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Contribution au diagnostic des défauts statoriques dans les machines électriques

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2026/2027

MINISTRY OF HIGHER EDUCATION AND SCIENTIFIC RESEARCH
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2026/2027

DEDICATION

I dedicate this modest work to:

My beloved parents for their encouragement, affection, advice and sacrifice.

My Wife, children ***Yakouta, Abdallah and Mohamed*** for their Time, Support and Patience.

All my family.

Bakhalti.

All my friends, colleagues and ***Co-workers***.

All my teachers.

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ABSTRACT

Three-phase Induction motors (IMs) are indispensable components in modern industrial operations, valued for their durability, affordability, and adaptability across a wide range of applications, from pumps and fans to electric vehicles and heavy industries like steel and cement. However, their susceptibility to faults, such as bearing, stator, and rotor issues, necessitates advanced condition monitoring (CM) and maintenance strategies to ensure reliability and longevity.

A significant contribution of this research is the development of a novel real-time scheme for diagnosing Inter-Turn Short Circuit (ITSC) faults in three-phase induction motors. The proposed method utilizes three-phase input voltage measurements and applies the Fortescue transform, combined with frequency estimation techniques such as FFT and STLSP. A new detection indicator, the Zero Voltage Factor (ZVF), is introduced and experimentally validated under varying load conditions, demonstrating its reliability, accuracy, and versatility in detecting ITSC faults. This innovation offers a cost-effective and robust solution for real-time fault diagnosis, with potential for broader industrial application.p

Furthermore, this thesis presents the integration of an Artificial Neural Network (ANN) within a LabVIEW interface for real-time fault detection and health status evaluation of three-phase induction motors. The interface was rigorously tested for detecting both ITSC faults and Unbalanced Supply Voltage (USV) conditions, showcasing its ability to accurately identify faults of varying severity and voltage imbalances. The system provides clear visual feedback through color-coded buttons and real-time graphs, enabling operators to take timely corrective actions. The integration of ANN enhances the precision and efficiency of fault detection, offering a user-friendly platform for real-time monitoring and diagnostics.

Keywords: Induction Motors, Condition Monitoring, Predictive Maintenance, Fault Detection, Artificial Neural Networks, LabVIEW, Zero Voltage Factor, Inter-Turn Short Circuit, Unbalanced Supply Voltage.

الملخص

محركات التحريض (IMs) هي مكونات أساسية في العمليات الصناعية الحديثة، تُقدّر لمتانتها وتكلفتها المعقولة وقدرتها على التكيّف من خلال مجموعة واسعة من التطبيقات، من المضخّات والمراوح إلى المركبات الكهربائية والصناعات الثقيلة مثل الصلب والأسمنت. ومع ذلك، تعرّض هذه المحرّكات للأعطال مثل أعطال المحامل والستاتور والروتور، مما يتطلّب استراتيجيات متقدّمة لمراقبة الحالة والصيانة لضمان الموثوقية والطول في العمر العملي.

من أهم مساهمات هذا البحث تطوير طريقة جديدة للكشف عن أعطال الدائرة القصيرة بين اللفّات (ITSC) في محرّكات التحريض بالوقت الفعلي. تستخدم الطريقة المقترحة قياسات الجهد الثلاثي الطور وتطبّق تحويل فورتسكيو، بالإضافة إلى تقنيات تقدير التردّد مثل FFT و STLSP يُقدّم في هذا السياق مؤشّر جديد للكشف هو معامل الجهد الصفري (ZVF)، ويُجري تحقيقه تجريبيًا تحت ظروف مختلفة من العزم، معرضًا موثوقيّته ودقّته ومرونته في الكشف عن أعطال (ITSC). تقدّم هذه الابتكارات حلًا موثوقًا ومتينًا لتشخيص الأعطال بالوقت الفعلي، بإمكانية للتطبيق الصناعي الأوسع.

بالإضافة إلى ذلك، تقدّم هذه الأطروحة دمج شبكة عصبية اصطناعية (ANN) ضمن واجهة LabVIEW للكشف عن الأعطال وتقييم حالة الصحّة لمحرّكات التحريض بالوقت الفعلي. تمّ اختبار الواجهة بدقّة للكشف عن أعطال ITSC وحالات عدم توازن الجهد (USV)، معرضةً قدرتها على تحديد الأعطال بدقّة وفي وقت فعّال، بالإضافة إلى عدم التوازن في الجهد. توفّر النظام على استعراضات واضحًة من خلال أزرار ملوّنة ورسومات بيانات فعلية، ممّكنًا المشغّلين من اتخاذ إجراءات تصحيحية مناسبة. يعزّز دمج ANN من دقّة وكفاءة الكشف عن الأعطال، مقدّمًا منصّة مستخدمة وديناميكية للمراقبة والتشخيص بالوقت الفعلي.

الكلمات المفتاحية: محرّكات التحريض، مراقبة الحالة، الصيانة التنبؤية، الكشف عن الأعطال، الشبكات العصبية الاصطناعية، LabVIEW، معامل الجهد الصفري ، الدائرة القصيرة بين اللفّات، عدم توازن الجهد.

Résumée

Les moteurs à induction (IM) sont des composants indispensables dans les opérations industrielles modernes, appréciés pour leur durabilité, leur coût abordable et leur adaptabilité à une large gamme d'applications, allant des pompes et des ventilateurs aux véhicules électriques et aux industries lourdes comme l'acier et le ciment. Cependant, leur sensibilité aux défauts, tels que les problèmes de roulements, de stator et de rotor, nécessite des stratégies avancées de surveillance de l'état (CM) et de maintenance pour garantir la fiabilité et la longévité.

Une contribution significative de cette recherche est le développement d'un nouveau schéma en temps réel pour diagnostiquer les défauts de Court-Circuit Inter-Spire (ITSC) dans les moteurs à induction. La méthode proposée utilise des mesures de tension d'entrée triphasée et applique la transformée de Fortescue, combinée à des techniques d'estimation de fréquence telles que FFT et STLSP. Un nouvel indicateur de détection, le Facteur de Tension Zéro (ZVF), est introduit et validé expérimentalement sous différentes conditions de charge, démontrant sa fiabilité, sa précision et sa polyvalence dans la détection des défauts ITSC. Cette innovation offre une solution robuste et rentable pour le diagnostic des défauts en temps réel, avec un potentiel d'application industrielle plus large.

En outre, cette thèse présente l'intégration d'un Réseau de Neurones Artificiels (ANN) dans une interface LabVIEW pour la détection des défauts en temps réel et l'évaluation de l'état de santé des moteurs à induction. L'interface a été rigoureusement testée pour détecter à la fois les défauts ITSC et les conditions de Tension d'Alimentation Déséquilibrée (USV), démontrant sa capacité à identifier avec précision les défauts de gravité variable et les déséquilibres de tension. Le système fournit un retour visuel clair via des boutons codés par couleur et des graphiques en temps réel, permettant aux opérateurs de prendre des mesures correctives opportunes. L'intégration de l'ANN améliore la précision et l'efficacité de la détection des défauts, offrant une plateforme conviviale pour la surveillance et le diagnostic en temps réel.

Mots-clés : Moteurs à induction, Surveillance de l'état, Maintenance prédictive, Détection des défauts, Réseaux de neurones artificiels, LabVIEW, Facteur de Tension Zéro, Court-Circuit Inter-Spire, Tension d'Alimentation Déséquilibrée.

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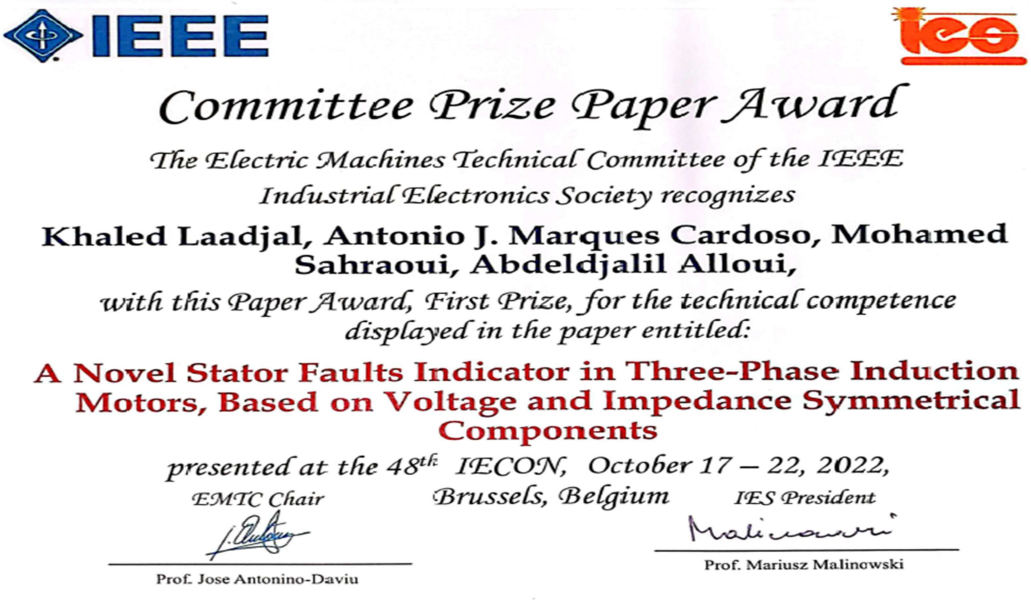

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Committee Prize Paper Award

The Electric Machines Technical Committee of the IEEE Industrial Electronics Society recognizes

Khaled Laadjal, Antonio J. Marques Cardoso, Mohamed Sahraoui, Abdeldjalil Alloui,

with this Paper Award, First Prize, for the technical competence displayed in the paper entitled:

A Novel Stator Faults Indicator in Three-Phase Induction Motors, Based on Voltage and Impedance Symmetrical Components

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AF	Activation Function
AI	Artificial Intelligence
ANN	Artificial Neural Network
ARMA	Autoregressive Moving Average
ART	Adaptive Resonance Theory
BRANN	Bidirectional Recurrent Artificial Neural Network
CBM	Condition-based monitoring
CIs	Condition Indicators
CM	Condition Monitoring
DAQ	Data Acquisition
DNNs	Deep Neural Networks
DWT	Discrete Wavelet Transform
FFT	Fast Fourier Transform
FL	Fuzzy Logic
FT	Fourier Transform
GANs	Generative Adversarial Networks
GAs	Genetic Algorithms
GUI	Graphical User Interface
HMI	Human-machine interface
IEC	International Electrotechnical Commission
IM	Induction Motors
ITSC	Inter-turn short circuit
KNN	K-Nearest Neighbors
LA	Learning Algorithm
LMA	Levenberg–Marquardt Algorithm
LSTM	Long Short-Term Memory
MCSA	Motor Current Signature Analysis
MLP	Multilayer Perceptron
MSE	Mean Squared Error
NVF	Negative Voltage Factor
PLCs	Programmable Logic Controllers
RBFNN	Radial Basis Function Neural Network
RNNs	Recurrent Neural Networks
SF	Stator faults
SOM	Self-Organizing Map

ST	Short-Time Fourier Transform
STLSP	Short Time Least Square Prony
SVM	Support Vector Machines
TBM	Time-Based Maintenance
UIs	User Interfaces
USV	Unbalanced Supply Voltage
VUF	Voltage Unbalance Factor
WT	Wavelet Transform
ZVF	Zero Voltage Factor

I

Introduction

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1.1 Context

Nowadays, diagnosis plays a crucial role in the industrial field by identifying and resolving issues in equipment, processes, and systems. It is essential for maintaining operational efficiency, reducing downtime, and minimizing costs. Through accurate diagnosis, industrial organizations can pinpoint the root causes of problems, whether they are related to machinery malfunctions, process inefficiencies, or quality defects. This enables timely repairs, adjustments, or improvements, ensuring that operations run smoothly and product quality remains high. Effective diagnosis also aids in predictive maintenance, allowing for proactive measures to prevent breakdowns and optimize equipment lifespan. Ultimately, diagnosis in the industrial field is vital for maximizing productivity, minimizing disruptions, and driving overall success.

Representing more than 85% of electric motors used in industry, three-phase induction motors (IMs) are widely used due to their reliability, convenience of design, high performance, in addition to their overloaded capacity, for different applications such as processing, manufacturing transportation, power systems, etc. Regardless of their capacity, they are evaluated as crucial movers in modern industrial facilities where the continuous functioning relies on the condition of these prime components. However, IMs are usually working under harsh electrical and mechanical operating conditions, making them vulnerable to numerous stator and/or rotor faults.

The work presented in the current thesis enters in the general context of the electrical machines fault diagnosis, selecting the field of the stator windings' faults having about 20-40 % of the general IM faults occurrence[1], [2] reaching up to 66% in the high voltage IM ranges. The inter-turn short circuit (ITSC) fault represents a big majority of the winding's faults and has been the subject of numerous research efforts, covering its origins, detection, location and effects using many approaches and different techniques.

1.2 Problematic

Based on an extensive review of literature, our research reveals that diagnosing faults in asynchronous machines typically involves monitoring specific components within the frequency spectrum of the machine's signals. The underlying philosophy of this approach assumes that each type of defect predominantly affects a particular harmonic, which serves as its distinctive signature. In real-world scenarios, it has been observed that when a machine exhibits a fault, it is typically accompanied by various intricate physical phenomena. These phenomena include heating, vibrations, and oscillations in the torque. Additionally, changes in the operating regime further amplify the impact of the fault on spectral components beyond its expected signature. As a result, maintenance operators who rely solely on checking fault signatures often find themselves facing uncertainty when trying to assess the condition of the machine. This raises doubts regarding the effectiveness of relying solely on fault signatures for diagnosis.

1.3 Objectives

The assessment of fault signatures in different signals presents a formidable and complex task for operators engaged in industrial process monitoring. This difficulty arises from the reliance on numerous interconnected physical phenomena, which adds to the challenge of accurately interpreting and analyzing the signals. Considering these challenges, and recognizing that fault diagnosis comprises four main steps, namely detection, identification or discrimination, localization and severity assessment, a decision has been made to prioritize the detection task as it is perceived to be the most crucial. By focusing primarily on fault detection, operators can swiftly determine whether a fault exists in the machine and take necessary measures to prevent further damage or plan for maintenance activities. Building upon this line of thinking, we have introduced a paradigm shift by replacing the concept of "Fault Signatures" with the concept of Condition Indicators -CIs- extracted from the induction machine's voltage signal through simple transformations and calculations.

Given the wide range of faults that can potentially impact induction motors, we concentrated on one of the most critical and significant faults concerning the stator: the Inter-turn Short Circuit (ITSC) fault. This fault has been identified as particularly dangerous and deserving of focused attention due to its potential severity and detrimental effects on the motor's performance.

The primary goal of this thesis is to design an automated monitoring system for induction motors. Aiming for the detection of the ITSC fault. This system will combine the utilization of specific condition indicators (Cis) extracted from the voltage signal of the motor with the application of an Artificial Neural Network (ANN) as a decision-making tool. Additionally, a user-friendly human-machine interface (HMI) will be developed using LabVIEW software to facilitate the interaction with the monitoring system.

CHAPTER 1

STATE OF THE ART

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2.1 Introduction

Three-phase induction Motors (IM) hold indispensable significance in today's industrial production processes. Their widespread utilization is primarily attributed to their sturdy construction, cost-effectiveness, versatility, and well-suited dimensions, making them a cornerstone of modern manufacturing practices.[3] Three-phase induction motors find extensive application in various sectors, including pumps, fans, elevators, electric vehicles, as well as steel and cement units[4]. contributing to roughly 60% of the industrial electricity consumption.[5] Despite their robust construction and reliability, these motors remain susceptible to various faults during their operation. If these faults go undetected, they have the potential to cause significant failures, even leading to machine shutdowns. Such interruptions can result in considerable economic losses in terms of raw materials and human resource. It is widely acknowledged that early detection of IM faults can effectively halt their progression, curtail their severity, and prevent unexpected downtimes. In the face of rising industrial equipment complexity, ensuring timely and accurate diagnosis to prevent defects becomes of utmost importance. Consequently, the primary goal of continuously monitoring the IM condition during operation is to analyze, detect, and prevent faults at their initial stages.[6]

Condition Monitoring (CM) for induction motors involves continuous observation or monitoring of the system's health, with the primary goal of improving productivity, efficiency, cost reduction, and machine availability. Traditionally, maintenance of induction motors has been performed at fixed intervals, but due to varying environmental and operating conditions, the motor's performance may deteriorate irregularly. To achieve higher efficiency, online monitoring of induction motors becomes essential. A critical aspect of modern approaches is predictive maintenance through CM, which aims to forecast maintenance schedules based on plant or process conditions. Condition-based monitoring (CBM) is employed to enhance the performance and efficiency of induction motors, prolong their lifespan, increase productivity, and reduce both internal and external damages. Implementing CM and fault detection for induction motors has become necessary to prevent unexpected breakdowns and minimize unscheduled downtime. An effective CM scheme is capable of providing early warning and predicting faults in their early stages, it gathers raw data from the motor using signal processing or data analysis techniques.

However, one significant drawback of these systems is human interpretation, which can be subjective and less efficient. Hence, automating the fault detection and diagnostic process represents a logical advancement in CM technologies. The development of automatic fault diagnostic systems requires intelligent techniques such as artificial intelligence (AI) methods, Genetic Algorithms (GAs), Fuzzy Logic (FL), Artificial Neural Networks (ANNs), and expert systems. These intelligent systems can improve the accuracy and efficiency of fault diagnosis, ultimately optimizing the overall condition monitoring process for induction motors.[7]

This chapter begins with an elaborate depiction of the induction motor, followed by an overview of maintenance, encompassing various types. The focus then shifts to explaining the most relevant fault types of induction motors, leading to a statistical analysis of these faults. Subsequently, a concise review of diagnosis is provided to set the stage for discussing detection schemes. Model-based methods are defined, along with approaches based on signal processing and advanced techniques like artificial intelligence.

2.2 induction motor

In the realm of electrical engineering, a system is defined as a well-defined collection of interconnected components working together. In this context, we focus on the three-phase squirrel cage asynchronous motor. The primary purpose of this motor system is to efficiently convert electrical energy into mechanical energy, achieving a specified level of performance in the process.[8][9] subsequently, we will provide comprehensive details regarding the components - Figure 2.1- and their respective functions within the three-phase squirrel-cage asynchronous motor. Although this motor is inherently intricate, it can be conceptually divided into three distinct subsystems, each serving a specific purpose.

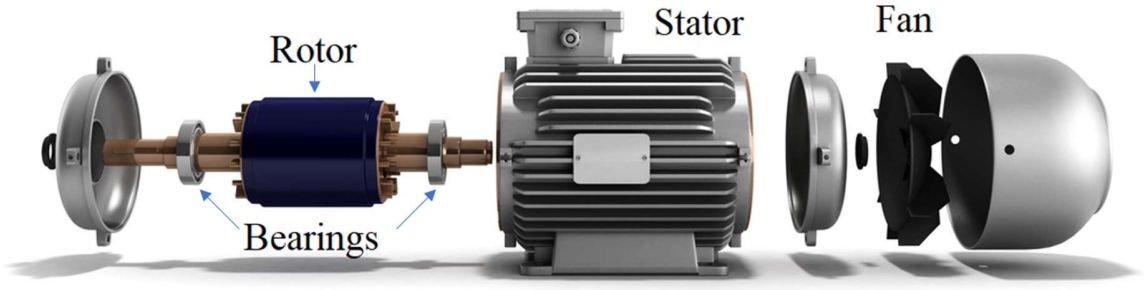


Figure 2.1: Different Parts of Induction Motor

2.2.1 Stator

The described component is a stationary part of the system, responsible for connecting the power supply. It comprises five essential elements:

- Crankcase
- Terminal box
- Magnetic circuit
- Conductors
- Insulators

These components collectively play significant roles in the motor's operation and electrical energy conversion process.

2.2.2 Rotor

The mentioned component is a rotating part that facilitates the rotation of the mechanical load. It consists of four fundamental elements:

- Magnetic circuit
- Conductors
- Shaft
- Fan

2.2.3 Bearings

The bearings are crucial mechanical components responsible for facilitating the smooth rotation of the rotor and providing support to various sub-assemblies. This essential part comprises two main components:

- Inner and outer rings
- Ball bearings

By effectively maintaining these elements, the bearings ensure the stable and reliable operation of the rotor, contributing to the overall performance of the motor.

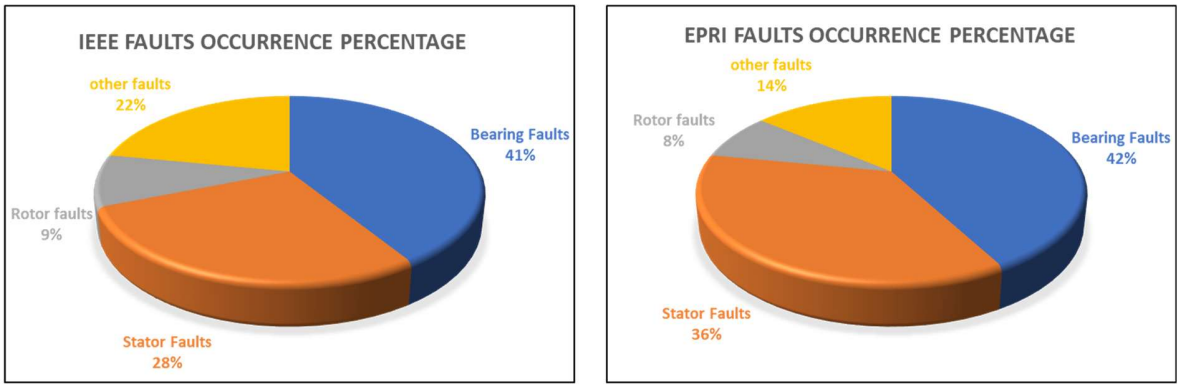
2.3 Failures in IMs

Induction motors are widely prevalent electric machines in various industries due to their cost-effectiveness, relatively compact size, durability, minimal upkeep requirements, and compatibility with readily accessible power sources. Nevertheless, they are susceptible to various fault modes that can result in malfunctions. These faults might originate from inherent issues within the machine itself or arise from operating conditions. Intrinsic defects could be attributed to mechanical or electrical forces exerted on the motor casing. Failure to identify and address a fault promptly could lead to a breakdown.

A statistical analysis of faults in the induction motor would offer a clear perspective on the distribution of fault types based on their occurrence. Table 2.1, classifies different faults types as per their percentage of occurrence[7]. Figure 2.2, provides a visual representation of the varying percentages of faults in induction motors, with bearing faults being the most frequently encountered, followed by stator faults.

Fault	Bearing faults	Stator faults	Rotor faults	Other faults
Occurrence percentage IEEE	**41%**	**28%**	**9%**	**22%**
Occurrence percentage EPRI	**42%**	**36%**	**8%**	**14%**

Table 2.1: Faults occurrence statistics [7]



a : EPRI Faults. **b : IEEE Faults statistics.**

Figure 2.2: Faults occurrence in Induction Motor.

