.**, **Hashish, E. and Kreitzer, S.** (2016). Rotating machines—Pros and cons of monitoring devices, *2016 Petroleum and Chemical Industry Technical Conference (PCIC)*, IEEE, pp.1–12.

[39] **Society, I.P.E.** (2017). IEEE standard test procedure for polyphase induction motors and generators, *ANSI, IEEE Standard 112*.

[40] **Kumar, S.**, **Mukherjee, D.**, **Guchhait, P.K.**, **Banerjee, R.**, **Srivastava, A.K.**, **Vishwakarma, D. and Saket, R.** (2019). A comprehensive review of condition based prognostic maintenance (CBPM) for induction motor, *Ieee Access*, *7*, 90690–90704.

[41] **Thorsen, O. and Dalva, M.** (1998). Methods of condition monitoring and fault diagnosis for induction motors, *European transactions on electrical power*, *8*(5), 383–395.

[42] **Randall, R.B.** (2021). *Vibration-based condition monitoring: industrial, automotive and aerospace applications*, John Wiley & Sons.

[43] **EN, I.** (2002). 13373-1:2002: Condition monitoring and diagnostics of machines — Vibration condition monitoring — Part 1: General procedures, *International Organization for Standardization*.

[44] **Thomson, W.T. and Fenger, M.** (2001). Current signature analysis to detect induction motor faults, *IEEE Industry Applications Magazine*, *7*(4), 26–34.

[45] **Gritli, Y.**, **Bellini, A.**, **Rossi, C.**, **Casadei, D.**, **Filippetti, F. and Capolino, G.** (2017). Condition monitoring of mechanical faults in induction machines from electrical signatures: Review of different techniques, *2017 IEEE 11th international symposium on diagnostics for electrical machines, power electronics and drives (SDEMPED)*, IEEE, pp.77–84.

[46] **Corne, B.**, **Knockaert, J. and Desmet, J.** (2017). Misalignment and unbalance fault severity estimation using stator current measurements, *2017 IEEE 11th International Symposium on Diagnostics for Electrical Machines, Power Electronics and Drives (SDEMPED)*, IEEE, pp.247–253.

[47] **Shaeboub, A.** (2018). The Monitoring of Induction Machines Using Electrical Signals from the Variable Speed Drive, *Ph.D. Dissertation*, University of Huddersfield.

[48] **Cernuda, C.**, (2019). On the relevance of preprocessing in predictive maintenance for dynamic systems, Predictive Maintenance in Dynamic Systems, Springer, pp.53–93.

[49] **Bonaldi, E.L.**, **de Oliveira, L.E.d.L.**, **da Silva, J.G.B.**, **Lambert-Torresm, G. and da Silva, L.E.B.**, (2012). Predictive maintenance by electrical signature analysis to induction motors, Induction Motors-Modelling and Control, IntechOpen.

[50] **Medjaher, K.**, **Camci, F. and Zerhouni, N.** (2012). Feature extraction and evaluation for Health Assessment and Failure prognostics., *Proceedings of First European Conference of the Prognostics and Health Management Society, PHM-E'12.*, https://www. phmsociety. org/events/conference/europhm/12/proceedings, Anibal Bregon, Abhinav Saxena, pp.111–116.

[51] **Soualhi, M.**, **Nguyen, K.T.**, **Soualhi, A.**, **Medjaher, K. and Hemsas, K.E.** (2019). Health monitoring of bearing and gear faults by using a new health indicator extracted from current signals, *Measurement*, *141*, 37–51.

[52] **Shukla, S.**, **Yadav, R.**, **Sharma, J. and Khare, S.** (2015). Analysis of statistical features for fault detection in ball bearing, *2015 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)*, IEEE, pp.1–7.

[53] **Croarkin, C. and Tobias, P.** (2012). e-Handbook of Statistical Methods, *NIST/SEMATECH*.

[54] **Sait, A.S. and Sharaf-Eldeen, Y.I.** (2011). A review of gearbox condition monitoring based on vibration analysis techniques diagnostics and prognostics, *Rotating Machinery, Structural Health Monitoring, Shock and Vibration, Volume 5*, 307–324.

[55] **Allen, R.L. and Mills, D.** (2004). *Signal analysis: time, frequency, scale, and structure*, John Wiley & Sons.

[56] **Ahmed, H. and Nandi, A.K.** (2019). *Condition Monitoring with Vibration Signals*, Wiley Online Library.

[57] **Orfanidis, S.J.** (1995). *Introduction to signal processing*, Prentice-Hall, Inc.

[58] **Hayes, M.H.** (2009). *Statistical digital signal processing and modeling*, John Wiley & Sons.

[59] **CusidÓCusido, J.**, **Romeral, L.**, **Ortega, J.A.**, **Rosero, J.A. and Espinosa, A.G.** (2008). Fault detection in induction machines using power spectral density in wavelet decomposition, *IEEE Transactions on Industrial Electronics*, *55*(2), 633–643.