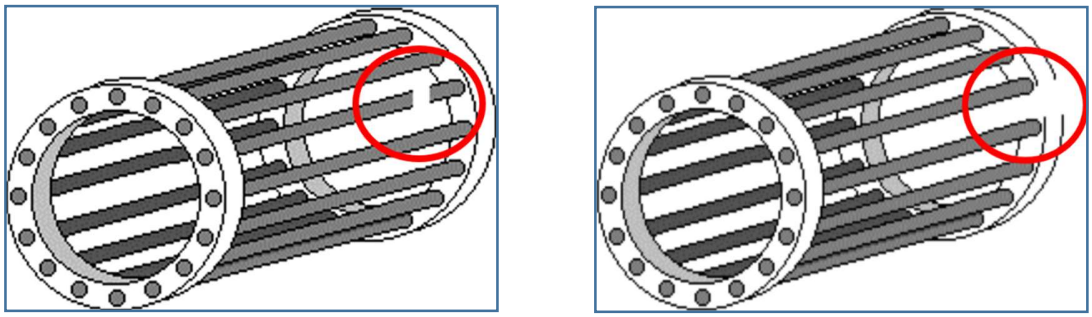
The primary faults encountered in squirrel cage induction motors can be categorized into two groups: rotor-related and stator-related faults.

2.3.1 Rotor faults

2.3.1.1 Broken bars

Bar breaks -Figure 2.3a- and sections of short-circuited rings represent prevalent issues. Detecting these malfunctions becomes challenging due to the motor's ability to continue functioning even when such faults are present (Figure 2.3b). Moreover, these faults exhibit an accumulative impact. For instance, the current that was initially intended for a broken bar gets distributed among adjacent bars. Consequently, these neighboring bars become burdened, resulting

in their eventual failure. This cycle continues until a significant number of bars fail, ultimately causing a complete machine shutdown. Furthermore, these faults introduce an imbalance in current distribution to the rotor, giving rise to pronounced fluctuations in torque and speed. These fluctuations, in turn, generate vibrations and contribute to the emergence of mechanical imperfections.



a : Bar break. **b : Short circuit ring break.**

Figure 2.3: Broken bar types in induction motor.

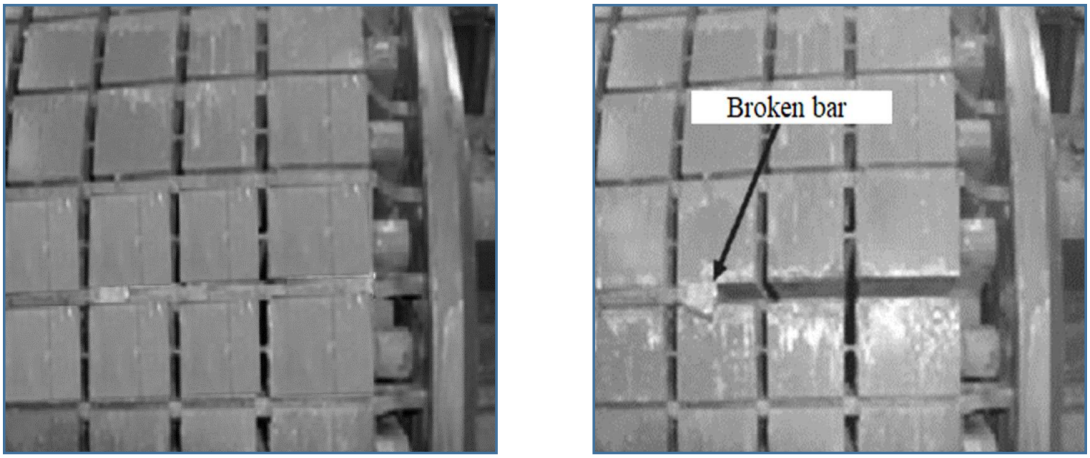


Figure 2.4: Broken bar example in induction motor.

2.3.1.2 Ball bearings fault

Ball bearings -Figure 2.5- assume a crucial function within various categories of rotating electrical apparatuses[10]. Typically, any instance of forcefully mounting ball bearings onto a shaft

could result in depressions forming on the contact surfaces, and in more severe cases, even lead to outright fractures. The axial field has the capacity to induce electric currents that circulate within the ball bearings, hastening their degradation. Furthermore, the lubricating grease essential for facilitating smooth bearing movement and rotation may, under certain circumstances, solidify and introduce resistance to the rotation process.

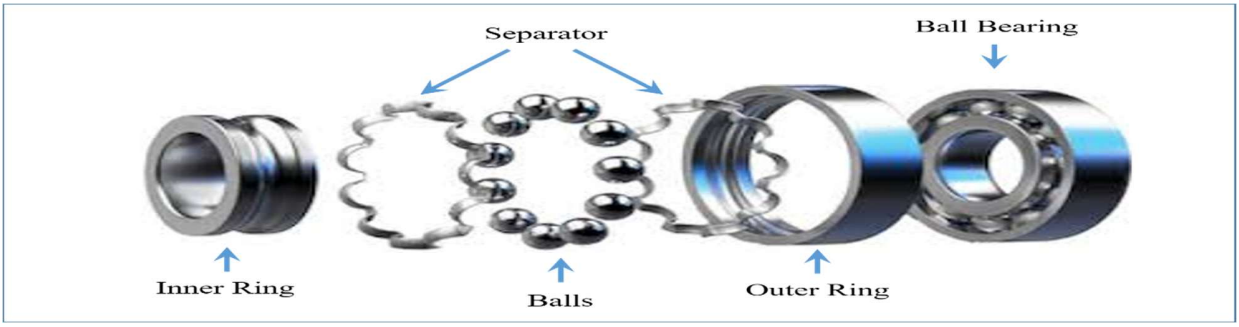


Figure 2.5: Ball bearing components.

Within the various fault categories found in a IM, approximately 52% are associated with bearing issues. Moreover, these faults frequently result in irreversible damage, leading to substantial maintenance expenses[11].

2.3.1.3 Eccentricity fault

The machine's eccentricity is a common rotor fault that arises from the unevenness of the air gap, as the machine may experience rotor displacement, leading to torque fluctuations caused by a deviation between the shaft's center of rotation and the rotor's center. This occurrence can be traced back to factors such as improper bearing placement during assembly, bearing wear and tear, load irregularities, or manufacturing imperfections in the machining process[12]. There exist three varieties of eccentricity:

2.3.1.3.a Static eccentricity fault

In this particular form of eccentricity, the location of the air gap's thinnest point remains stationary in space. This situation can arise due to the interior section of the stator having an oval shape or as a result of improper alignment between the rotor and stator during the construction process. However, if the connection between the rotor and shaft is adequately rigid, the degree of static eccentricity remains constant and does not fluctuate

2.3.1.3.b Dynamic eccentricity fault

Dynamic eccentricity manifests when the rotor's center does not align with its rotational center [13], causing the position of the minimum air gap thickness to rotate along with the rotor. The factors contributing to this form of eccentricity include shaft bending, bearing wear or misalignment, the deformation of the rotor or stator cylinder and mechanical resonance occurring at critical speeds

2.3.1.3.c Mixed eccentricity fault

The coexistence of both types -mentioned earlier- is referred to as mixed eccentricity. This condition can be attributed to a range of factors, including the ovality of the stator core, incorrect alignment between the stator and rotor during commissioning, misalignment, a bent rotor shaft, bearing wear, and mechanical resonance at critical speeds [14]

2.3.1.4 Cooling Fan fault

The cooling fan Figure 2.6 is typically situated at the non-driving end of the motor, which is the opposite side of the load, to facilitate forced cooling of both the stator and rotor[15]. Improper attachment of the fan to the shaft or the presence of multiple damaged blades causes an abnormal temperature increase in the machine [16] . It is reported that the abnormal condition of the cooling system would lead to a rapid deterioration of the stator windings.

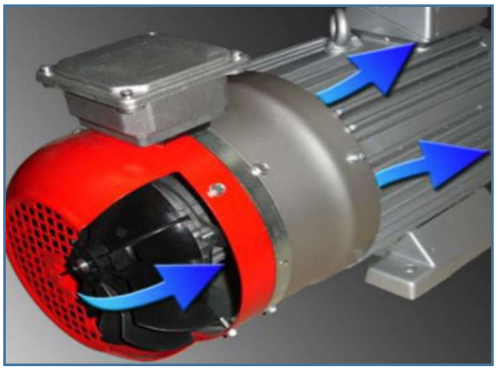


Figure 2.6: Cooling fan.

2.3.2 Stator faults

The stator comprises a laminated core, an external frame, and insulated electrical windings. These constituents endure electrical and environmental stresses, resulting in significant degradation of the stator's condition, ultimately culminating in various faults. Stator faults (SF) can be classified based on their location, encompassing issues in the stator frame, faults within the stator windings, and problems within the laminations of the stator core [17] . Stator faults predominantly involve short-circuit issues that can occur in one of three ways: between a phase and the ground, between phases, or between individual turns, as illustrated in Figure 2.7. Primarily arising from insulation breakdown in the windings, leading to localized overheating. If left unattended, this localized heating can progressively deteriorate the insulation of the stator winding Figure 2.8, potentially escalating into a catastrophic failure.

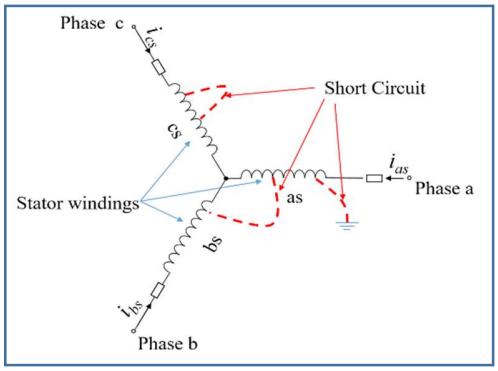


Figure 2.7: Short circuit modes.



a : winding insulation deterioration 1



b : winding insulation deterioration 2

Figure 2.8 : Short Circuit Fault results.

2.4 Maintenance

Once we have given a brief explanation of the various components of the asynchronous cage machine, we will delve into the presentation of fundamental concepts related to maintenance and diagnostic activities. In this context, we will also discuss the different faults that may occur and affect the IM.

Maintenance in modern manufacturing systems is often perceived as a repetitive set of tasks carried out in dynamic and fast-paced environments. If not executed appropriately, it can have adverse effects on production schedules, product quality, and overall competitiveness. Regrettably, the industry has sometimes viewed maintenance as a less appealing and semi-skilled profession. However, there has been a notable shift in recent years, as new maintenance concepts have emerged, integrating smart devices such as micro and nano sensors, controllers, actuators, and intelligent algorithms like Neural Networks, Fuzzy Logic, Match Matrix, Bayesian Network, and Hidden Markov Model. This transformation is a direct response to the increasing number of physical assets that operate well beyond their expected lifespan, necessitating a greater emphasis on reliability and maintainability in equipment design[18]

Maintenance practices can be broadly divided into two overarching categories: Corrective Maintenance (CM) and Preventive Maintenance (PM). Preventive Maintenance further consists of two subtypes: Time-Based Maintenance (TBM) and Condition-Based Maintenance (CBM).

2.4.1 Corrective Maintenance

Corrective Maintenance (CM) involves restoring the system to its intended functional state by repairing or replacing any failed components. However, this approach often leads to extended downtime and potential safety risks.

2.4.2 Preventive Maintenance

The objective of this maintenance type is to minimize the likelihood of failures and prevent equipment breakdowns during operation. The objectives of preventive maintenance include:

Prolonging the lifespan of equipment.

Reducing the maintenance budgets.

Recently, preventive maintenance, as mentioned earlier, underwent a structural division by introducing two subtypes, which are referred to as:

2.4.2.1 Time-Based Maintenance (TBM)

TBM is based on the system's service time and the probability distribution of its trouble-free operation period. Despite being a cautious approach, TBM may result in unnecessary maintenance activities.

2.4.2.2 Condition-Based Maintenance (CBM)

CBM relies on continuously monitoring the system's condition over time and performing maintenance only when there is clear evidence of a need for it. In modern engineering applications, CBM has gained widespread acceptance and is now the most favored maintenance strategy. [18]

2.5 Fault monitoring and diagnostics

2.5.1 Monitoring

Monitoring serves as an observant, information-driven tool that assesses the system's condition and offers informative cues. It primarily entails the detection and categorization of faults through the

continuous observation of the system's behavior. Subsequently, it engages in the diagnostic process by pinpointing the faulty components and uncovering the underlying causes of the problem. Consequently, it encompasses two primary functions, namely, detection and diagnosis.

2.5.2 Detection

To identify system failures, it is essential to differentiate between situations that are deemed normal and those considered abnormal. This classification is a non-trivial task, primarily due to the limited information typically associated with abnormal scenarios. A frequently employed simplification involves categorizing any situation outside the norm as abnormal.

2.5.3 Diagnostic

Recognizing that fault diagnosis comprises four main steps, namely detection, identification or discrimination, localization, and severity assessment. The diagnostic function aims to uncover the reasons behind a specific observation and determine the responsible components or events. Within this framework, localization involves pinpointing the malfunctioning sub-component or functional area, while identification (or discrimination) focuses on isolating the factors that have triggered the abnormal situation. Together, these steps contribute to a systematic understanding and evaluation of faults.

2.6 Methods of Diagnosing Faults in Induction Motor

Over the past few years, the literature has witnessed the emergence of numerous fault detection techniques that have garnered significant attention from researchers. These approaches have been tailored to address a wide array of issues, underscoring their importance. It is necessary

to provide a comprehensive overview of diagnostic techniques applied to induction machines, categorizing them into two primary groups: model-based approaches and model-less approach[9] [19], [20].

2.6.1 Model-free (knowledge-based) diagnostic approaches

Model-free approaches can further be categorized into two distinct families. The first family revolves around the analysis of signals (signal-based approaches) originating from sensors measuring electrical or mechanical parameters impacted by faults. The second family employs expert systems that integrate artificial intelligence methodologies[21]

2.6.1.1 Signal-based approaches

The concept of detecting faults through a signal-based approach hinges on identifying specific characteristics within the physical signals obtained from a machine in operation when faults occur. By developing signal models through analytical means or simulations, distinct patterns indicative of faults can be established. Many studies apply these principles, employing suitable signal processing techniques to extract these patterns, thereby confirming the presence of a fault in asynchronous machines. Within this framework, several methods are worth mentioning, including currents, power, torque, speed, flux, vibrations, and more.

2.6.1.1.a vibration-based diagnostics

Vibration-based fault diagnosis stands as the predominant and practical method in use. In asynchronous machines, induction motors without vibration in the operating environment are something non-existent [7], the radial forces induced by the air gap field generate vibrations. These forces are in a proportional relation to the square of the magnetic induction[22]. The distribution of magnetic induction in the air gap is a function of both the magnetomotive Force (MMF) and the permeance. To measure machine vibrations, accelerometers are strategically placed in axial, vertical, and radial orientations on the bearings housing. The spectra of vibration signals from a faulty motor are then compared to reference spectra recorded when the motor was in normal - healthy- condition. This method enables the identification of both electrical and mechanical faults

[5][23], as the Magnetomotive force encapsulates the impacts of stator or rotor asymmetries, while Permeance accounts for air gap variations caused by stator/rotor slots and/or eccentricity.

Nonetheless, while there are many limitations, the primary drawback of vibration-based monitoring lies in the expense associated with vibration sensors, which can be a limiting factor in various applications, especially when cost considerations are paramount. This limitation is particularly noticeable in smaller machinery.

2.6.1.1.b Stator current based diagnostic

- **A. Fast Fourier transform**

Numerous techniques and methodologies have been put forward for monitoring the condition of induction motors. Among these approaches, motor current signature analysis (MCSA) despite its numerous handicaps, this method stands out as one of the most popular strategies. This is largely due to its cost-effectiveness, noninvasive characteristics, and various other inherent advantages .[23]

The utilization of the fast Fourier transform (FFT) to analyze stator current signatures is regarded as a benchmark in fault diagnosis for asynchronous machines. It entails identifying faults by detecting the emergence of specific frequency components within the stator current spectrum, indicating the presence of faults. This approach is highly favored due to its simplicity, affordability, and ease of implementation. It proves effective in detecting a broad range of faults, encompassing both electrical and mechanical issues.

The Fourier transform (FT) is a mathematical operation that converts a signal from the time domain to the frequency domain, while the inverse Fourier transform does the opposite, transforming a signal from the frequency domain back to the time domain. However, the traditional FT requires a substantial number of computations, specifically 2N2, where N represents the amount of data. In contrast, the Fast Fourier Transform (FFT) achieves the same signal transformation from time domain to frequency domain and vice versa. The key distinction lies in the computational efficiency. With FFT, the number of computations needed is significantly reduced to 2N log2N. This vast difference in computational requirements compared to the traditional Fourier transform

allows FFT to perform signal transformations rapidly. Consequently, this efficiency has earned it the name "FFT" (Fast Fourier Transform).

Nevertheless, relying solely on Fourier analysis or the Short-Time Fourier Transform (ST) is insufficient when it comes to identifying low-magnitude transients, primarily due to their heightened sensitivity to abrupt changes in the signal. While the Fourier Transform (FT) excels at breaking down a signal into its constituent frequency components and is exceptionally adept at recognizing stationary signals, the S-transform provides a time-frequency representation of the signal, making it better suited for capturing high-frequency bursts. However, in the context of power systems, where the current and voltage exhibit nonstationary behavior, employing FT alone is not well-suited for the task[24].

- **B. Discrete Wavelet Transform**

The wavelet transform stands as a potent and sophisticated signal processing technique, offering valuable insights into both temporal and frequency characteristics of a signal. It achieves this by breaking down the signal into various scales, each offering a different level of resolution. This process is facilitated by modifying the time widths of these scales to match the frequencies of a fundamental waveform known as the mother wavelet. This adjustment, often referred to as dilation, ensures that wavelets with higher frequencies undergo compression, while those with lower frequencies experience stretching [4]. In contrast to the Fast Fourier Transform (FFT), the Wavelet Transform (WT) offers greater flexibility in selecting a basis function that can be tailored to suit specific fault symptoms. This adaptability proves advantageous for the extraction of distinctive fault features. Wavelet theory is rooted in the concepts of expansion and translation, making it a form of inner product transformation that effectively scrutinizes non-stationary components within a signal through the utilization of a pre-defined wavelet basis [21]. In [25]authors carried out an analysis on the stator current using the Daubechies1 wavelet through Discrete Wavelet Transform (DWT). The L2 norm of statistical parameters is calculated for both the detailed and approximate coefficients at various decomposition levels to then successfully determined the most accurate ITSC fault feature. Furthermore, (DWT) is utilized in [26]for analyzing the raw current data in the time domain, aiming to identify early-stage ITSC faults and accurately determine the quantity of shorted turns in the faulty phase. DWT technique is generally

merged with others. Authors in [27]deployed Discrete Wavelet Transform in conjunction with artificial neural network (ANN) in the aim of detecting rotor broken bars fault.

- **C. Park Transform "Park's Vector & EPVA Approaches"**

To depict the behavior of three-phase asynchronous motors, a useful approach involves employing a two-dimensional representation. One of the most recognized and fitting methods involves the computation of what are referred to as Park currents. These Park currents, denoted as id(t) and iq(t), are determined based on the phase stator currents ia(t), ib(t), and ic(t) through the Park Transform[28]. In the literature different works have used the Park transform[29], like in [30]a fault diagnosis was proposed for the open-phase problem was successfully obtained.

The Extended Park Vector Approach builds upon the traditional Park Transform by integrating additional dimensions or parameters, enabling a more thorough analysis of motor behavior. This enhanced method strengthens fault detection and diagnosis, providing deeper insights into motor performance and potential anomalies. By expanding the vector approach, it captures finer details of motor operation, allowing for more precise and timely corrective actions. Particularly valuable in complex scenarios where conventional methods may be insufficient, this approach contributes to more resilient and dependable motor control systems[31][32].

- **D. Hilbert Transform**

It is a widely recognized technique within the realm of signal processing, primarily employed to derive an analytical signal from a real signal. This method can be harnessed for fault detection by analyzing both the initial transient and steady-state current. It exhibits reduced susceptibility to variations in motor load levels compared to continuous current analysis. Moreover, it yields dependable insights from data analysis, even under conditions of minimal or no mechanical load. To enhance the effectiveness of fault detection, combining TH with other signal processing techniques is recommended. In this regard, extensive literature exists, highlighting various studies that have explored the incorporation of this approach[4].

2.6.1.1.c Voltage based diagnostics

The approach relies on leveraging the spectral characteristics of the voltage difference between the power source's neutral and the asynchronous machine's neutral. This technique has proven effective in identifying both stator faults [33]and the same technique was deployed for the rotor faults detection[34]. However, its application becomes more challenging when there is a significant distance between the machine's neutral and the source's neutral.

2.6.1.1.d Artificial intelligence diagnostics

Over the past few years, the surveillance and detection of faults in electrical machines have shifted away from conventional methods towards what are known as artificial intelligence (AI) techniques. AI proves to be a proficient approach for modeling intricate nonlinear systems, employing specific structures and rules grounded in prior knowledge of the system. It places reduced importance on the physical structure and interim outcomes of the system, focusing instead on the direct emulation of the input/output relationship. Noteworthy methods in this category include fuzzy logic and neural networks [35].

- **A. Fuzzy Logic**

The application of the fuzzy logic method for detecting faults in induction machines involves interpreting the machine's condition through linguistic parameters. These parameters serve as the primary instruments of fuzzy logic, with their values expressed as words or sentences in either a natural or artificial language. This process utilizes a systematic approach to manipulate vague and imprecise concepts. In [36] authors expressed the application of fuzzy logic (FL) as a diagnostic technique for identifying faults in induction machines enabling the monitoring of fuzzy information derived from various signals. This approach enhances the precision of assessing the engine's health by employing a multi-winding model of the induction machine to simulate broken bars during the diagnostic process. Generally artificial intelligence techniques work in hybrid modes. This scheme is described in [37] where a genetic algorithm is applied along with fuzzy logic to determine both the type and severity of the target fault.

- **B. Neural Networks**

Artificial Neural Networks (ANN) have recently attracted considerable attention in industrial applications, serving as a key tool for data processing and classification[38]. ANNs have found application in system diagnosis and have proven valuable in addressing diverse challenges in engineering and science. Particularly, in fields where conventional modeling approaches faced limitations, ANNs emerged as data-processing systems inspired by the biological neural system. When appropriately trained, ANNs could serve as predictive models for specific programs [39].in fault diagnosis neural network had gained a very important position.[40] is a work where artificial neural network was used In conjunction with current signature to diagnosis broken bars fault, furthermore, authors in [41] deployed a solution to detect and diagnose six different types of faults in an electric motor using two accelerometers measuring in two different directions basing on ANN scheme. An outlined model utilizes a multilayer neural network to replicate the current signatures linked to (ITSC) fault conditions. This model accounts for five different severities of ITSC faults and encompasses four distinct torque levels [42]. In addition to this paper, [43] and [44] show the utilization of ANN in ITSC fault detection in IMs.

2.6.2 Model based diagnostic approaches

These techniques predominantly originate from the field of automation and presuppose a priori knowledge of the system. They often involve monitoring the dynamic changes in characteristic parameters of the system under investigation. By comparing the measured parameters reflecting the system's operation with the parameters calculated by models (or estimated parameters), these methods facilitate the detection and identification of potential failures. However, these approaches rely on an understanding of the range of variation in these models and their parameters based on the operating conditions of the system[45]. These approaches refer to mathematical models of the system and parameters that characterize the physical process under investigation [4]. Nevertheless, these approaches possess limitations as obtaining a precise mathematical model for a physical system is challenging. System parameters tend to fluctuate over time, and accurately modeling fault and noise characteristics is often intricate. Consequently, there is an inherent lack of congruence between the actual system (motor) and its mathematical model,

even under fault-free conditions. These disparities pose challenges in fault detection and condition monitoring applications, potentially leading to erroneous or overlooked alarms [46].

2.7 Conclusion

This chapter highlights the essential role of induction motors in contemporary industrial operations, emphasizing their durability, affordability, and adaptability. These motors are vital across numerous industries, ranging from pumps and fans to electric vehicles and heavy sectors like steel and cement. However, their vulnerability to faults, including bearing, stator, and rotor problems, demands meticulous condition monitoring and maintenance protocols. Traditional scheduled maintenance is increasingly being replaced by more effective predictive maintenance methods, which utilize continuous monitoring and smart diagnostic systems.

Condition Monitoring stands out as a crucial method for boosting productivity, efficiency, and equipment uptime. By continuously assessing the system's condition, CM facilitates the early identification and prevention of faults, thereby reducing unexpected downtimes and financial losses. The incorporation of artificial intelligence and sophisticated signal processing methods, such as Fast Fourier Transform and Discrete Wavelet Transform, has markedly enhanced the precision and effectiveness of fault diagnosis. These intelligent systems automate the fault detection process, minimizing the need for subjective human analysis and improving overall condition monitoring.

Furthermore, this chapter underscores the significance of preventive maintenance, especially Condition-Based Maintenance, which is performed only when there is clear evidence of a need. This strategy not only extends the lifespan of equipment but also lowers maintenance costs. In contrast, model-based diagnostic methods, although useful, encounter difficulties due to the intricacies of developing accurate mathematical models of physical systems.

Effective management of induction motors through advanced condition monitoring and maintenance practices is vital for ensuring the reliability and longevity of industrial equipment. Embracing intelligent diagnostic systems and predictive maintenance strategies signifies a logical progression in CM technologies, ultimately enhancing the overall condition monitoring process for induction motors.

CHAPTER 2

INTER-TURN SHORT CIRCUIT ITSC FAULT DETECTION

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3.1 Introduction

In the contemporary industrial landscape, over 85% of electric motors utilized are three-phase induction motors (IMs)[47]. Their widespread adoption can be attributed to their dependability, design convenience, high performance, and ample capacity for various applications, such as manufacturing, processing, power systems, and transportation. These IMs play a pivotal role in modern industrial sectors, where uninterrupted operation hinges on the health of these primary movers. Despite their significance, IMs often operate in demanding mechanical and electrical conditions, rendering them susceptible to numerous stator and/or rotor faults.

Numerous research papers highlight that stator windings' faults are the most prevalent cause of breakdown in electrical machines. Specifically, this type of fault accounts for 20% to 40% of faults in induction machines[48], [49], with the rate escalating to 66% for high voltage motors[50]. A major contributor to stator faults is the occurrence of Inter-Turn Short-Circuit (ITSC) faults, known for their critical and hazardous consequences. Typically, an ITSC fault commences as an inconspicuous electrical contact between two turns, resulting from localized insulation degradation due to a combination of thermal, electrical, mechanical, and environmental stresses. This triggers a high current in the affected turns, leading to a significant temperature rise in the region (hot spot). Rapid additional insulation failures ensue, ultimately culminating in a complete stator winding failure. The time elapsed from the initial fault stage to total machine damage is crucial, representing the maximum lead time available to avert catastrophic failure[51],[52]. However, determining this timeframe accurately remains a contentious issue, with conflicting evaluations in various studies[53],[54].

This challenge has prompted extensive research, yielding diverse results that suggest the evolution of the ITSC fault is influenced by various parameters, with durations ranging from seconds to days[53]. Failure to take corrective action at the right time can result in severe damage to the motor and associated equipment, leading to unexpected industrial process shutdowns and substantial economic losses. To mitigate such issues, the adoption of reliable condition monitoring methods is imperative. Generally, the condition monitoring function encompasses a robust fault detection algorithm that facilitates swift identification of defects or undesirable changes in system performance before a complete failure occurs.

3.2 Short Circuit Fault

Primarily, short-circuit faults constitute the predominant category of stator faults, these faults initiate with a short circuit between turns and progress towards more severe issues. A key factor contributing to these defects is the degradation of the insulating material that covers the windings. This deterioration primarily results from abnormal heating within the winding. The current flowing through the short-circuited turns reaches significant values, leading to a subsequent increase in temperature, ultimately causing the destruction of all insulators and resulting in complete engine failure.

The short circuit fault encompasses different types (Figure 3.1) according to the two ends of the short:

- Phase to phase short circuit.
- Winding to case (ground) short circuit.
- Inter-turn short circuit.

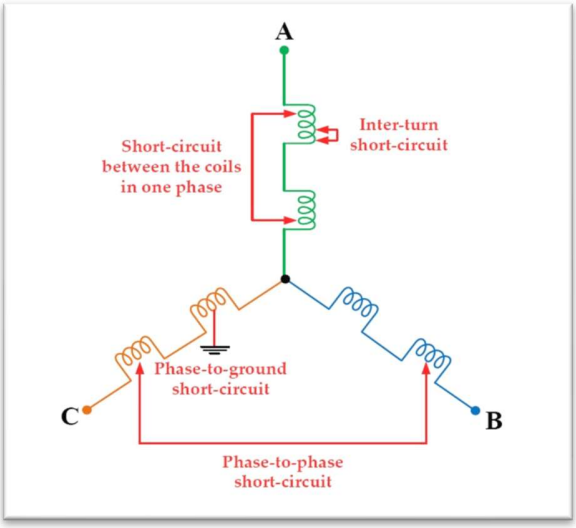

Figure 3.1: Different short-circuit modes.

3.2.1 Phase-to-phase short-circuit

A machine experiences an abrupt halt when there is a short-circuit between phases. Conversely, a short-circuit in the winding, either close to the neutral point or between turns, lacks

the immediate severity of causing a sudden stop. Instead, it induces a phase imbalance, directly affecting the torque.

3.2.2 Winding-to-case short-circuit

The frame is typically connected to the ground. When the case lacks significance in terms of security, it generates capacitive effects. In the event of a short-circuit, the frame adopts the potential of the winding. This poses an unforeseen safety risk, making protective devices, such as security circuit breakers, essential for personal safety.

3.2.3 inter-turn short circuit (ITSC)

A short-circuit occurring between turns of the same phase leads to heightened stator currents in the affected phase and a slight amplitude variation in the other phases. This alteration in amplitude affects the power factor and magnifies currents in the rotor circuit, resulting in an elevation of temperature at the winding level. Consequently, this accelerated heat can lead to the degradation of insulators, potentially causing a subsequent short-circuit. Additionally, it is important to consider that turns in a short-circuit produce a resistive torque due to the induced currents from the circulating excitation flow and the mutual inductances of the operating machine.

3.3 ITSC fault indicators

The significance of the ITSC fault detection process arises from the critical nature of this fault. To ensure effective detection - as discussed in earlier chapters - numerous techniques and schemes have been implemented. Among the most robust and commonly employed methods is the utilization of Fault Indicators (FI).

A condition indicator refers to a characteristic of system data that exhibits predictable changes as the system deteriorates or operates under varying operational modes. These indicators serve to differentiate between normal and faulty operation. They encompass a wide range of features, from basic analyses like the mean value of data over time to more intricate signal analyses, such as the magnitudes of specific components within a signal spectrum.

In contemporary literature, there is a noticeable rise in the utilization of fault indicators for machine diagnosis. Authors are exploring diverse criteria for this purpose. For example, in [55], the authors rely on the Discrete Wavelet Energy Ratio (DWER) of three stator currents, while in [56], statistical indicators are employed for detecting faults in machine windings. An instance of such a statistical indicator, as discussed in[57], involves utilizing the ratio of the third harmonic to the fundamental Fast Fourier Transform (FFT) magnitude component of the three-phase stator line currents and supply voltage to identify Inter-Turn Short Circuit (ITSC) faults. Numerous other studies have also experimented with different indicators to enhance and streamline the fault detection process.

3.3.1 Indicators choice and extraction

3.3.1.1 Indicator choice

Given that an Inter-Turn Short Circuit (ITSC) fault disrupts the balance in both stator voltages and currents, The Voltage Unbalance Factor (VUF), as defined by the International Electrotechnical Commission (IEC), offers a valuable metric for assessing voltage imbalances in power supply networks, as evidenced in previous studies[58] [59] [60]. Drawing inspiration from the VUF, this paper introduces the Zero Voltage Factor (ZVF) as an indicator for detecting ITSC faults, representing the ratio of the zero to the positive voltage symmetrical components.

3.3.1.2 Indicator extraction

A signal-based condition indicator is a quantity that can be extracted using any type of signal processing, including time-domain, frequency-domain, and time-frequency analysis. As illustrated in Figure 3.2, the extraction of the proposed indicator is performed in real-time through simple measurements of the stator's three-phase voltages. Each of the voltage signals are then analyzed using an amplitude and phase analyzing technique either is the (Short Time Fast Fourier Transform) STFFT or the (short time least square Prony) STLSP technique to estimate and track amplitudes and phase angles of the fundamental component. After that, the Fortescue Transform will be

applied to compute the required positive - and zero-sequences, which will be used to generate ZVF.

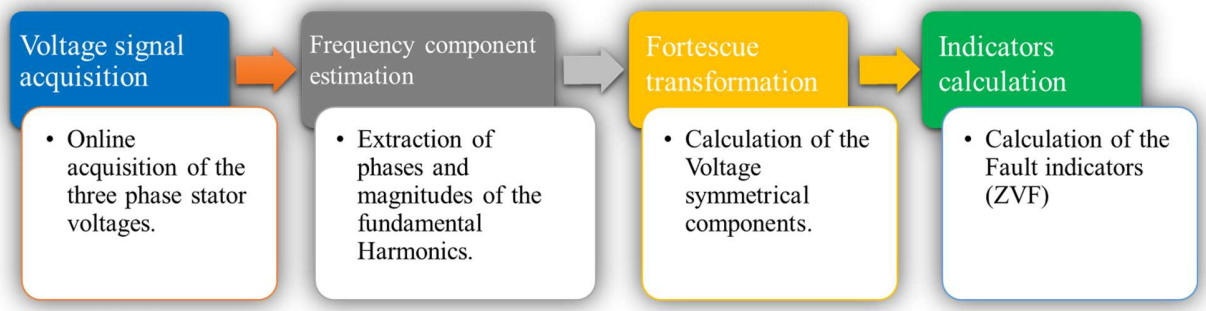

Figure 3.2: Description of the proposed method indicator extraction

a. Fundamental component estimation:

Analyzing the frequency domain signals are very important as they are rich in information, specialists consider the temporal evolution and spectral content of these signals vital for detecting anomalies that affect the proper functioning of machines [61]. One of the most basic tools in spectral components determination is the Fourier Transform or Fast Fourier Transform (FFT) as well as its discrete mode (DFFT).

- **a.1 Fast Fourier Transform (FFT):**

The conventional FFT spectral estimation is based on a Fourier-series model of the data, assuming the process comprises harmonically related sinusoids. This method is computationally efficient and provides reasonable results for many signal processes. However, it has inherent performance limitations, the most significant being frequency resolution, or the ability to distinguish between the spectral responses of multiple signals. Because of assumptions like zero data or repetitive data outside the observation period, the estimated spectrum can appear as a blurred representation of the true spectrum [62].

- **a.2 Short-Time Least Square Prony's method (STLSP):**

Furthermore, the Prony method was as well utilized to estimate both the magnitude and phase of the fundamental spectral component, The Prony method is a technique used to model sampled data by representing it as a linear combination of exponentials. This method is closely related to the least squares linear prediction algorithms utilized for estimating parameters in autoregressive (AR) and autoregressive moving average (ARMA) models Improved Prony algorithms as well are used for spectral components estimation as in[63].

At first, using the sampled data, Prony's method creates a linear difference equation with constant coefficients (with a0=1).

$$\sum_{k=0}^{P} a_k x[n-k] = 0 \tag{1}$$

The linear difference equation (13) can be expressed in matrix form as follows:

$$\begin{bmatrix} x[P] & \cdots & x[1] \\ \vdots & \ddots & \vdots \\ x[N-1] & \cdots & x[N-P] \end{bmatrix} \begin{bmatrix} a_1 \\ \vdots \\ a_P \end{bmatrix} = - \begin{bmatrix} x(P+1) \\ \vdots \\ x(N) \end{bmatrix} \tag{2}$$

Later on, by solving equation (1) the unknown parameters ak that fit the observed data can be determined. After that, a characteristic zk root polynomial is formed using the linear prediction, following the below formula:

$$F(z) = \sum_{k=0}^{P} a_k z^{P-k} \tag{3}$$

Using the roots z_k, P linear system matrices can be written as follows:

$$Z.H = C \tag{4}$$

$$\text{with} \quad z = \begin{bmatrix} 1 & \dots & 1 \\ Z_1 & \dots & Z_p \\ \vdots & \dots & \vdots \\ Z_1^{N-1} & \dots & Z_p^{N-1} \end{bmatrix}, \quad H = \begin{bmatrix} h_1 \\ \vdots \\ h_P \end{bmatrix} \text{ and } C = \begin{bmatrix} x(1) \\ \vdots \\ x(N) \end{bmatrix} \tag{4}$$

Determining the complex variable hk by solving equation (4) allows completing the equations needed to deduce the amplitude Ak, frequency fk, phase angle φk and damping factor α_k, using the following expressions:

$$\begin{cases} A_k = |h_k| \\ f_k = \frac{1}{2\pi T_s} tan^{-1}\left[\frac{Im(z_k)}{Re(z_k)}\right] \\ \varphi_k = tan^{-1}\left[\frac{Im(h_k)}{Re(h_k)}\right] \\ \alpha_k = \frac{Ln|z_k|}{T_s} \end{cases} \tag{5}$$

- **a.3 Online estimation (Sliding Window):**

In order to assure an online estimation aspect, the use of a sliding window give an important opportunity, Figure 3.3 depicts the principle of sliding window, using this method, a very short time window of the three-phase line-to-neutral voltages is acquired and analyzed permanently by the one of the predefined algorithms to estimate the required quantities.

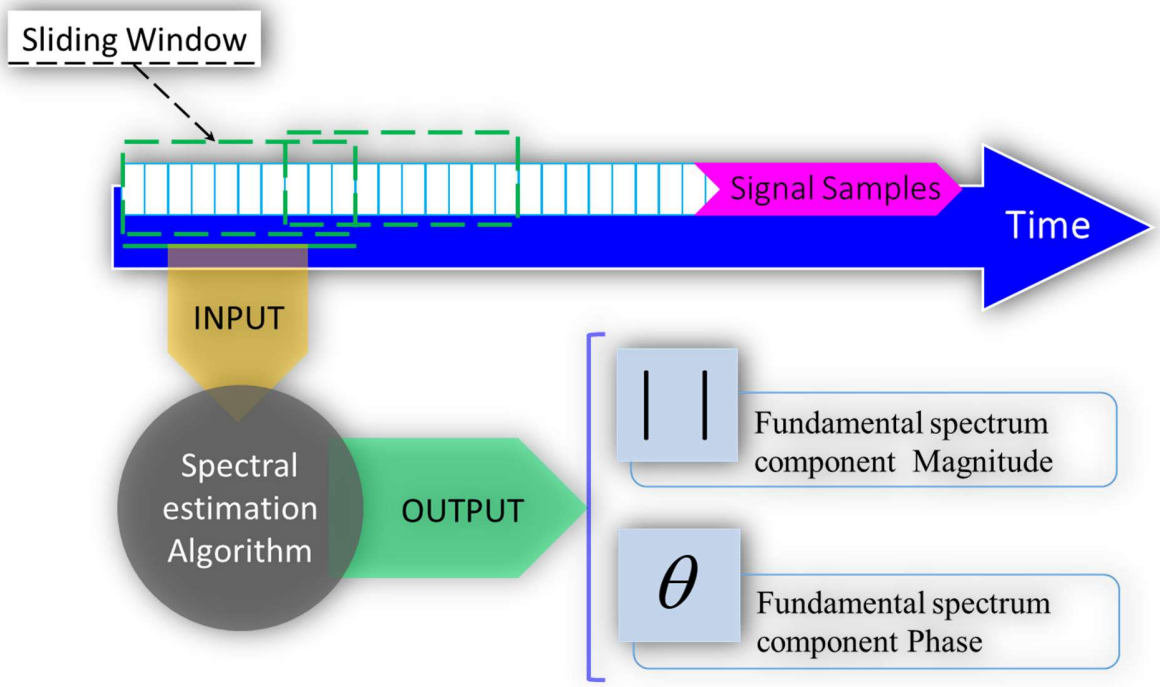

Figure 3.3: Description of the proposed method indicator extraction.

b. Symmetrical Components (Fortescue Transform)

In 1918, C. L. Fortescue introduced his inaugural mathematical approach tailored for polyphase networks [64]. This technique subsequently found application across diverse disciplines, emerging as a benchmark in numerous studies and theoretical frameworks. One of the paramount applications of this ingenious method lies in determining the symmetrical components of any three-phase power supply voltage, encompassing positive, negative, and zero components. Below is a concise overview of how the method is applied.

Let v_a, v_b and v_c be a set of balanced line-to-neutral stator voltages. For healthy IM, their expressions can be written as:

$$\begin{cases} v_a(t) = V_m \sin(\omega_s t) \\ v_b(t) = V_m \sin(\omega_s t - {}^{2\pi}/_{3}) \\ v_c(t) = V_m \sin(\omega_s t - {}^{4\pi}/_{3}) \end{cases} \quad (6)$$

The Positive, Negative and Zero-sequence components can be obtained using Fortescue Transform, as follows:

$$\begin{bmatrix} V_+ \\ V_- \\ V_o \end{bmatrix} = \frac{1}{3} \begin{bmatrix} 1 & a & a^2 \\ 1 & a^2 & a \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix} \quad (7)$$

where : $a = e^{j{}^{2\pi}/_{3}}$

- **b.1 Application of the Fortescue transform**

For the case of three phase IM balanced and healthy situation, only positive-sequence voltage exists, the other symmetrical components (negative- and zero-sequences) remain zero [65]. Thus:

$$|V_+| = V_m \quad (8)$$

In our application, the selection fell at the zero-voltage factor, consequently, the Zero Voltage Factor (ZVF), which is given by Eq. 4, will be equal to zero for healthy motors.

$$\text{ZVF} = \frac{|V_0|}{|V_+|} \quad (9)$$

ZVF holds significant value when the motor is in an unstable condition. By closely monitoring this factor, we can assess its effectiveness as an indicator for the target fault (ITSC). To achieve this, a specific experimental setup was implemented.

c. Experimental Setup

The proposed ITSC fault indicator Zero Voltage Factor (ZVF), will be analyzed under various motor operating conditions. The experimental setup includes a three-phase Y-connected squirrel-cage induction motor (Table 3.1), powered by a balanced three-phase 50 Hz sinusoidal voltage supply. The mechanical load is composed of a three-phase synchronous generator that supplies power to a variable resistor bank, (Figure 3.4).

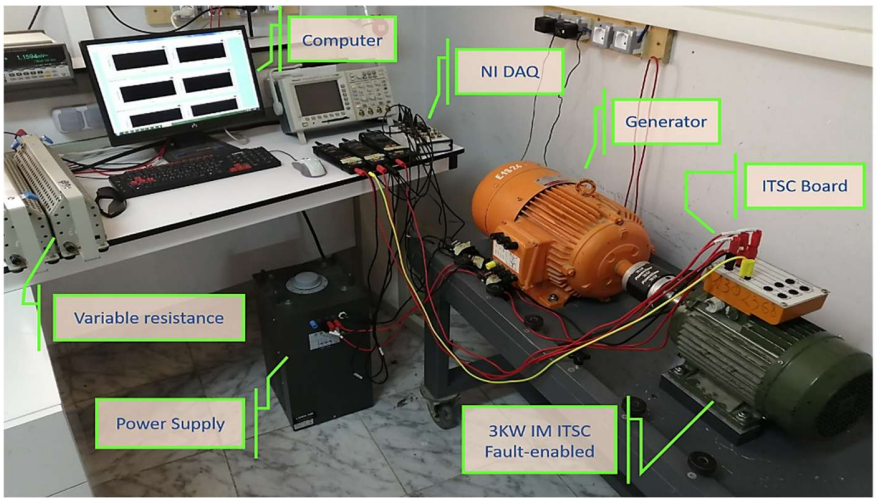

Figure 3.4: General view of the experimental test bench.

Parameter	Value	Unit
Number of poles	4	/
Rated Power	3	kW
Rated Voltage	400	V
Rated current	6	A
Rated Frequency	50	Hz
Rated Speed	1450	rpm

Table 3.1: IM Parameters.

The stator windings of the induction motor were modified by adding tap connections to the stator coils. The opposite ends of these external wires are connected to the motor terminal box, enabling the simulation of ITSC faults with varying severities in any stator phase (Figure 3.5).



Figure 3.5: Induction motor's modified terminal box with ITSC fault.

The chosen fault severities involve 3 and 6 turns, corresponding to 1.5% and 3% of the total number of turns, respectively. These two levels of ITSC faults are accessible on the board via

internal winding connections. Fault activation at any severity level is controlled by a dedicated switch. Figure 3.5 provides an overview of the ITSC fault activation scheme.

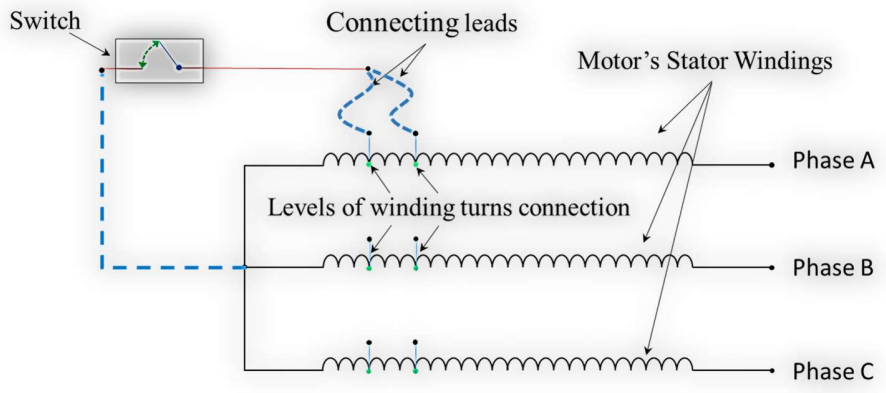

Figure 3.5: ITSC fault-enabling scheme.