[60] **Irvine, T.** (2002). *An introduction to shock & vibration response spectra*.

[61] **Zerdani, S.**, **El Hafyani, M.L. and Zouggar, S.** (2020). Inter-Turn Stator Winding fault Diagnosis for Permanent Magnet Synchronous Motor based Power Spectral Density Estimators, *2020 International Conference on Smart Grid and Clean Energy Technologies (ICSGCE)*, IEEE, pp.137–142.

[62] **Heydarzadeh, M.**, **Madani, N. and Nourani, M.** (2016). Gearbox fault diagnosis using power spectral analysis, *2016 IEEE International Workshop on Signal Processing Systems (SiPS)*, IEEE, pp.242–247.

[63] **Stoica, P.**, **Moses, R.L.** *et al.* (2005). *Spectral analysis of signals*, Pearson Prentice Hall Upper Saddle River, NJ.

[64] **Schmid, H.** (2012). How to use the FFT and Matlab's pwelch function for signal and noise simulations and measurements, *FHNW/IME*, 2–13.

[65] **Al Ahmar, E.**, **Choqueuse, V.**, **Benbouzid, M.**, **Amirat, Y.**, **El Assad, J.**, **Karam, R. and Farah, S.** (2010). Advanced signal processing techniques for fault detection and diagnosis in a wind turbine induction generator drive train: A comparative study, *2010 IEEE Energy Conversion Congress and Exposition*, IEEE, pp.3576–3581.

[66] **Jin, Z.**, **Han, Q.**, **Zhang, K. and Zhang, Y.** (2020). An intelligent fault diagnosis method of rolling bearings based on Welch power spectrum transformation with radial basis function neural network, *Journal of Vibration and Control*, *26*(9-10), 629–642.

[67] **Ayhan, B.**, **Chow, M.Y.**, **Trussell, H.J. and Song, M.H.** (2003). A case study on the comparison of non-parametric spectrum methods for broken rotor bar fault detection, *IECON'03. 29th Annual Conference of the IEEE Industrial Electronics Society (IEEE Cat. No. 03CH37468)*, volume 3, IEEE, pp.2835–2840.

[68] **Canbek, G.**, **Sagiroglu, S.**, **Temizel, T.T. and Baykal, N.** (2017). Binary classification performance measures/metrics: A comprehensive visualized roadmap to gain new insights, *2017 International Conference on Computer Science and Engineering (UBMK)*, IEEE, pp.821–826.

[69] **Seliya, N.**, **Khoshgoftaar, T.M. and Van Hulse, J.** (2009). A study on the relationships of classifier performance metrics, *2009 21st IEEE international conference on tools with artificial intelligence*, IEEE, pp.59–66.

[70] **Grandini, M.**, **Bagli, E. and Visani, G.** (2020). Metrics for Multi-Class Classification: an Overview, *arXiv preprint arXiv:2008.05756*.

[71] **He, H. and Garcia, E.A.** (2009). Learning from imbalanced data, *IEEE Transactions on knowledge and data engineering*, *21*(9), 1263–1284.

[72] **Janssens, O.**, **Slavkovikj, V.**, **Vervisch, B.**, **Stockman, K.**, **Loccufier, M.**, **Verstockt, S.**, **Van de Walle, R. and Van Hoecke, S.** (2016). Convolutional neural network based fault detection for rotating machinery, *Journal of Sound and Vibration*, *377*, 331–345.

[73] **Widmann, M. and Roccato, A.** (2021). *From Modeling to Model Evaluation*, Knime Press.

[74] **Fawcett, T.** (2004). ROC graphs: Notes and practical considerations for researchers, *Machine learning*, *31*(1), 1–38.

APPENDICES

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PROFESSIONAL EXPERIENCE AND REWARDS:

- 1950-1956 Istanbul Technical University at the Central Laboratory of Theoretical Physics.
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PUBLICATIONS, PRESENTATIONS AND PATENTS ON THE THESIS:

- **Ganapuram S., Hamidov A., Demirel, M. C., Bozkurt E., Kındap U., Newton A.** 2007. Erasmus Mundus Scholar's Perspective On Water And Coastal Management Education In Europe. *International Congress - River Basin Management*, March 22–24, 2007 Antalya, Turkey. (Presentation Instance)

- **Satoğlu, Ş.I., Durmuşoğlu, M. B., Ertay, T. A.** 2010. A Mathematical Model And A Heuristic Approach For Design Of The Hybrid Manufacturing Systems To Facilitate One-Piece Flow, *International Journal of Production Research,* 48(17), 5195–5220. (Article Instance)

- **Chen, Z.** 2013. Intelligent Digital Teaching And Learning All-In-One Machine, Has Projection Mechanism Whose Front End Is Connected With Supporting Arm, And Base Shell Provided With Panoramic Camera That Is Connected With Projector. Patent numarası: CN203102627-U. (Patent Instance)

OTHER PUBLICATIONS, PRESENTATIONS AND PATENTS:

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2020