For online implementation of the proposed method, the algorithm that generates the Zero Voltage Factor (ZVF) was developed using the STLSP/FFT method in Matlab. It was then integrated into LabVIEW through the Matlab script code. Other steps of the techniques, including filtering, down-sampling, and/or offset removal, were performed directly using LabVIEW palettes. The three-phase voltage signals and line stator currents of the induction motor were acquired and sampled at 10 kHz using an NI 6036-E Series data acquisition card. These processes are carried out continuously, enabling effective online monitoring and tracking of the ZVF's time evolution, along with other motor parameters such as voltages, currents, impedances, and voltage symmetrical components.

d. Online ITSC fault detection under Unbalance condition

The experimental study is conducted based on four evaluation criteria: sensitivity to a minor ITSC fault, sensitivity to varying fault severities, robustness against load variations, and robustness against other operating conditions with similar effects, specifically unbalanced supply voltage conditions.

- **d.1 Sensitivity to a Minor ITSC Fault**

The induction motor was first started with a balanced supply voltage and no load. The acquisition of three-phase voltage and current signals started when the motor was running in good condition. A few seconds later, three turns of the stator phase *a* stator were suddenly short-circuited. Thanks to the implemented algorithm, the temporal evolution of the proposed indicator (ZVF) is illustrated in (Figure 3.6).

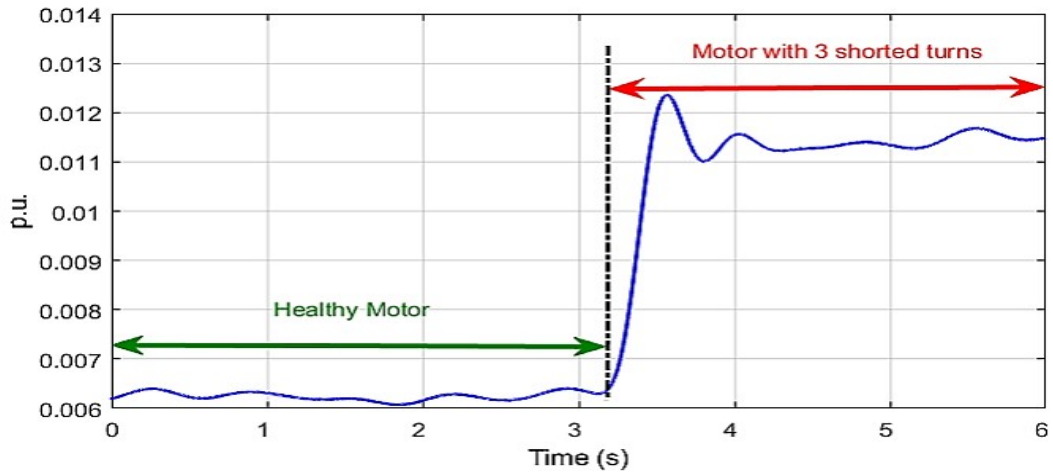

Figure 3.6: ZVF evolution for an IM in healthy state, and then and with three shorted turns.

As can be seen, this curve provides a clear physical interpretation of the ITSC fault. In healthy mode, the ZVF presents stable values with low amplitudes (due to intrinsic motor asymmetries), then it increases significantly when a minor ITSC fault is introduced, which confirms previous mathematical predictions. Indeed, Figure 3.6 shows that the ZVF rises quickly (in less than 0.4 s) from 0.0061 p.u. to 0.0114 p.u., an increase of 86.8%. This result clearly demonstrates that the fault

indicator reacts predictably and meaningfully to the occurrence of an ITSC fault, which is very useful for detecting minor stator faults.

- **d.2 Sensitivity to different fault severities**

The ITSC fault can manifest at various levels of severity, making it essential to test the stability and responsiveness of the proposed indicator to different fault intensities. The experimental approach involves starting the induction motor under healthy, no-load conditions. After a few seconds, ITSC faults of increasing severity are introduced by shorting three stator turns in phase-a, followed by six turns. The test concludes by gradually reducing the fault severity, eventually restoring the motor to its healthy state. Throughout these sequential tests, the Zero Voltage Factor (ZVF) is calculated and monitored in real time. The resulting curve is shown in Figure 3.7, and Table 3.2 provides a quantitative assessment of the indicator, measuring its change relative to the number of shorted turns. As observed, the ZVF remains stable with small amplitudes during the motor's healthy operation. However, the introduction of three and then six shorted turns triggers immediate responses in the ZVF. Specifically, the indicator rises significantly from 0.0061 to 0.0114 and then to 0.0191, representing increases of 86.8% and 213%, respectively. This demonstrates the ZVF's clear tracking ability, with its amplitude increasing in direct correlation with the severity of the fault.

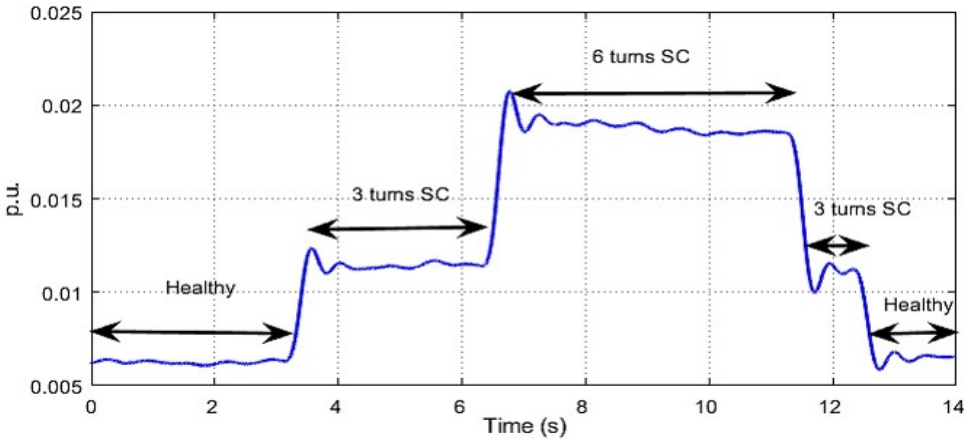

Figure 3.7: ZVF response for different severities of ITSC faults.

Furthermore, Figure 3.7 shows that by reducing the fault level by three turns, the ZVF returns almost to the same values as before. This result is significant because it demonstrates the reliability of the proposed indicator, not only to detect an incipient ITSC fault, but also to assess the severity of the fault.

Healthy state	Faulty state	Values	Variation (%)
0.0061	3 shorted turns	0.0114	+86.8 %
	6 shorted turns	0.0191	+213 %

Table 3.2: ZVF response for different severities of ITSC faults.

- **d.3 Robustness against load variation**

The previous tests were conducted without any mechanical load. However, in real-world applications, the motor load can fluctuate gradually or change suddenly at any moment. These changes can directly affect motor parameters such as voltages and currents, and potentially influence the proposed fault indicator. To ensure reliability, a fault indicator must demonstrate insensitivity to load variations. To assess this, several experimental tests were performed to analyze the behavior of the ZVF when subjected to random step load changes.

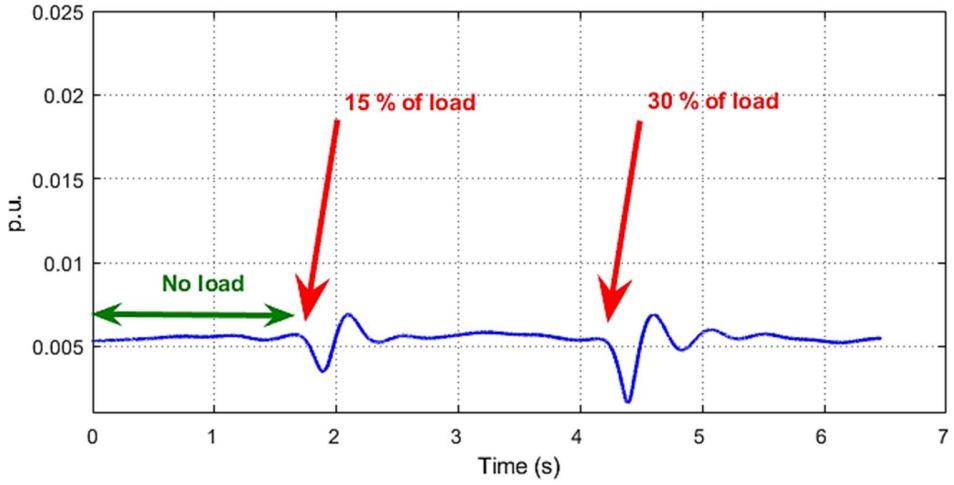

Figure 3.8: ZVF response for different severities of ITSC faults

The resulting curve of ZVF's time evolution is shown in Figure 3.8. As observed, the motor load variations have no significant impact on the proposed fault indicator, confirming its robustness against load fluctuations.

- **d.4 Robustness against unbalanced supply voltage**

It has been reported that 98% of generated electricity experiences less than 3% voltage unbalance [66], [67]. Typically, an Unbalanced Supply Voltage (USV) leads to unbalanced line currents, increased losses, and excessive heating, which can diminish motor performance and shorten its lifespan. Similarly, the occurrence of an ITSC fault in induction motors creates an imbalance in supply voltages, stator currents, and stator winding impedances. Consequently, an ITSC fault shares many symptoms with USV, making it challenging to distinguish between the two. Therefore, it is crucial to study the behavior of the proposed fault indicator under USV conditions, as the reliability of any fault indicator also depends on its robustness against other faults with similar symptoms.

To address this, one more experimental test was conducted. The test involved initially running the healthy induction motor with balanced supply voltages. After a few seconds, a 3% USV was introduced. During the test, the ZVF was continuously monitored, and the resulting curve is presented in Figure 3.9.

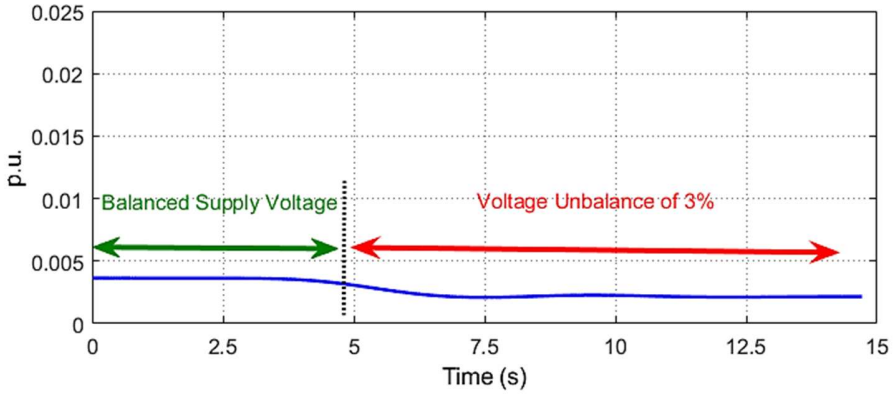

Figure 3.9: ZVF reaction under USV condition.

Despite the high level of applied voltage unbalance (3%), Figure 3.9 clearly indicates that the ZVF remains virtually unaffected by the presence of this USV. This confirms the ZVF's strong resilience to USV conditions, allowing for easy differentiation between an ITSC fault and a USV condition. in addition to the previously described experiment, the ZVF was further evaluated under various unbalanced supply voltage levels, starting from the healthy state, increasing up to 4% USV, and then returning to the healthy condition. The response of the proposed indicator is shown in Figure 3.10. Once again, the ZVF demonstrated its insensitivity to the USV fault, remaining nearly constant throughout the entire testing process.

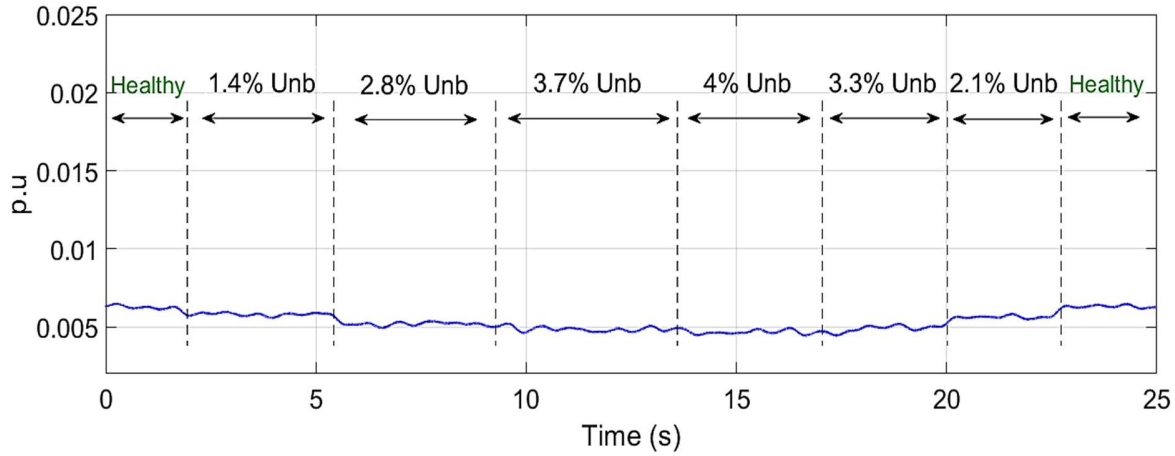

Figure 3.10: ZVF response to varying USV levels

To further demonstrate the effectiveness of the ZVF in reliably detecting ITSC faults under complex operating conditions, an additional experimental scenario was conducted. This scenario involved seven successive tests, outlined as follows:

1. Starting the motor in a healthy state with balanced supply and no load.
2. Increasing the motor load by 30%, while maintaining a healthy state with balanced supply.
3. Returning to no-load operation.
4. Introducing a 3% USV in phase "a" while keeping the motor in a healthy state.
5. Shorting six turns in phase "a" under the 3% USV.
6. Removing the USV, with the motor still operating with the ITSC fault.
7. Elimination of the ITSC fault and returning to the healthy conditions.

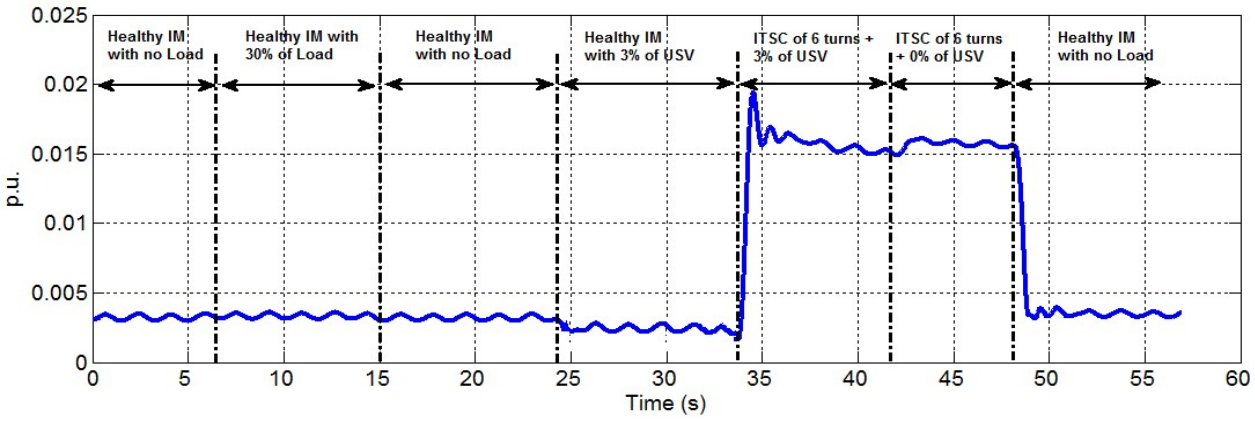

Figure 3.11 Time evolution of the ZVF under complex test scenarios.

During these tests, only the three-phase voltages were sampled and processed by the proposed algorithm, enabling real-time calculation and continuous display of the ZVF, as shown in Figure 3.11, Throughout the first four tests, the ZVF remained nearly constant, with a small amplitude of around 0.00248 p.u., clearly indicating that the ZVF shows no significant reaction to load variations or USV conditions. However, Figure 3.11 also demonstrates a rapid and substantial increase in the ZVF immediately after shorting six turns, reaching 0.0164 p.u. Notably, during this fifth test, the IM was subjected to a 3% USV, and when the USV condition was removed in the sixth test, the ZVF remained at a similar level, confirming that the ZVF is sensitive only to the ITSC fault. Furthermore, when the ITSC fault was eliminated, the ZVF quickly dropped back to its initial value, indicating that the IM had returned to its healthy state.

When it comes to reliability and accuracy, these two characteristics are crucial for any quantitative research. Reliability indicates how consistently the ZVF measures the severity of the fault. This can be validated using a test-retest approach, meaning the method should be subjected to repeated tests at different times, under identical conditions with the same motor, and yield consistent results. If not, the method may be considered unreliable and inaccurate. In fact, all the aforementioned tests were conducted experimentally and in real-time, meaning they were continuously repeated several times. The results obtained were nearly identical to those theoretically expected, confirming the method's reliability and accuracy.

3.4 Conclusion

In this chapter, a description of the ITSC fault was provided, followed by the introduction of a detailed description of a new real-time scheme for ITSC faults diagnosis. Based only on the three-phase input voltages measurement using terminal voltage sensors which are cheap and always available, and applying the Fortescue transform, the proposed strategy uses different frequency estimation methods (FFT, STLSP, …). Furthermore, a novel detection indicator was illustrated in this chapter as well, called the Zero Voltage Factor (ZVF). A thorough explanation of the extraction process for this indicator was given.

The behavior of the proposed indicator has been experimentally studied and then validated on a specialized lab bench to ensure its robustness under varying loads and conditions, as well as to test its response to a similar operating condition with shared symptoms. The ZVF indicator was further confirmed through a specific testing scenario that included similar operating condition and variable load conditions. The capabilities for the online calculation and the continuous displaying of the ZVF have been effectively demonstrated.

This testing process demonstrated the ZVF's reliability, accuracy and the versatility in detecting the target fault (ITSC), and highlighted its potential for broader application and further exploration

CHAPTER 3

AUTOMATIC ONLINE ITSC FAULT DETECTION INTERFACE USING AI

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Artificial Neural Network (ANN) For ITSC and USV fault detection 69

LabVIEW Monitoring interface 95

Conclusion 109

4.1 Introduction

Induction motors play a vital role in various industrial applications due to their reliability, efficiency, and cost-effectiveness. Despite their durability, these motors are susceptible to electrical faults, with one of the most common and harmful being the inter-turn short-circuit (ITSC) fault. This fault occurs when the insulation between turns in a motor winding deteriorates, causing an unintended short circuit. If not identified promptly, ITSC faults can severely damage the motor, shortening its lifespan, raising maintenance expenses, and potentially leading to unplanned downtime in industrial operations.

Traditional fault detection techniques, such as periodic inspections and offline testing, often struggle to identify ITSC faults in their early stages. These methods are typically labor-intensive, time-consuming, and may fail to detect intermittent or gradually developing faults. As industries increasingly adopt smarter automated systems, there is a growing demand for real-time, online monitoring solutions that continuously track motor performance and detect faults as soon as they emerge.

Recent advances in artificial intelligence (AI), particularly in machine learning and neural networks, have created new opportunities for improving fault detection in electric motors. AI techniques, especially artificial neural networks (ANNs), have shown significant promise in analyzing large datasets and recognizing patterns indicative of faults. By training ANNs on historical data, they can detect subtle signs of developing ITSC faults, providing early warnings and enabling timely interventions before serious damage occurs.

This chapter introduces an innovative online interface for detecting ITSC faults as well as distinguishing it from Unbalanced Supply Voltage (USV) problem in induction motors, using both, Indicators and AI to offer real-time monitoring and fault diagnosis. The proposed system employs an ANN-based model to detect ITSC faults by analyzing the online behavior of the two proposed faults indicators Zero Voltage Factor (ZVF) for the ITSC fault in addition to the Negative Voltage Factor (NVF) as an indicator for the USV condition, which are continuously monitored during operation. This AI-driven approach enables early fault detection, giving operators crucial insights and facilitating proactive maintenance strategies.

In addition to AI-based fault detection, the system includes a user-friendly interface, developed using the LabVIEW platform. This interface allows operators to monitor motor performance, receive real-time fault alerts, as well as detailed information regarding fault severity. By combining AI with an intuitive interface, the system enhances both the accuracy of fault detection and ease of use, making it highly suitable for industrial applications.

4.2 Artificial intelligence for fault detection

Conventional methods of fault detection in induction motors typically involve offline testing, periodic inspections, or condition monitoring techniques. These methods, while somewhat effective, are usually reactive and can miss early-stage or transient faults. Offline testing, such as insulation resistance, requires motor downtime, which can be costly in continuous operation environments. Periodic inspections also risk missing faults that develop between inspection intervals. Condition monitoring techniques, such as motor current signature analysis (MCSA), are widely used but often require complex signal processing algorithms and expert interpretation. Furthermore, these traditional methods can be labor-intensive, time-consuming, and ineffective at detecting evolving faults. As the industrial landscape moves toward automation and Industry 4.0 [68], there is a growing demand for intelligent systems that can continuously monitor motor performance, detect faults in real-time, and provide actionable insights. This is where AI plays a critical role, enabling smarter, more efficient fault detection that minimizes downtime and maintenance costs. Recently, various types of artificial intelligence have emerged in the literature, creating opportunities for evaluation and development. AI approaches are generally divided into machine learning, deep learning, and hybrid solutions, each contributing to the ongoing advancement of the field:

4.2.1 Machine Learning for fault detection

Machine learning plays a crucial role in fault detection, providing precise and efficient methods applicable across many sectors. Algorithms such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Artificial Neural Networks (ANN) are frequently employed to detect and classify faults from sensor data, enhancing maintenance and system dependability.

4.2.1.1 Support Vector Machines (SVMs)

Support Vector Machines (SVM) are commonly used in detecting faults in induction motors because of their efficiency in distinguishing motor conditions. SVM identifies the best hyperplane to separate normal and faulty motor states using features like current, voltage, or vibration signals. After being trained on labeled data, SVM can categorize different fault types, such as rotor imbalances or inter-turn short circuits. Its capability to process complex, high-dimensional data

and offer reliable fault classification makes it an essential component in real-time systems for accurate fault detection and diagnosis in IMs. A novel two-level hybrid hierarchical convolution neural network with support vector machine (HCNN-SVM) is proposed for incipient inter-turn fault diagnosis of drive fed machines in [69]

4.2.1.2 K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a popular machine learning technique employed for fault detection in Induction Motors, valued for its straightforward approach and efficacy in classifying motor states based on past data. The algorithm functions by evaluating the feature vector of a new observation, obtained from motor signals like current or vibration, against the nearest data points in a pre-labeled dataset, determining the classification based on the predominant category among these neighbors. KNN has been demonstrated to effectively detect various faults in IMs, including Inter-Turn Short Circuit (ITSC), rotor bar failures, and bearing degradation. Research conducted in [70] emphasizes KNN's application in diagnosing IM faults, showing its high accuracy when paired with feature extraction methods like Fast Fourier Transform (FFT) and wavelet decomposition. This technique is especially beneficial in industrial settings where the need for clarity and computational efficiency is paramount.

4.2.1.3 Artificial Neural Networks (ANNs)

ANNs, are advanced computational systems modeled after the neural structure of the human brain, extensively utilized in numerous applications, including the detection of faults in induction motors. Comprising interconnected nodes or "neurons" arranged in multiple layers, ANNs can recognize intricate patterns within input data. In the realm of induction motor fault diagnosis, ANNs process historical information, such as motor current signatures and vibration data, to detect and categorize faults like stator winding issues, rotor bar failures, and bearing malfunctions. A study reported in [71] proposes a discrete wavelet transform (DWT)-based method combined with artificial neural networks (ANN) to detect broken rotor bars in squirrel cage induction motors (SCIMs) under frequency regulation, validated using MATLAB/Simulink and LabVIEW for real-time implementation. Additionally, [72] presents an AI-based diagnosis system using artificial neural networks (ANN) to distinguish between stator inter-turn short-circuits and

unbalanced supply voltage in induction motors, ensuring accurate fault detection to prevent false alarms and motor failure.

4.2.2 Deep learning techniques

Deep learning methods have become increasingly important for detecting faults in induction motors due to their ability to automatically extract complex patterns from raw data such as current, voltage, and vibrations. Unlike traditional machine learning, which relies on manual feature selection, deep learning can handle high-dimensional data and detect intricate fault patterns with minimal preprocessing [73]

4.2.2.1 Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are also commonly used for IM fault detection because they can capture time-based patterns. LSTMs have proven effective in continuous monitoring of motor signals, allowing for early detection of faults like rotor misalignment. In [74] found that LSTMs provided strong performance in diagnosing intermittent electrical faults by analyzing motor data sequences.

4.2.2.2 Convolutional Neural Networks

(CNNs) are frequently employed in IM fault detection, particularly for time-series and spatial data analysis. CNNs have been shown to achieve high accuracy in identifying bearing issues, rotor bar problems, and inter-turn short circuits by analyzing motor signals. In [75] it was demonstrated that CNNs could detect bearings for failure from vibration data with over 98% accuracy.

4.2.2.3 Autoencoders

Autoencoders represents another deep learning technique applied in IMs, especially for anomaly detection. They create a compressed model of the motor's normal behavior and identify deviations that indicate faults. In [76] it was showed that autoencoders can detect subtle abnormalities in motor performance, surpassing traditional methods.

4.2.2.4 Combined Approaches

Additionally, hybrid approaches combining deep learning with signal processing, such as wavelet transform with CNNs, are showing promising results. Generative Adversarial Networks (GANs) are also being applied for bearing fault diagnosis, as explored in [77].

These innovations demonstrate how deep learning is enhancing IM fault detection, offering more accurate and real-time diagnostics for industrial applications.

4.3 Artificial Neural Network (ANN) For ITSC and USV fault detection

4.3.1 Overview of Artificial Neural Networks (ANNs) and Their Structure

Artificial Neural Networks (ANNs) are a class of machine learning models inspired by the human brain's neural networks, designed to recognize patterns and relationships in data. ANNs are used extensively across various fields, including image recognition, natural language processing, and fault detection, due to their ability to learn and adapt to complex datasets.

4.3.1.1 Neurons

Artificial neurons, also known as **nodes** or **units**, are the fundamental processing units of an ANN. They are loosely inspired by biological neurons (Figure 4.1), which transmit information through electrical impulses. Each artificial neuron takes inputs, processes those using weights and biases, and then produces an output through an activation function.

- **Inputs:** Neurons receive multiple inputs, often represented as a vector x=(x1,x2,...,xn) These inputs can represent various features of the data, such as pixel intensities in an image or sensor readings in an industrial system.

- **Weights:** Each input is multiplied by a weight w_i, which determines the importance of the input in producing the final output. Weights are the parameters of the network that are updated during training, and their optimization is key to improving the performance of the model.

- **Bias**: A bias b term is added to the weighted sum of inputs. It allows the neuron to shift the activation function to better fit the data, helping the network model complex patterns.

- **Output**: The weighted sum of inputs and the bias is passed through an activation function, which introduces non-linearity into the model. The output z of a neuron is typically expressed as:

$$z = \sum(w_i x_i) + b \tag{10}$$

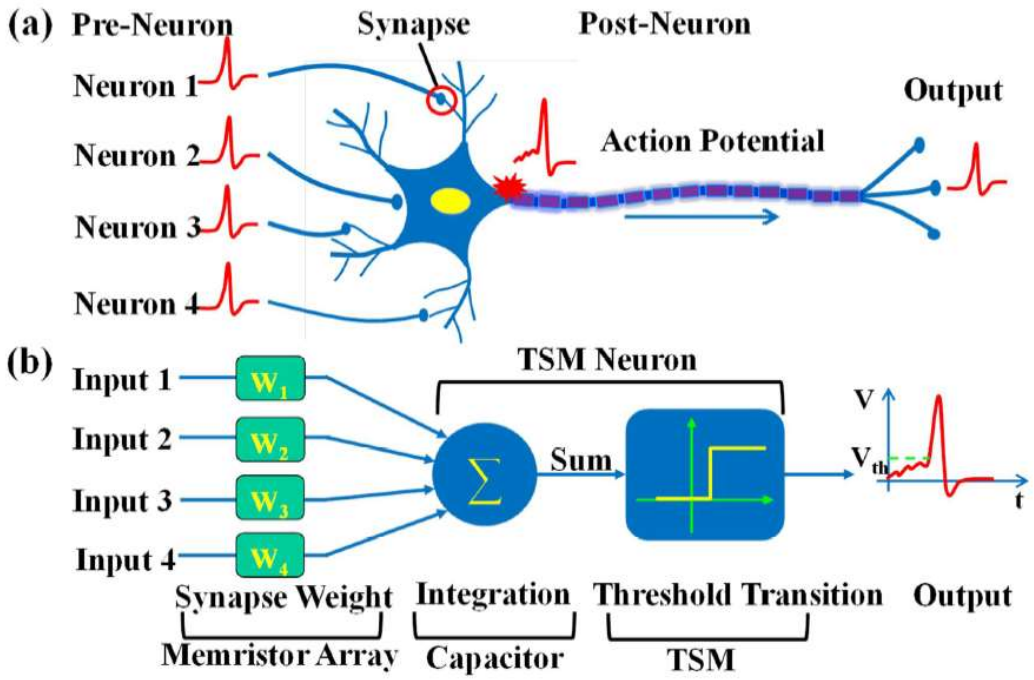

Figure 4.1: Artificial Neuron [78]

4.3.1.2. Layers in ANNs

ANNs are structured as layers of interconnected neurons, and these layers can be categorized into three main types**:**

- **Input Layer:** The first layer of an ANN, the input layer receives raw data and passes it into the network. Each neuron in the input layer corresponds to a feature or attribute of the input dataset, such as pixel values in an image or sensor readings in industrial fault detection.

- **Hidden Layers**: Positioned between the input and output layers, hidden layers perform the core computation and transformation of the network. These layers enable the model to capture complex relationships and patterns in the data. The number of hidden layers and the number of neurons in each layer define the depth of the network, with deeper networks (those with more hidden layers) often referred to as deep neural networks (DNNs). These layers are crucial for enabling the model to learn non-linear and abstract representations of the input data.

- **Output Layer:** The final layer in an ANN, the output layer provides the network's prediction or classification. For example, in a binary classification problem, the output layer may consist of a single neuron with a probability value indicating one of two possible outcomes. In multi-class classification tasks, the output layer can have multiple neurons, each representing a different class.

4.3.1.3. Activation Functions

Activation functions introduce non-linearity into the model, allowing ANNs to solve complex problems. Without non-linear activation functions, ANNs would be equivalent to a linear regression model, limiting their capacity to learn intricate patterns. Common activation functions include [79]

- **Sigmoid:** The sigmoid activation function squashes the input to a range between 0 and 1, making it useful for binary classification tasks. Its formula is:

$$\boldsymbol{\sigma(z) = \frac{1}{1 + e^{-z}}} \tag{11}$$

However, the sigmoid function suffers from the vanishing gradient problem, where gradients become extremely small during backpropagation, leading to very slow or ineffective learning in deep neural networks[80]

- **Tanh (Hyperbolic Tangent)**: Similar to the sigmoid but maps inputs to a range between -1 and 1, making it useful when data is centered around zero. Its formula is:

$$\tanh(z) = \frac{2}{1+e^{-2z}} - 1 \tag{12}$$

- **ReLU (Rectified Linear Unit)**: The most commonly used activation function, especially in deep networks, as it mitigates the vanishing gradient problem. ReLU outputs the input directly if it is positive, otherwise, it returns zero. The function is defined as:

$$\mathrm{ReLU}(z) = \max(0.z) \tag{13}$$

- **Softmax**: Used in multi-class classification, the softmax function converts the output of the neurons into probabilities, with all the values summing to 1.

$$\mathrm{softmax}(z_i) = \frac{\mathrm{e}^{z_i}}{\sum_j \ e^{z_i}} \tag{14}$$

4.3.2. Types of ANN Networks

Artificial Neural Networks (ANNs) can be classified based on factors like structure, layer depth, data flow, and learning methods (Figure 4.2). Below is an outline of major ANN categories:

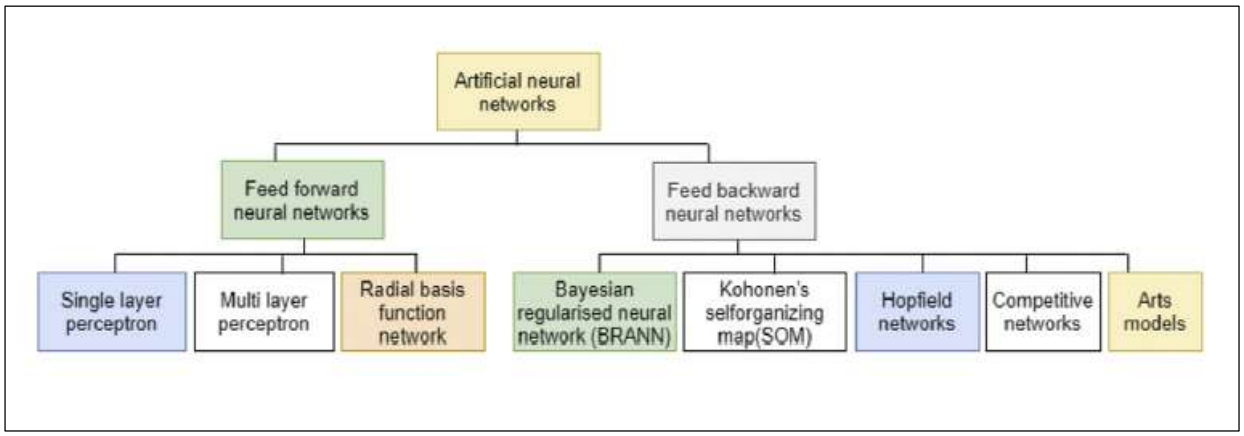

Figure 4.2 ANN main classification.

4.3.2.1 Feedforward Neural Networks:

4.3.2.1.a Single-Layer FFNN:

A basic neural network structure connects the input layer directly to the output layer without incorporating hidden layers. Each input is associated with every output through weighted links, enabling the network to separate data that is linearly distinguishable. This straightforward design is effective for simpler tasks like basic classification or regression but lacks the complexity needed to handle non-linear patterns or intricate relationships within the data[81].

4.3.2.1.b Multi-Layer FFNN:

This type of neural network is composed of an input layer, one or multiple hidden layers, and an output layer, where data flows sequentially from one layer to the next. Hidden layers play a crucial role in identifying and learning non-linear relationships within the data, allowing the network to handle more sophisticated tasks. Such architecture is highly adaptable, making it suitable for applications like analyzing time-series data or recognizing patterns in images.

4.3.2.1.c Radial Basis Function NN (RBFNN)

A radial basis function neural network (RBFNN) employs radial basis functions as activation mechanisms, emphasizing the distance of data points from a specific center. This network transforms inputs into outputs using non-linear mapping, which makes it particularly effective for applications such as function estimation, pattern classification, and managing control processes.

4.3.2.2 Feedbackward Neural Networks:

4.3.2.2.a Bidirectional Recurrent ANN (BRANN):

This network processes information in two directions—forward and backward—by utilizing feedback connections. Such bidirectional flow allows it to preserve and leverage contextual details, making it highly suitable for sequential data tasks, including language translation and speech analysis.

4.3.2.2.b Self-Organizing Map (SOM):

A self-organizing map (SOM) is an unsupervised neural network that projects data from a high-dimensional space onto a simpler, low-dimensional grid. During the training process, neurons compete to represent input data, with similar data points being grouped closer together. This structure makes SOMs effective for tasks such as clustering and visualizing complex datasets.

4.3.2.2.c Hopfield Network:

A Hopfield network is a type of recurrent neural network where all neurons are interconnected. It is primarily used for associative memory, allowing the network to store and recall patterns. The retrieval process relies on stable states, known as attractors, which represent the stored information, often in binary form.

4.3.2.2.d Competitive and ART models:

Competitive Neural Networks operate by allowing neurons to compete in their response to input data, with only the most responsive neuron, known as the "winning node," updating its weights. This winner-takes-all approach enables the network to self-organize, making it highly effective for clustering tasks. As input data is presented, the network adapts by adjusting the winning neuron's weights to better represent similar data points in the future. Over time, neurons specialize in different clusters, dividing the input space into distinct regions. Competitive networks are widely used in unsupervised learning for tasks like data grouping, pattern recognition, and dimensionality reduction [82] [83]

4.3.2.2.e Adaptive Resonance Theory (ART):

A self-organizing network can learn new patterns while preserving previously learned information, preventing catastrophic forgetting. This feature is essential for tasks like pattern recognition and classification. Techniques like Adaptive Resonance Theory (ART) enable these networks to adapt to new data while maintaining the stability of earlier knowledge, making them suitable for dynamic environments[84] .

4.3.3 ANN Training

ANN training process is an optimization task with the aim of finding a set of weights to minimize an error measure [85]The use of the ANN considers three aspects: train the network, validate and finally test it. During training and validating, the ANN acquires knowledge and later uses this knowledge to test on the data [86]

Training involves presenting a series of examples, or patterns, to the neural network. Learning methods are categorized as either supervised or unsupervised. In supervised learning, the network is trained with input-output pairs, where each input pattern (S,E) is associated with a target output (s,e). The backpropagation algorithm is a widely used approach in this category. In contrast, unsupervised learning involves classifying input patterns without requiring target output information, with Kohonen's algorithm being a prominent method in this class. Learning

algorithms typically rely on two key functions in addition to the activation function: the error calculation function, e=f3(s,E,W), which determines how weights (W) are adjusted, and the weight update function, ΔW=f2(S,e,W), which iteratively updates weights until the error converges to an acceptable level. Each algorithm follows its own specific learning rules tailored to its design and objectives[86]

The ANN implementation included three main stages, which were the selection of input and output parameters, training process, and testing. Normally, data of the input and output parameters were handled by being normalized in a certain range. However, several studies took the data “as is” instead of doing any forms of scaling. Then, in turn, the data was apportioned in a random way regarding training, testing, and validation. Among the crucial parameters identified before any ANN analysis were the activation function (AF), the selection of inputs and outputs, the neuron number in the hidden layers, the number of hidden layers, and the training (learning) algorithms [87]. It was important to note since the ANN was classified as supervised learning because it was trained on the basis of the input parameters and output data. The main responsibility of the learning algorithm (LA) is to adjust the network parameters, such as the weights and biases. That adjustment was used to ensure the predictions with a reasonable accuracy or acceptable error limits. Due to this reason, often was the error signal that was presented through mean squared error known as the cost function. In addition, the error signal was also backpropagated until the minimum of signal could reach based on many training iterations (so-called epochs). The LAs or backpropagation training commonly used were train-bfg, -lm, -rp, -scg, -gdx,-cgf, and -gda [88], [89], [90]. After the training stage was completed, the testing and validation phase was important because it offered a thorough awareness of the effectiveness of ANN prediction models which were technologically advanced. The accuracy of the training, validation, and testing was determined by the correlation coefficient (R) and the coefficient of determination (R2). The validation was carried out providing a new package of input data for the network. Normally, to evaluate the efficiency of the predicted responses, additional statistical analysis such as RMSE, MAPE, MAP, MSRE, MEP, MRE, and others were conducted.

4.3.4 ANN Testing

Testing and validating an Artificial Neural Network (ANN) is essential to confirm its ability to handle new, unfamiliar data effectively. This involves measuring the model's accuracy using a dataset distinct from the one used for training. The main objective is to determine the model's capability to deliver precise predictions on entirely unseen information.

4.3.4.1 Data Preparation

The initial phase of evaluating an artificial neural network involves preparing a test dataset. To maintain uniformity, this dataset must undergo the same preprocessing steps as the training data. Common preprocessing methods include scaling data to a specific range (e.g., 0 to 1), standardization, and addressing any missing values. Scaling, in particular, enhances stability during training and supports faster convergence [91] .

4.3.4.2 Performance Metrics

After preparing the test dataset, the trained model is used to generate predictions. The model's performance is then evaluated using various metrics. For classification tasks, commonly used metrics include accuracy, precision, recall, and the F1-score. In regression tasks, metrics like Mean Squared Error (MSE) and R-squared are typically employed.

- **Accuracy**: Reflects the ratio of correct predictions to the total cases.
- **Precision**: Evaluates the correctness of positive predictions.
- **Recall**: Assesses the model's ability to capture all relevant cases.
- **F1-Score**: Combines precision and recall into a single metric through their harmonic mean.
- **Mean Squared Error (MSE)**: Quantifies the average squared difference between predicted and actual values.
- **R-Squared**: Represents the proportion of variation in the target variable explained by the predictors [92] .

4.3.4.3 Confusion Matrix and ROC Curve

For classification problems, a confusion matrix and ROC curve with AUC "Area Under the Curve" offer valuable details about model performance. The confusion matrix -Figure 4.3- is a chart that compares actual and predicted classifications, illustrating the model's accuracy. The ROC curve displays the relationship between the true positive rate and the false positive rate across different thresholds Figure 4.4, while the AUC provides a numerical summary of the model's overall effectiveness [93]

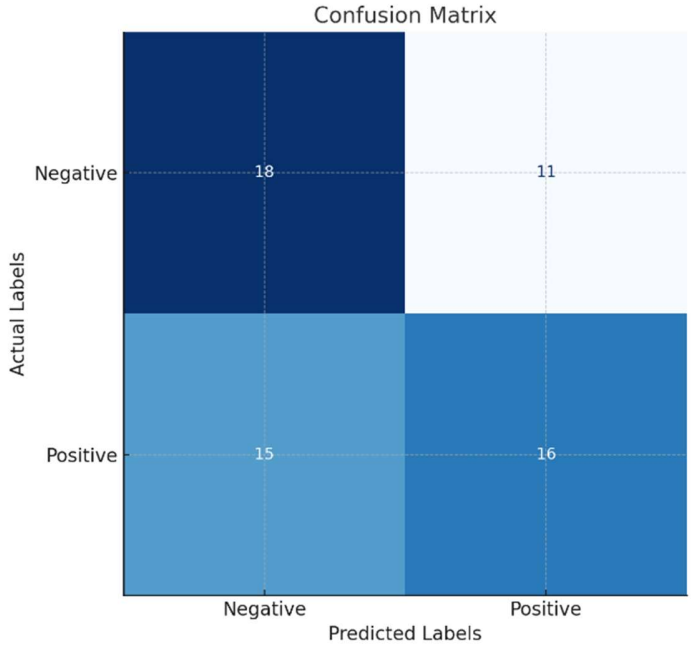

Figure 4.3 Confusion Matrix.

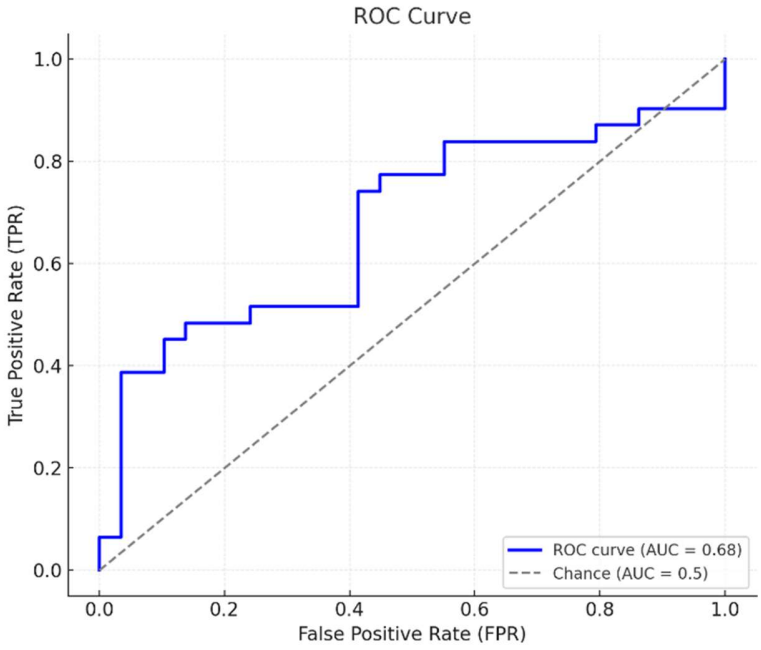

Figure 4.4 ROC Curve.

4.3.4.4 Error Analysis

Analyzing errors reveals patterns or biases in a model's predictions. Reviewing the mistakes a model produces provides valuable insight into areas that may need refinement. This approach often includes examining misclassifications or evaluating residuals in regression models.

4.3.4.5 Overfitting and Generalization

Preventing overfitting is essential for a model's success. Overfitting happens when a model excels on training data but struggles with test data. To gauge its ability to generalize, methods such as cross-validation are useful. This approach divides the dataset into several parts, allowing the model to train and be tested on various combinations, providing a more comprehensive performance evaluation.

4.3.4.6 Bias-Variance Tradeoff

Striking the right balance between bias and variance is crucial for achieving optimal results. Excessive bias results in underfitting, where the model oversimplifies and fails to grasp data

patterns. On the other hand, excessive variance leads to overfitting, where the model becomes overly complex and captures irrelevant noise. Properly managing this trade-off ensures the model performs well on unseen data [94]

4.3.5 Proposed ANN Architecture

The approach employs a combination of three key axes. First, it utilizes ITSC and USV condition indicators derived from voltage symmetrical components to assess system conditions. Second, an artificial intelligence (AI) technique is integrated to serve as a decision-making tool for identifying the type and severity of faults. Lastly, a monitoring interface is developed, building on the insights from the first two axes. This interface is designed to function as a human-machine interface (HMI), enabling users to interact with the system effectively. The implementation leverages a LabVIEW-based interface to provide a user-friendly platform for real-time monitoring and fault analysis. Together, these axes create a comprehensive framework for fault detection and monitoring, combining advanced computational techniques with practical visualization tools to enhance system reliability and operational efficiency. This approach ensures accurate fault identification, intuitive interaction, and seamless integration into existing monitoring systems (Figure 4.4 a/b).

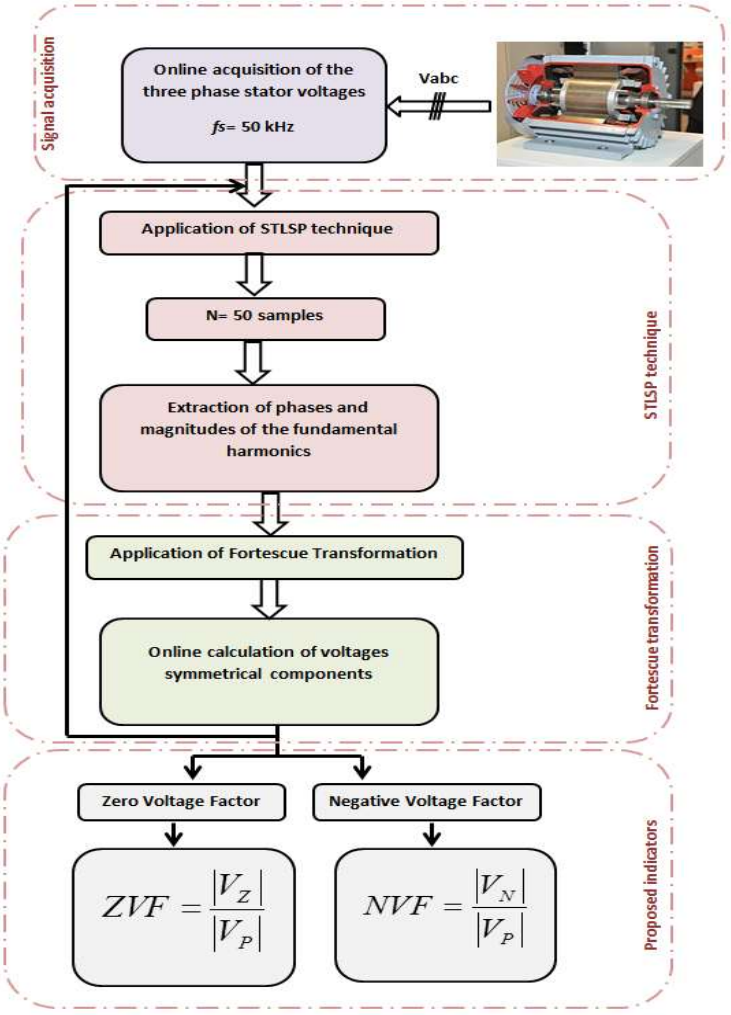

Figure 4.4.a Indicators extraction scheme.

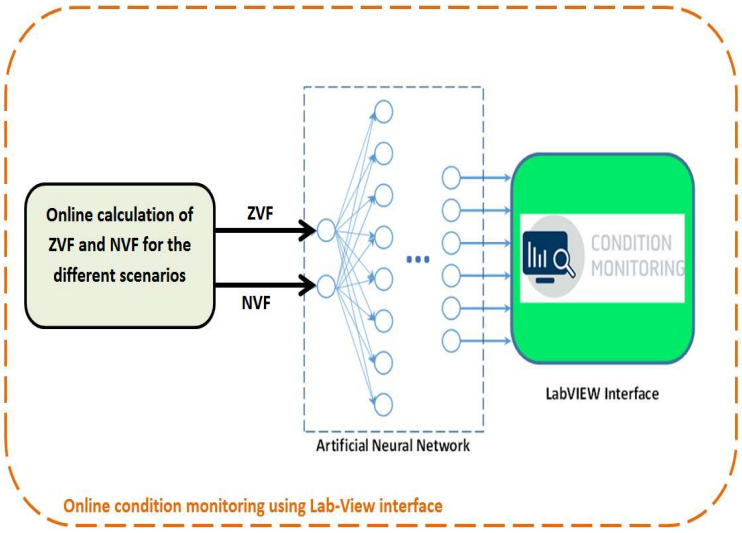

Figure 4.4 b Online detection and monitoring scheme.

The utilized AI technique is the artificial neural network. Feed-forward artificial neural networks (FFNs), also known as Multilayer Perceptron (MLP) networks, are widely recognized as the most commonly used architecture for ANNs [95] . For our purpose, we propose a model comprising three distinct layers. The first layer is the input layer, which receives the initial data. Following this, there is a hidden layer consisting of 10 neurons, which processes the input data through a series of computations. Finally, the output layer contains 6 neurons, delivering the final results of the network's processing. The activation function used in this model is the hyperbolic tangent (Tansig) function, known for its smooth gradient and ability to handle both positive and negative input values. The Tansig function maps inputs to a range of -1 to 1, making it effective for neural networks requiring zero-centered outputs. This characteristic helps in improving the convergence speed during training [96], illustrated in Figure 4.5.

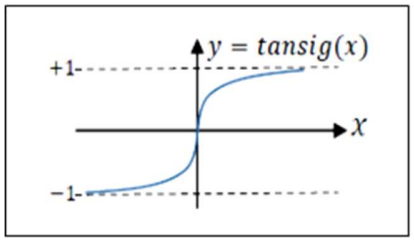

Figure 4.5 Sigmoid function.

The designed network is trained using an experimentation dataset, leveraging the Levenberg–Marquardt algorithm (LMA). The LMA algorithm is an iterative optimization method designed for solving non-linear least squares problems. It merges the strengths of gradient descent and the Gauss-Newton method, enabling efficient minimization of the cost function by adjusting weights and biases. Known for its fast convergence and stability, LMA is especially suitable for training small to medium-sized neural networks. By dynamically balancing exploration (gradient descent) and precision (Gauss-Newton), it effectively addresses optimization challenges, making it a popular choice in machine learning and curve-fitting applications[97]

This choice is motivated by LMA's documented efficiency in handling small network cases [98]-[99]. The LMA is particularly effective because it adjusts both the weights and biases of the network, optimizing performance by minimizing the cost function. This iterative process ensures that the network's parameters are fine-tuned to achieve the best possible outcomes.

The entire process of conceiving and training the neural network was carried out using the MATLAB Neural Network Toolbox [100]. This toolbox provides a comprehensive suite of tools for designing, training, and analyzing neural networks, making it an ideal choice for this research. The toolbox facilitates the implementation of various neural network architectures and training algorithms, allowing for a streamlined and efficient workflow.

A general overview of the proposed FNN is presented in Figure 4.6. This visual representation helps in understanding the structure and flow of the network, from the input layer through the hidden layer to the output layer. The figure also highlights the interconnections between the neurons and the role of the activation function in transforming the input data into meaningful output.

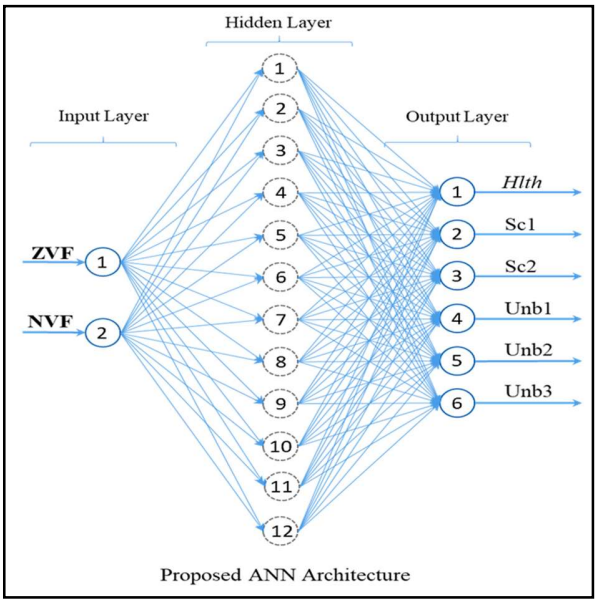

Figure 4.6 Proposed ANN architecture.

In summary, the proposed FNN model, with its three-layer architecture and the use of the Tansig activation function, trained with the Levenberg–Marquardt algorithm, offers a robust framework for various applications. The MATLAB Neural Network Toolbox played a crucial role in the development and training of this model, ensuring that the network's parameters were optimally adjusted for enhanced performance.

4.3.5.1 Training and testing of the proposed ANN

The proposed network was trained using a dataset collected from experimental testing with a specialized setup. This data, acquired through meticulous experiments, provided a robust foundation for training the neural network, ensuring that it could accurately learn and generalize from real-world scenarios. The dedicated experimental setup was crucial in gathering high-quality data, which is essential for effective model training. Figure 3.4 depicts the related setup.

The database consists of input attributes (Ii) and corresponding output targets (Ti), which are essential for training the ANN. The input attributes include two key fault diagnostic indicators: Zero-Sequence Voltage Fault ZVF (I1) and Negative-Sequence Voltage Fault NVF (I2). These indicators provide critical information for fault detection, serving as the primary inputs to the ANN,

enabling it to learn and map the relationship between these inputs and the desired output targets effectively. The neural network outputs represent six health indicators of the induction motor (IM), which are detailed as follows:

- ✓ Hlth : Healthy IM Status (No Fault).
- ✓ Sc1: Low ITSC fault (2 Turns ITSC).
- ✓ Sc2: High ITSC fault (9 Turns ITSC).
- ✓ Unb1: Low USV condition (1%).
- ✓ Unb2: Medium USV condition (2%).
- ✓ Unb3: High USV condition (3%).

The database was generated through experimental testing across various induction motor (IM) operating conditions. The outputs are organized into a dedicated (6×1) binary vector, as outlined below:

$$\begin{bmatrix} \mathbf{Hlth} \\ \mathbf{Sc_1} \\ \mathbf{Sc_2} \\ \mathbf{Unb_1} \\ \mathbf{Unb_2} \\ \mathbf{Unb_3} \end{bmatrix}$$

Indicators / Fault	ZVF0 & NVF0	ZVF0 & NVFL	ZVF0 & NVFM	ZVF0 & NVFH	ZVFL & NVF0	ZVFL & NVFL	ZVFL & NVFM	ZVFL & NVFH	ZVFH & NVF0	ZVFH & NVFL	ZVFH & NVFM	ZVFH & NVFH
Hlth	1	0	0	0	0	0	0	0	0	0	0	0
Sc1	0	0	0	0	1	1	1	1	0	0	0	0
Sc2	0	0	0	0	0	0	0	0	1	1	1	1
Unb 1	0	1	0	0	0	1	0	0	0	1	0	0
Unb 2	0	0	1	0	0	0	1	0	0	0	1	0
Unb 3	0	0	0	1	0	0	0	1	0	0	0	1

Table 4.1 Output vector VS input indicators.

Table 4.1 represents the training dataset for the proposed Artificial Neural Network (ANN) used to detect and classify electrical faults in a system. It maps various combinations of input indicators, namely the Zero Voltage Factor (ZVF) and Negative Voltage Factor (NVF), against specific fault statuses, including "Healthy" (Hlth), "Short Circuit Fault Level 1" (Sc1), "Short Circuit Fault Level 2" (Sc2), and "Unbalance Faults" (Unb 1, Unb 2, and Unb 3). These inputs and outputs form a supervised learning framework where the ANN learns to associate patterns in the inputs with corresponding fault categories. Each row in the table represents a distinct training sample, with binary values (0 or 1) indicating the presence or absence of specific indicator levels and faults.

The input features, ZVF and NVF, are critical parameters for the fault detection process. ZVF can vary between "0" (indicating no fault), "L" (low-level variation), and "H" (high-level variation). Similarly, NVF has a broader range, varying from "0" (no fault) to "L" (low-level), "M" (medium-level), and "H" (high-level). The combination of these parameters results in twelve unique input conditions, represented as pairs of ZVF and NVF values, such as ZVF0 & NVF0, ZVF0 & NVFL, ZVFL & NVFH, and so forth. Each column under the "Indicators" section corresponds to one such combination, allowing the ANN to recognize patterns across different input scenarios. The output section of the table represents the fault classifications. The "Healthy" state (Hlth) is associated with the absence of faults, occurring only when both ZVF and NVF are at their baseline levels (ZVF0 & NVF0). For fault states, the ANN learns distinct mappings based on the indicator levels. For example, Short Circuit Fault Level 1 (Sc1) occurs when ZVF is at a low level (ZVFL) combined with any NVF variation (0 to H). Similarly, Short Circuit Fault Level 2 (Sc2) arises when ZVF is at a high level (ZVFH), regardless of NVF values. Unbalance faults (Unb 1, Unb 2, and Unb 3) are more nuanced and depend on NVF levels combined with ZVF variations. Unb 1 is associated with low NVF (NVFL), Unb 2 with medium NVF (NVFM), and Unb 3 with high NVF (NVFH), spanning all ZVF conditions.

This table is essential for ANN training as it provides a comprehensive dataset to generalize fault detection. During training, the ANN processes this binary-encoded data, adjusting its internal weights to minimize the error in predicting fault statuses. The variety in input-output combinations ensures the model can handle diverse scenarios and accurately classify faults. Furthermore, the

structured nature of the dataset - where each fault is tied to specific ZVF and NVF patterns - facilitates effective learning, making the ANN capable of distinguishing between similar but distinct fault conditions. Once trained, the ANN can use this learned knowledge to diagnose faults in real-time, ensuring quick and reliable fault detection in complex systems. This training table exemplifies how structured data can be leveraged for machine learning applications in fault analysis, showcasing the power of supervised learning techniques in predictive maintenance and system reliability.

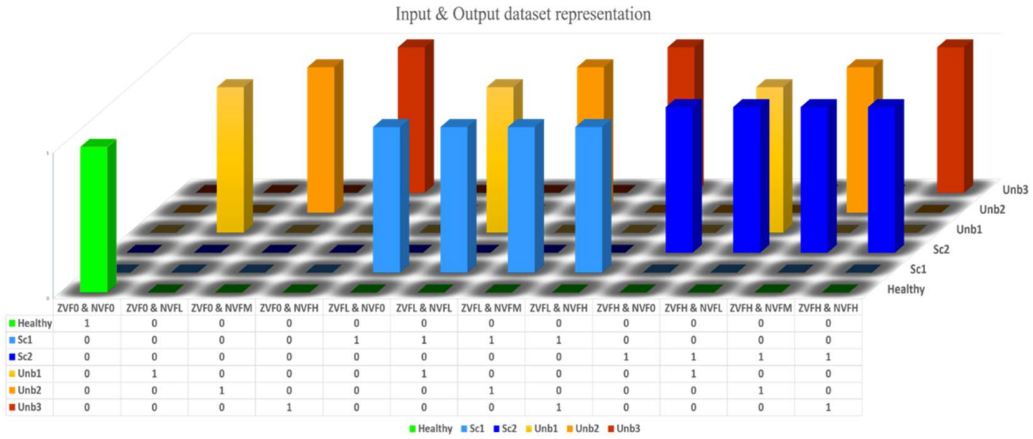

Figure 4.7 3D representation of the training Data set (Input vs Output).

The multidimensional 3D graphical representation in Figure 4.7 maps the correlations between voltage-based parameters and system malfunction indicators within the neural network's learning set. The horizontal plane incorporates dual voltage metrics - the Zero and Negative components - arranged in various permutations (baseline, reduced, and elevated states). The vertical dimension catalogs six distinct operational states, ranging from optimal performance to multiple grades of electrical anomalies, each assigned a unique chromatic identifier. The amplitude component employs a binary classification system to denote the presence or absence of specific operational states under given voltage conditions. The dataset's architecture reveals distinct patterns in system behavior across different operational scenarios. Normal functioning exhibits a singular correlation with baseline voltage readings, while various malfunction categories

demonstrate more complex relationships across multiple voltage configurations. Circuit irregularities manifest across several voltage combinations, and load imbalances show systematic progression through increasing voltage factor levels. The spatial arrangement of these relationships creates readily identifiable clusters of related phenomena. This graphical interface serves as a crucial analytical instrument for comprehending the underlying data architecture and validating the machine learning model's classification framework. It offers a comprehensive perspective on system dynamics across various operational parameters, enhancing our ability to accurately diagnose and categorize electrical system anomalies. The visualization's structured approach to data representation facilitates both intuitive understanding and technical analysis of the system's behavioral patterns

4.3.5.2 Recording Training Data Set

Figure 4.8 depicts a detailed graph illustrating the training and test dataset inputs for the target Artificial Neural Network (ANN) chosen. In fact, and in order to training the ANN several bench tests were performed using the prepared experimental setup varying multiple situations to make sure the coverage of all possible combinations, focusing on the Zero Voltage Factor (ZVF) and Negative Voltage Factor (NVF) across approximately 18,500 samples collected. The x-axis represents the sample number, while the y-axis denotes the values of ZVF and NVF in per unit (p.u.), ranging from 0 to 6 x 10^{-4}. The graph features two distinct lines: a black line for ZVF and a blue line for NVF, showcasing their variations across the dataset. The data is segmented into different combinations of ZVF and NVF, such as ZVF (0/L/H) & NVF (0/L/M/H). The displayed sequences int the figure are made through the combination of faults generation levels (Inter-turn short circuit “Sc” impaction the ZVF values and the Unbalanced Power supply “Unb” fault impacting the NVF) to then arrange them in related arrays to be used for training.

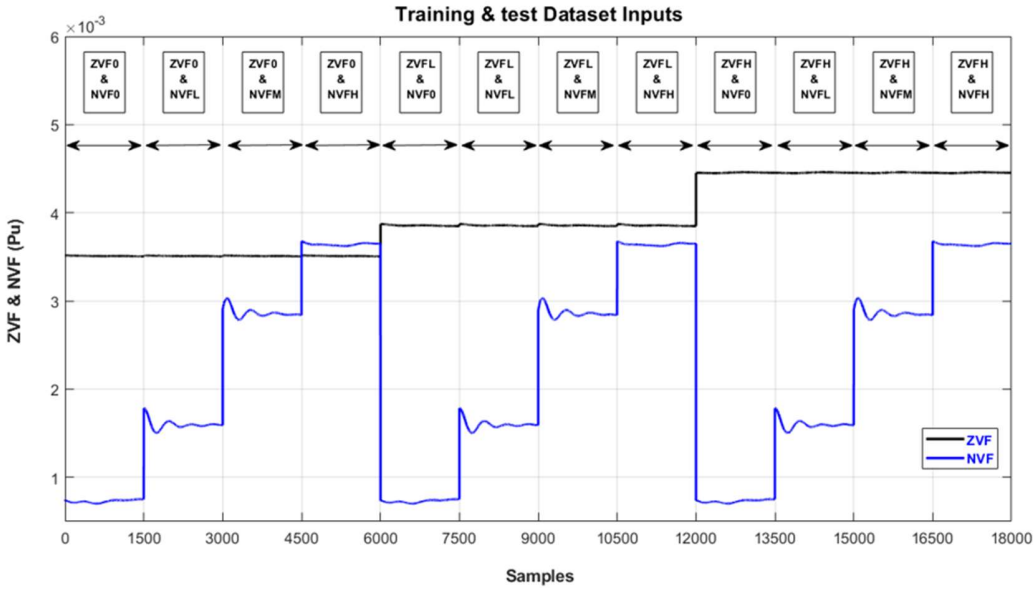

Figure 4.8 Experimental training dataset.

4.3.5.3 Training Process of the ANN

The training of the preset ANN was concluded successfully after 183 epochs, achieving a notable milestone with a minimum gradient of 7.93 x 10^{-8} (Figure 4.9). This rigorous training process, which utilized the MATLAB Levenberg-Marquardt (LM) training method.

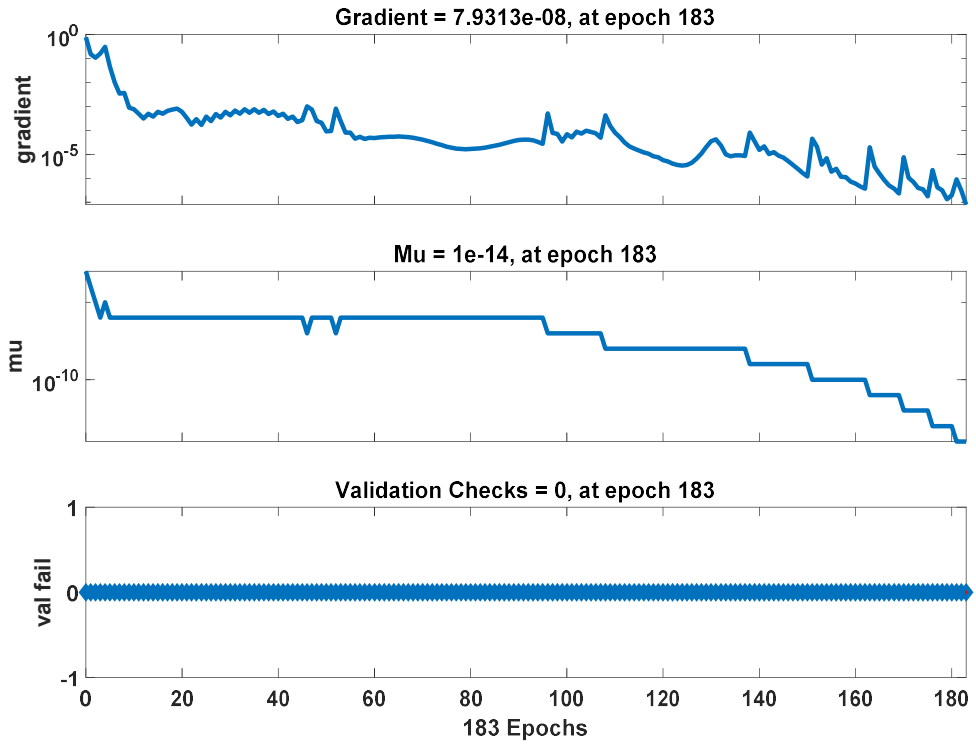

Figure 4.9 The ANN training process result.

In addition, resulted in an exceptionally low minimum Mean Square Error (MSE) of 1.83 x 10^{-12} -Figure 4.10-. Such a low MSE indicates that the ANN has effectively learned to minimize the differences between its predicted outputs and the actual target values, demonstrating a high level of accuracy and precision in its learning process. This achievement underscores the network's robustness and readiness for application in real-world scenarios, where accurate predictions are crucial for reliable performance.

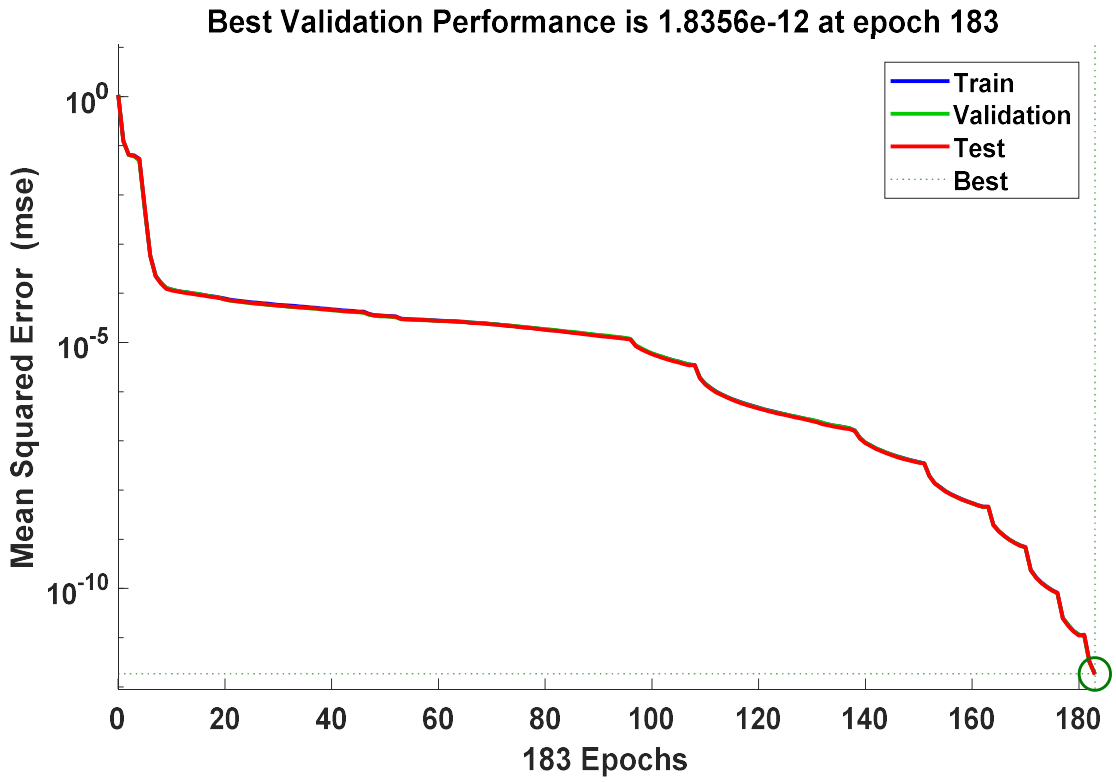

Figure 4.10 MSE of the training process.

4.3.5.4 AN Network testing and validation

To validate the effectiveness of the Artificial Neural Network (ANN) training, a comprehensive testing scheme was developed. The primary objective was to confirm the training efficiency and ensure that the ANN could generalize well to new, unseen data. For this purpose, a distinct input/output dataset scenario, as depicted in Figure 4.11, was employed to rigorously test the neural network's performance. This dataset comprised approximately 42,000 samples, providing a robust and diverse foundation for evaluating the ANN's capabilities.

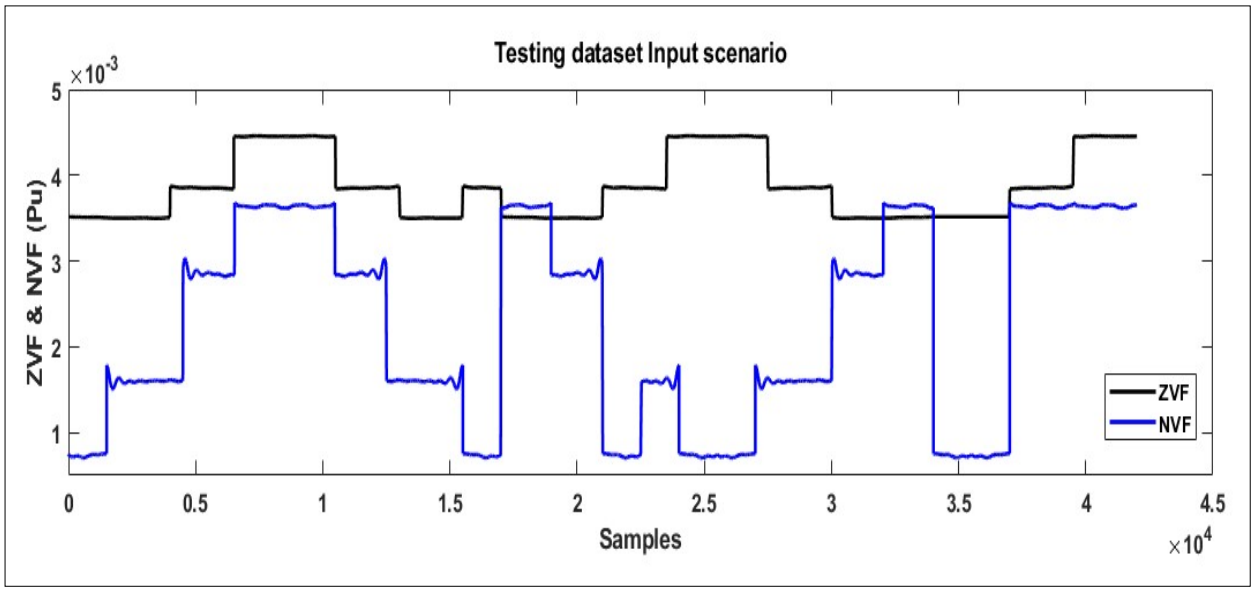

Figure 4.11 Testing dataset

The testing scheme incorporated two different methodologies to assess the ANN's response to the test data, each offering unique insights into the network's performance. The first approach utilized a general MATLAB Mean Square Error (MSE) function to measure the overall performance of the ANN. The MSE is a widely used metric in machine learning, calculated using the following equation:

$$MSE = \frac{1}{n}\sum_{i=0}^{n}(X_i - Y_i)^2 \tag{15}$$

where n is the number of data points, X_i is the actual value, and Y_i is the predicted value. This method provided a holistic view of the network's accuracy by calculating the overall MSE across all samples. The result was an impressively low ANN MSE error of 2.49 x 10^{-11}, indicating that the network had learned to predict the outputs with a high degree of precision. The second method delved deeper into the ANN's performance by computing the MSE for each target versus its output and displaying these values across all samples. This granular analysis allowed for a more detailed understanding of the network's strengths and weaknesses, highlighting areas where the ANN excelled and where it might need further refinement. Remarkably, all targets showed an MSE of less than 10^{-8} (Figure 4.12), with a general MSE of 2.49 x 10^{-11}. This consistent performance across all targets underscored the network's robustness and reliability.

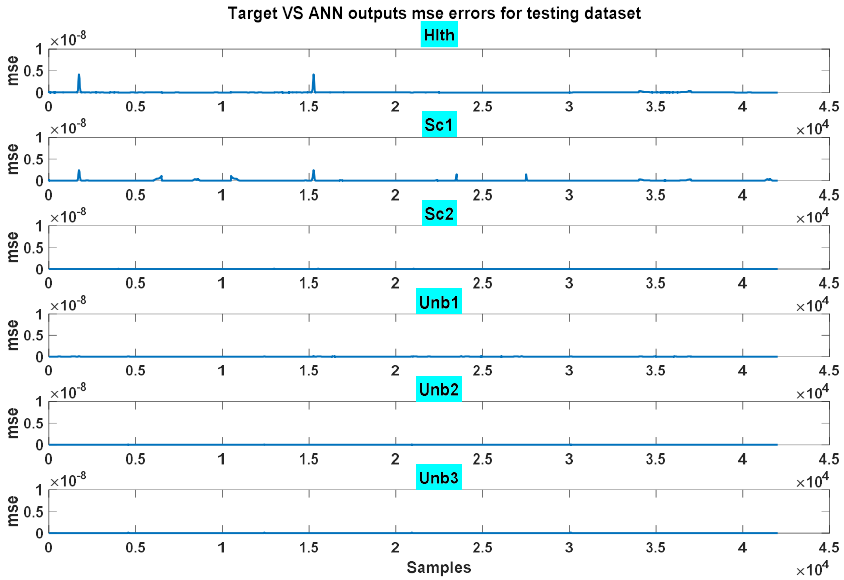

Figure 4.12 Validation test results.

By employing these two complementary approaches, the testing scheme provided a thorough evaluation of the ANN's capabilities. The low MSE values obtained through both methods underscored the network's robustness and reliability, demonstrating its potential for accurate fault detection and classification in electrical systems. The detailed performance analyses, as presented in Figure 4.12, offered a visual representation of the ANN's performance across the entire test dataset, further reinforcing its effectiveness.

The proposed feed-forward Artificial Neural Network (FFN), also known as a Multilayer Perceptron (MLP) network, was meticulously designed with three layers: an input layer, a hidden layer containing ten neurons, and an output layer with six neurons. The hyperbolic tangent (Tansig) function was employed as the activation function, ensuring efficient and effective processing within the network. The network was trained using the Levenberg-Marquardt algorithm (LMA), renowned for its speed and efficiency in optimizing small network cases, with the support of the MATLAB Neural Network Toolbox.

The training and testing of the proposed ANN were conducted using a comprehensive dataset acquired through experimental testing on a dedicated setup. This dataset included input attributes such as the Zero-Voltage Factor (ZVF) and Negative-Voltage Factor (NVF), along with output targets representing various health indicators of the induction motor (IM). These indicators encompassed the motor's healthy status, low and high Inter-Turn Short Circuit (ITSC) faults, and low, medium, and high Unbalanced Supply Voltage (USV) conditions. The outputs were organized in a binary vector format, where each component indicated the presence or absence of a specific condition. Experimental tests were categorized into healthy conditions and varying severity levels of ITSC and USV faults. The training process was rigorously executed, and the network's performance was evaluated using two distinct methodologies. The first approach utilized a general MATLAB Mean Square Error (MSE) function to assess the overall performance of the ANN, providing a holistic view of the network's accuracy. The second approach involved a more granular analysis by computing the MSE for each target versus its output, offering detailed insights into the network's strengths and areas for potential refinement. Validation examinations and the selection of optimal validation performance further confirmed the network's robustness and reliability.

The designed network demonstrated exceptional performance in both training and testing phases, showcasing its potential for accurate fault detection and classification in electrical systems. This robust and reliable tool is well-suited for real-time monitoring and diagnostics of induction motors, ensuring their optimal performance and longevity in various industrial applications.

4.4 LabVIEW monitoring interface

4.4.1 Introduction

LabVIEW, an acronym for Laboratory Virtual Instrument Engineering Workbench, is a sophisticated and versatile system-design platform and development environment developed by National Instruments. Since its inception, LabVIEW has become a cornerstone in various industries, renowned for its exceptional capabilities in data acquisition, instrument control, and industrial automation. The platform's widespread adoption can be attributed to its unique blend of powerful features and user-friendly design, which cater to the needs of engineers, scientists, and researchers across a multitude of disciplines.

One of the standout features that distinguish LabVIEW from other development environments is its innovative graphical programming approach, commonly known as "G" programming. Unlike traditional text-based programming languages, which can be abstract and challenging to master, LabVIEW's visual programming paradigm offers a more intuitive and accessible method for designing and implementing complex systems. This graphical interface allows users to create programs by connecting various functional blocks, which represent different operations and data flow paths. This approach not only simplifies the programming process but also makes it more engaging and easier to understand, particularly for those who are new to programming or prefer a visual representation of their work.

The advantages of LabVIEW's graphical programming extend beyond ease of use. By enabling users to visualize the flow of data and control logic more naturally, LabVIEW enhances the efficiency of the development process. Engineers and scientists can quickly prototype and iterate their designs, identifying and rectifying issues more swiftly than with text-based languages. This visualization also reduces the likelihood of errors, as the graphical representation makes it easier to spot inconsistencies or logical flaws in the program's structure. Consequently, LabVIEW facilitates a more streamlined and effective development workflow, allowing users to focus on innovation and problem-solving rather than debugging and syntax errors.

LabVIEW's capabilities are not limited to its programming environment. The platform is designed to interface seamlessly with a wide range of hardware devices, including data acquisition (DAQ) modules, sensors, actuators, and industrial control systems. This hardware compatibility makes LabVIEW an ideal choice for applications that require real-time data acquisition and control, such as automated test systems, process monitoring, and machine control. Furthermore, LabVIEW's extensive library of built-in functions and tools, along with its support for various communication protocols, enables users to create highly customized and integrated solutions tailored to their specific needs.

The versatility and robustness of LabVIEW make it an invaluable tool for a broad spectrum of applications. From simple data logging tasks to complex automated test systems and real-time control applications, LabVIEW provides the necessary tools and flexibility to meet the demands of modern industrial and research environments. Its ability to handle large volumes of data, perform advanced signal processing, and integrate with other software and hardware systems makes it a powerful asset for driving innovation and improving operational efficiency.

LabVIEW's combination of a user-friendly graphical programming environment, extensive hardware compatibility, and robust development tools has established it as a leading platform for system design and automation. Its widespread adoption across various industries is a testament to its effectiveness and reliability, making it an essential tool for engineers, scientists, and researchers seeking to develop cutting-edge solutions in data acquisition, instrument control, and industrial automation[101]

4.4.2 Applications of LabVIEW in industrial monitoring

4.4.2.1 Data acquisition and logging:

LabVIEW is a powerful tool widely utilized for data acquisition and logging in industrial environments. Its versatility allows it to collect data from a diverse array of sensors and instruments, making it an essential component in modern industrial settings. One of LabVIEW's standout features is its ability to seamlessly interface with a broad spectrum of hardware devices. This includes Data Acquisition (DAQ) modules, which are crucial for capturing and converting

analog signals into digital data that can be processed and analyzed. Additionally, LabVIEW can integrate with Programmable Logic Controllers (PLCs) and other industrial control systems, enabling comprehensive monitoring and control of various industrial processes. This capability ensures that data from different sources can be consolidated and managed efficiently, providing valuable insights and enhancing operational efficiency. By facilitating robust data acquisition and logging, LabVIEW supports industries in making informed decisions, improving process control, and ensuring overall system reliability[102]

4.4.2.2 Real-Time monitoring and control

LabVIEW's advanced real-time capabilities make it an ideal platform for continuous monitoring and control of industrial processes. These capabilities allow for the development of real-time applications that demand deterministic performance, ensuring that operations run smoothly and efficiently. In manufacturing, LabVIEW can be employed to oversee production lines, ensuring that each stage of the process is precisely controlled and monitored to maintain quality and consistency. In chemical processing, it can manage complex reactions and ensure safety protocols are adhered to, reducing the risk of accidents and optimizing yield. Similarly, in power generation, LabVIEW can monitor and control various parameters such as temperature, pressure, and output levels, ensuring that power plants operate at peak efficiency and reliability. By providing real-time data and control, LabVIEW enables industries to respond quickly to any deviations or issues, thereby enhancing operational efficiency, reducing downtime, and improving overall productivity[102]

4.4.2.3 Predictive maintenance

Predictive maintenance is a critical application where LabVIEW demonstrates its advanced capabilities. By integrating LabVIEW with machine learning algorithms, industries can develop sophisticated predictive maintenance systems. These systems leverage the power of data analytics to monitor and analyze sensor data in real-time, identifying patterns and anomalies that may indicate impending equipment failures. By detecting potential issues before they escalate, these systems enable proactive maintenance strategies, significantly reducing unplanned downtime and minimizing maintenance costs.

The integration of LabVIEW with machine learning allows for the continuous monitoring of machinery and equipment, ensuring that any deviations from normal operating conditions are promptly identified. This proactive approach not only enhances the reliability and longevity of industrial assets but also optimizes maintenance schedules, leading to more efficient use of resources. As a result, industries can achieve higher operational efficiency, improved safety, and substantial cost savings [103]

4.4.2.4 Process automation

LabVIEW plays a crucial role in process automation, significantly enhancing efficiency and minimizing human error in industrial settings. By leveraging LabVIEW's capabilities, industries can automate a wide range of processes, leading to more streamlined and reliable operations. One of the key advantages of using LabVIEW for process automation is its ability to control and monitor various parameters in real-time. This real-time monitoring ensures that processes operate smoothly and within predefined limits, thereby maintaining consistency and quality.

LabVIEW's graphical programming environment allows engineers to develop complex automation systems more intuitively, reducing the time and effort required for implementation. The platform's compatibility with various industrial hardware, such as sensors, actuators, and control systems, enables seamless integration and effective management of automated processes. Additionally, LabVIEW's data acquisition and analysis capabilities provide valuable insights into process performance, allowing for continuous improvement and optimization.

By automating industrial processes with LabVIEW, companies can achieve higher productivity, reduce operational costs, and enhance overall system reliability. This makes LabVIEW an indispensable tool for industries seeking to stay competitive in today's fast-paced and technologically advanced market[104]

4.4.2.5 Test and measurement

LabVIEW is a highly effective tool for test and measurement applications across various industries, including aerospace, automotive, and electronics. Its robust capabilities enable the

development of automated test systems that are crucial for validating the performance and reliability of products. In the aerospace industry, LabVIEW is used to test components and systems under rigorous conditions to ensure they meet stringent safety and performance standards. In the automotive sector, it facilitates the testing of vehicle subsystems, such as engines, transmissions, and electronic control units, to guarantee their functionality and durability. Similarly, in the electronics industry, LabVIEW is employed to test a wide range of devices, from semiconductors to consumer electronics, ensuring they operate correctly and reliably.

By automating the test processes, LabVIEW not only enhances the efficiency and accuracy of testing but also reduces the time and cost associated with manual testing methods. Its graphical programming environment allows engineers to quickly develop and deploy test systems tailored to specific requirements, making it an invaluable asset for quality assurance and product validation[105], [106]

4.4.2.6 Human-Machine Interface (HMI)

LabVIEW's advanced graphical user interface (GUI) capabilities are instrumental in developing intuitive and user-friendly Human-Machine Interfaces (HMIs). These HMIs are designed to provide operators with real-time visualization of process data, which is crucial for making informed decisions promptly. By leveraging LabVIEW's powerful GUI tools, engineers can create interactive and visually appealing interfaces that display critical information in an easily digestible format. This real-time data visualization allows operators to monitor key performance indicators, identify trends, and detect anomalies swiftly, thereby enhancing operational efficiency and responsiveness. The user-friendly nature of these HMIs ensures that even operators with minimal technical expertise can effectively interact with the system, reducing the likelihood of errors and improving overall productivity. As a result, LabVIEW-based HMIs play a pivotal role in optimizing industrial processes and ensuring smooth, efficient operations[103] [107]

4.4.3 Online ITSC and USV condition Detection LabVIEW interface

In our thesis, we developed a comprehensive LabVIEW monitoring dashboard interface - Figure 4.13 - specifically designed for real-time fault detection and health status evaluation of an induction motor (IM). This advanced interface seamlessly integrates an artificial neural network (ANN) to enhance its capabilities in monitoring and diagnosing two critical types of faults: Inter-Turn Short Circuit (ITSC) faults and Unbalanced Supply Voltage (USV) conditions. The dashboard is meticulously organized into two primary sections, each dedicated to providing essential information about the motor's operational health.

The first section focuses on the ITSC fault state. ITSC faults occur when there is a short circuit between the turns of the motor's stator winding, which can lead to overheating and potential motor failure if not addressed promptly. This section of the dashboard is equipped with various tools and indicators that allow for the continuous monitoring of ITSC faults. It provides real-time data and alerts, enabling operators to quickly identify and respond to any ITSC faults, thereby preventing further damage to the motor.

The second section is dedicated to monitoring USV conditions. Unbalanced supply voltages can cause uneven current distribution and increased stress on the motor, leading to reduced performance and potential faults. This section of the dashboard offers detailed insights into the USV conditions, allowing operators to track voltage imbalances and take corrective actions as needed. By providing real-time data and visual indicators, this section helps ensure that the motor operates under balanced voltage conditions, thereby enhancing its overall performance and longevity.

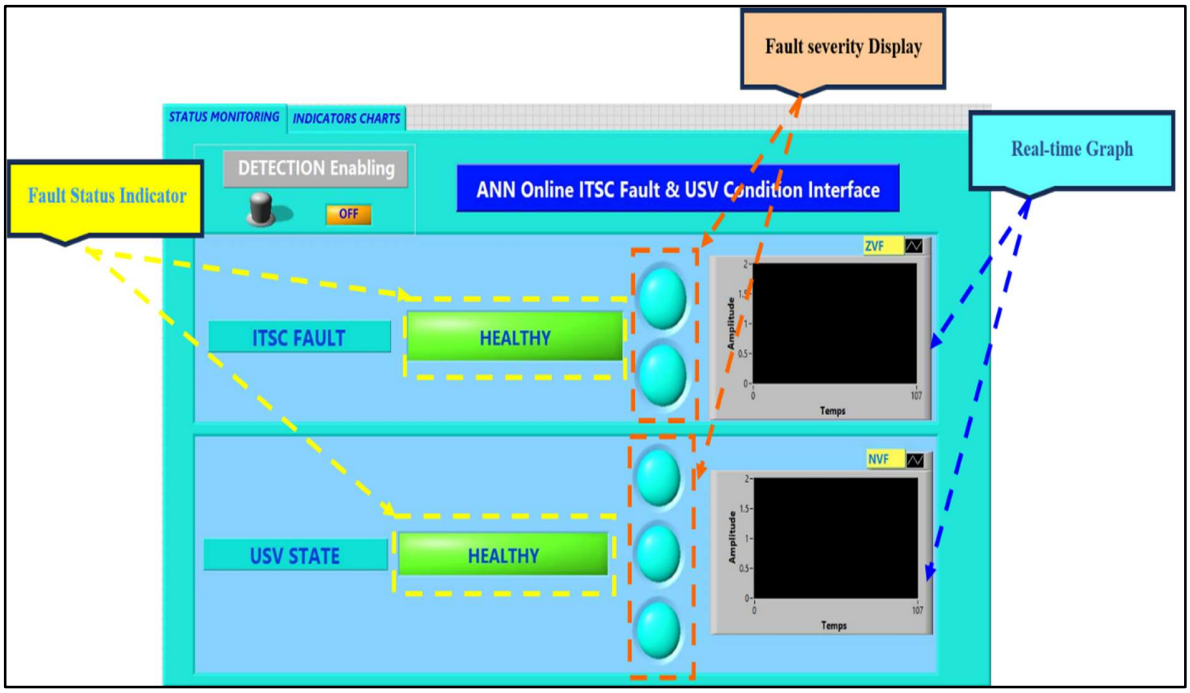

Figure 4.13 Online AI fault detection interface.

4.4.3.1 ITSC Fault USV State Section

The upper section of the interface is dedicated to monitoring ITSC faults. This type of fault occurs when there is a short circuit between turns of the motor's stator winding, which can lead to overheating and potential motor failure if not detected early. The ITSC fault state section includes several key elements:

4.4.3.2 Fault Status Indicator

This section features a color-coded button that displays the current status of the motor regarding ITSC faults. The button turns green when the motor is healthy and red when an ITSC fault is detected. This visual indicator allows operators to quickly assess the motor's condition at a glance, enabling prompt identification and response to any ITSC faults. By providing clear, immediate feedback, the Fault Status Indicator helps ensure the motor's optimal performance and prevents potential damage.

4.4.3.3 Fault Severity Display

Upon detecting an ITSC fault, the interface offers detailed information about the fault's severity. It specifies the number of shorted turns, such as "2 turns" or "9 turns," helping operators understand the extent of the fault and the urgency of the required maintenance. This feature ensures that operators can prioritize and address critical issues promptly, thereby preventing further damage to the motor and maintaining its operational efficiency.

4.4.3.4 Real-Time Graph

A graph displaying the amplitude of the calculated ZVF indicator over time. This graph is crucial for visualizing the indicator behavior and identifying any anomalies that may indicate an ITSC fault. The graph updates in real-time, providing continuous monitoring of the motor's health situation.

4.4.3.5 USV Condition Section

The lower section of the interface focuses on monitoring USV conditions. Unbalanced supply voltages can cause uneven current distribution and increased stress on the motor, leading to reduced performance and potential faults.

4.4.3.6 USV Status Indicator

Similar to the ITSC section, this section features a color-coded button that indicates the current USV condition. The button displays three different colors based on the severity of the USV fault: green for a balanced supply voltage, orange for a moderate unbalanced condition, and red for a severe unbalanced condition. This visual indicator helps operators quickly identify and assess the severity of USV issues, allowing for timely and appropriate corrective actions. By providing clear, color-coded alerts, the USV Status Indicator ensures that operators can promptly address voltage imbalances, thereby maintaining the motor's optimal performance and preventing potential faults. This feature is crucial for the overall health and efficiency of the induction motor, as it enables proactive management of USV conditions.

4.4.3.7 USV condition Severity Display

This section of the interface provides a reliable and efficient method for monitoring supply voltage conditions. Similar to the ITSC section, it features a color-coded button that indicates the severity of USV faults. The indicator was tested under three distinct unbalanced voltage levels: yellow for low imbalance (1%), orange for medium imbalance (2%), and red for high imbalance (3%). The NVF indicator responded as expected, accurately reflecting the generated operating conditions. This system enables operators to quickly identify and assess the severity of voltage imbalances, allowing for timely and precise corrective actions. By delivering clear, color-coded alerts, the indicator ensures effective management of USV conditions, helping to maintain optimal motor performance. Promptly addressing imbalances minimizes the risk of faults, enhances the induction motor's reliability, and supports long-term operational efficiency. This proactive approach to voltage monitoring is essential for maintaining system stability and avoiding potential disruptions.

4.4.3.8 Real-Time Graph

This section features a graph that displays the amplitude of the NVF indicator values over time, specifically for monitoring USV conditions. The graph updates in real-time, providing operators with continuous visual feedback on the voltage balance. By tracking these values, operators can quickly identify any deviations that may indicate an unbalanced supply voltage, enabling prompt corrective actions to maintain optimal motor performance and prevent potential faults.

4.4.4 ANN LabVIEW Interface Testing & Validation

4.4.4.1 ITSC Fault Detection

The developed LabVIEW interface underwent rigorous testing using a prescribed experimental setup designed to simulate and monitor various fault conditions in real-time. This

setup allowed for the generation and online observation of all studied faulty cases, ensuring a comprehensive evaluation of the interface's capabilities.

The experimental process began with the introduction of an Inter-Turn Short Circuit (ITSC) fault involving 2 shorted turns, which corresponds to 1% of the total winding turns. This initial fault scenario was crucial for assessing the interface's sensitivity and responsiveness to minor faults. The reaction of the detection system to this fault was meticulously displayed in the monitoring interface, as depicted in Figure 4.14.

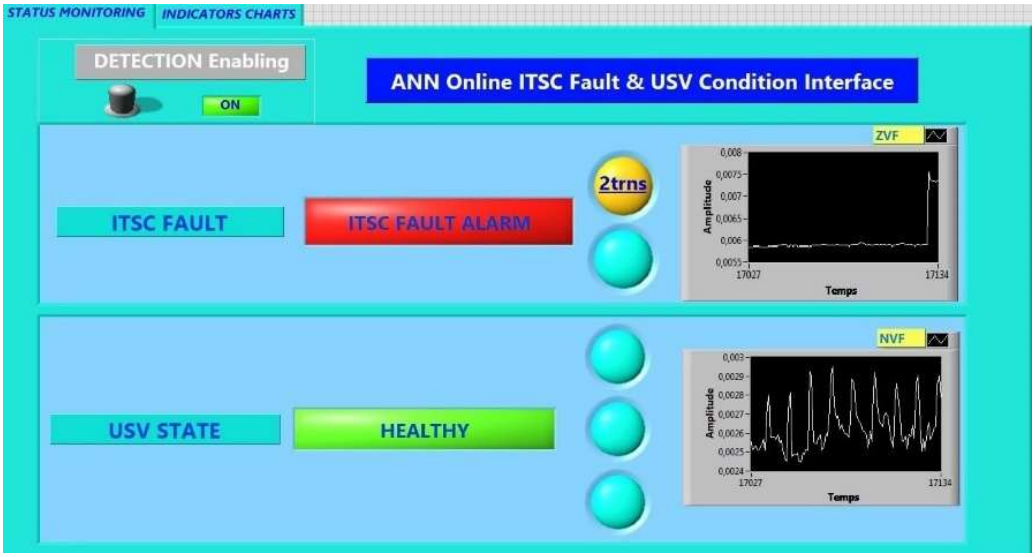

Figure 4.14 ITSC fault of 2 shorted turns (1%).

The interface provided clear visual indicators, such as color-coded buttons and real-time graphs, which allowed operators to quickly identify and assess the ITSC fault. The system's ability to accurately detect and display this minor fault demonstrated its high sensitivity and precision, which are essential for early fault detection and prevention of further damage.

Following the successful detection of the 2 shorted turns fault, a more severe ITSC fault involving 9 shorted turns was introduced. This fault represents 4.5% of the total winding turns and poses a greater risk to the motor's health and performance. The LabVIEW interface promptly

responded to this more significant fault, with the display changing to reflect the increased severity, as represented in Figure 4.15.

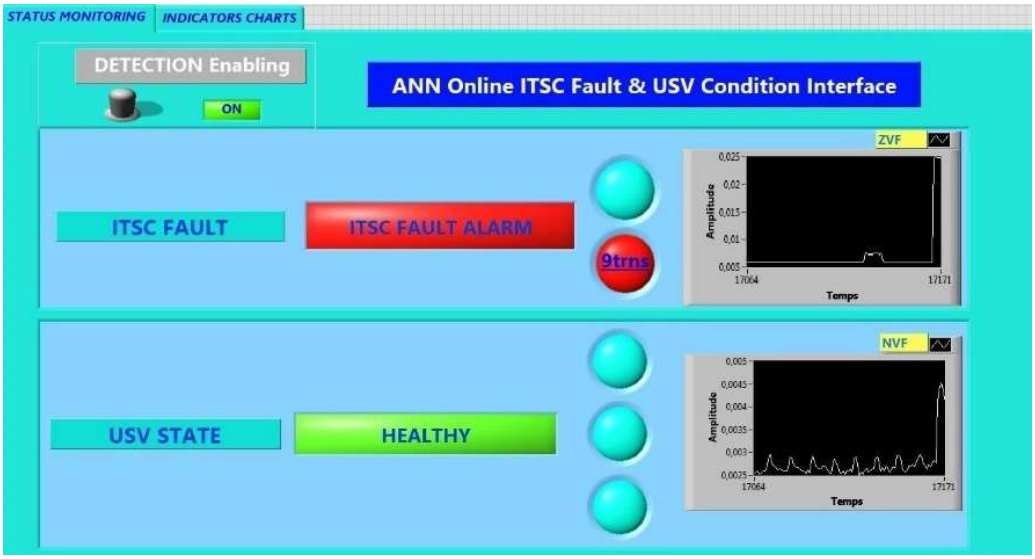

Figure 4.15 ITSC fault of 9 shorted turns (4.5%).

The interface's ability to differentiate between faults of varying severity is a testament to its robustness and reliability. By providing clear and immediate visual feedback, the interface enabled operators to take appropriate and timely corrective actions, thereby preventing potential motor failures and ensuring continuous and safe operation.

The seamless transition of the LabVIEW interface from detecting a minor fault to a more severe one highlights its versatility and effectiveness in real-time fault monitoring. The interface's capacity to accurately identify and display faults of different magnitudes ensures that operators are well-informed and equipped to manage the motor's health and performance efficiently. This comprehensive testing process underscores the interface's potential as a valuable tool for enhancing the reliability and safety of induction motors in various industrial applications.

4.4.4.2 Unbalanced supply voltage condition detection

The Unbalanced Supply Voltage (USV) condition was thoroughly tested by applying three distinct levels of voltage imbalance: low (1% unbalanced voltage), medium (2% unbalanced voltage), and high (3% unbalanced voltage). This comprehensive testing aimed to evaluate the interface's ability to accurately detect and respond to varying degrees of USV conditions, ensuring its reliability and effectiveness in real-world applications.

The testing process began with the application of a low-level USV condition, characterized by a 1% unbalanced voltage. Figure 4.16 illustrates the state change in the interface under this low-level USV condition.

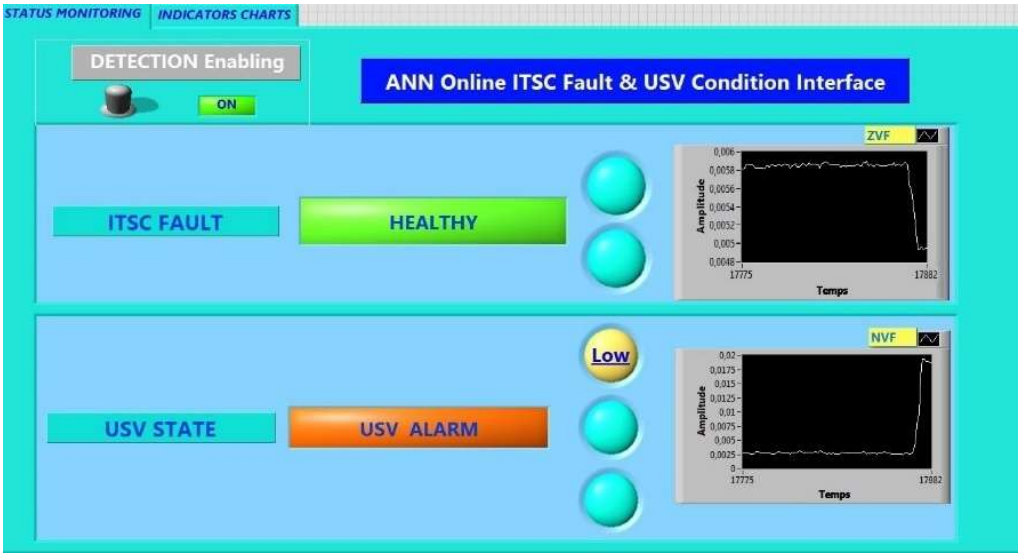

Figure 4.16 Low level USV condition.

As clearly shown in the figure, the Negative Voltage Factor (NVF) indicator reacted precisely as expected to the generated operating condition. Simultaneously, the dedicated interface button changed its state coherently, turning yellow to indicate the low-level USV condition. This correct response of the adopted scheme demonstrated the interface's sensitivity and accuracy in detecting minor voltage imbalances, which are crucial for early fault detection and prevention of potential motor damage.

Following the successful detection of the low-level USV condition, a medium-level USV condition was initiated, characterized by a 2% unbalanced voltage. Figure 4.17, illustrates the state changes of the neural network-based interface under this medium-level USV condition.

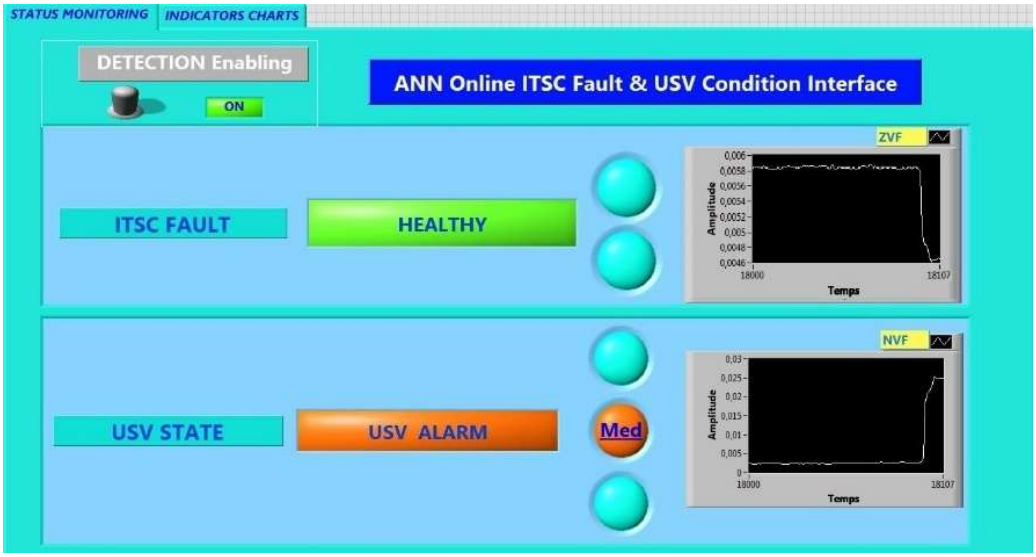

Figure 4.17 Medium level USV condition.

The medium button on the interface lit up, correctly indicating the detected operating condition level. This accurate response of the interface to the medium-level USV condition further validated its reliability and effectiveness in differentiating between varying degrees of voltage imbalance. The interface's ability to provide clear and immediate visual feedback enabled operators to take appropriate and timely corrective actions, ensuring the motor's continuous and safe operation.

Finally, a high-level USV condition was introduced, characterized by a 3% unbalanced voltage. The reaction of the detection technique to this severe USV condition is displayed in Figure 4.18 In this case, the high button on the interface changed its state, turning red to indicate the high-level USV condition.

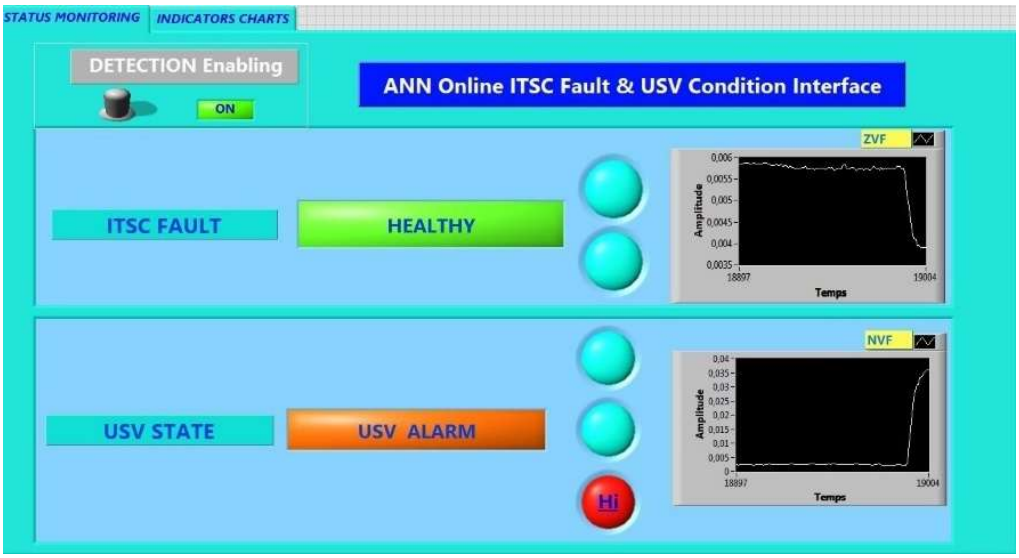

Figure 4.18 High level USV condition.

Simultaneously, the healthy button switched to faulty, providing a clear and immediate visual indication of the severe voltage imbalance. This accurate and prompt response of the interface to the high-level USV condition underscored its robustness and reliability in detecting and responding to critical fault conditions.

The smooth transition of the LabVIEW interface from detecting low to high-level USV conditions demonstrates its adaptability and effectiveness in real-time fault monitoring. The interface's ability to precisely identify and display varying fault severities ensures that operators are well-informed and capable of managing the motor's health and performance efficiently. This thorough testing process emphasizes the interface's potential as a crucial tool for enhancing the reliability and safety of induction motors across various industrial applications. By offering clear and immediate visual feedback, the interface allows operators to take appropriate and timely corrective actions, thereby preventing potential motor failures and ensuring continuous and safe operation.

4.5 Conclusion

The integration of an Artificial Neural Network (ANN) within a LabVIEW interface for real-time fault detection and health status evaluation of induction motors (IMs) marks a significant advancement in industrial monitoring and maintenance. The comprehensive testing and validation of this interface, focusing on both Inter-Turn Short Circuit (ITSC) faults and Unbalanced Supply Voltage (USV) conditions, have demonstrated its robustness, reliability, and effectiveness.

The LabVIEW interface underwent rigorous testing using a prescribed experimental setup designed to simulate and monitor various fault conditions in real-time, ensuring a thorough evaluation of its capabilities. The experimental process for ITSC fault detection began with the introduction of a minor fault involving two shorted turns. The interface's ability to accurately detect and display this minor fault, using clear visual indicators such as color-coded buttons and real-time graphs, showcased its high sensitivity and precision, which are essential for early fault detection and prevention of further damage. Following this, a more severe ITSC fault involving nine shorted turns was introduced. The interface promptly responded to this more significant fault, demonstrating its ability to differentiate between faults of varying severity and providing clear and immediate visual feedback to operators. This seamless transition from detecting minor to severe faults highlights the interface's versatility and effectiveness in real-time fault monitoring, ensuring that operators are well-informed and equipped to manage the motor's health and performance efficiently. Similarly, the USV condition was thoroughly tested by applying three distinct levels of voltage imbalance: low, medium, and high. The interface's ability to accurately detect and respond to these varying degrees of USV conditions, as evidenced by the precise reactions of the Negative Voltage Factor (NVF) indicator and the coherent state changes of the dedicated interface buttons, demonstrated its sensitivity and accuracy in detecting voltage imbalances. The smooth transition of the interface from detecting low to high-level USV conditions further underscored its adaptability and effectiveness in real-time fault monitoring. By providing clear and immediate visual feedback, the interface enabled operators to take appropriate and timely corrective actions, ensuring the motor's continuous and safe operation.

This thorough testing process emphasizes the interface's potential as a crucial tool for enhancing the reliability and safety of induction motors across various industrial applications. The

integration of ANN within the LabVIEW interface not only enhances the accuracy and efficiency of fault detection but also provides a user-friendly platform for real-time monitoring and diagnostics, making it a valuable asset for industrial monitoring and maintenance.

CHAPTER 4

CONCLUSION

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5.1 Conclusion

In this thesis, a novel real-time scheme for diagnosing Inter-Turn Short Circuit (ITSC) faults in induction motors is presented. The method relies on three-phase input voltage measurements and employs the Fortescue transform, combined with frequency estimation techniques such as Fast Fourier Transform (FFT) and STLSP. A new detection indicator, called the Zero Voltage Factor (ZVF), is introduced and experimentally validated under various load conditions. The ZVF demonstrates high reliability, accuracy, and versatility in detecting ITSC faults, showcasing its potential for broader application in fault diagnosis. This innovation underscores the importance of developing real-time, accurate fault detection tools to enhance motor reliability and safety in industrial settings. By enabling early detection of faults, the ZVF contributes to minimizing downtime and preventing costly equipment damage, making it a valuable addition to modern condition monitoring systems.

Furthermore, the integration of an Artificial Neural Network (ANN) within a LabVIEW interface for real-time fault detection and health status evaluation of induction motors is explored. The LabVIEW interface was rigorously tested for its ability to detect ITSC faults and Unbalanced Supply Voltage (USV) conditions. The testing process involved simulating various fault scenarios, including minor and severe ITSC faults, as well as different levels of voltage imbalance (low, medium, and high). The interface demonstrated high sensitivity and precision in identifying both minor and severe faults, as well as accurately responding to varying degrees of voltage imbalance. This capability ensures that operators can detect faults at their earliest stages, preventing further damage and maintaining motor performance.

The LabVIEW interface provides clear visual feedback through color-coded buttons and real-time graphs, enabling operators to quickly assess the motor's health and take timely corrective actions. This user-friendly design ensures that even non-expert users can effectively monitor and manage motor conditions. The integration of ANN within the interface enhances fault detection accuracy by leveraging the network's ability to learn and adapt to complex fault patterns. This combination of advanced AI and intuitive visualization tools makes the LabVIEW interface a powerful and practical solution for real-time monitoring and diagnostics in industrial applications.

The experimental validation of both the ZVF indicator and the LabVIEW interface highlights their effectiveness in real-world scenarios. The ZVF's ability to detect ITSC faults under

varying load conditions, combined with the LabVIEW interface's capability to monitor and diagnose multiple fault types, demonstrates the potential of these tools to improve the reliability and safety of induction motors. By providing early and accurate fault detection, these systems help reduce maintenance costs, extend equipment lifespan, and ensure continuous operation in industrial environments.

The current thesis had introduced innovative approaches to real-time fault detection in induction motors, focusing on the development of the ZVF indicator and the integration of ANN within a LabVIEW interface. These advancements represent significant progress in condition monitoring and fault diagnosis, offering practical solutions for improving motor reliability and operational efficiency. The successful experimental validation of these tools underscores their potential for widespread adoption in industrial applications, paving the way for more advanced and user-friendly monitoring systems in the future.

5.2 Future works

Future research could focus on the development of a standalone system for online fault detection in induction motors, utilizing cost-effective and compact development platforms such as Raspberry Pi. Such a system would enable real-time monitoring and diagnostics without the need for complex setups, making it more accessible for small and medium-sized industries. By integrating the proposed fault detection algorithms, including the Zero Voltage Factor (ZVF) and ANN-based diagnostics, into a Raspberry Pi-based platform, the system could provide a portable, low-cost solution for continuous motor health monitoring.

Additionally, the deployment of Internet of Things (IoT) technologies could further enhance the system's capabilities. IoT-enabled sensors and communication modules could facilitate remote monitoring and data collection from multiple motors across industrial facilities, allowing for centralized diagnostics and predictive maintenance on a larger scale. This integration would enable real-time data transmission to cloud-based platforms, where advanced analytics and machine learning algorithms could be applied to predict potential faults and optimize maintenance schedules. Exploring these avenues could lead to more robust, scalable, and cost-effective solutions for industrial motor monitoring, ultimately improving operational efficiency, reducing downtime, and advancing the adoption of smart manufacturing practices.

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