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ANN based default diagnosis of induction machine with Co-simulation using FPGA

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الملخص
أصبح الاكتشاف التلقائي للأخطاء عاملًا بشريًا مهمًا بشكل متزايد ؛ وهو نتيجة الإرهاق وسقوط الذاكرة وأحيانًا بسبب الضغط البيئي (الضوضاء والحرارة ... إلخ). في واقع الأمر ، نحن مهتمون تمامًا بالتشخيص التلقائي ؛ والتي تمكن من الكشف المبكر عن الحالات الشاذة ، وهي إحدى الوسائل المؤكدة للمساهمة في تحسين إنتاجية القطاعات المختلفة. لهذا الغرض ، يتعامل البحث المقترح مع المحاكاة المشتركة باستخدام معالج ناعم مكون من FPGA للتشخيص القائم على الشبكة العصبية الاصطناعية لأعطال الآلة غير المتزامنة. بمجرد اختيار بنية ANN وتطبيق تدريب خارج الخط مما يجعل ANN قادرة على تحديد أخطاء الآلة غير المتزامنة المختلفة ، يتم اقتراح طريقة لتنفيذ ANN باستخدام صندوق أدوات مولد النظام الذي توفره XILINX. يسمح مولد النظام بتنزيل خوارزمية ANN التي تم الحصول عليها في شريحة VIRTEX4 FPGA. النتائج التي تم الحصول عليها من خلال المحاكاة المشتركة لمحرك الحث في MATLAB / SIMULINK و ANN على FPGA مرضية وواعدة للغاية.

ABSTRACT
The automatic detection of errors is becoming increasingly important human operator weakness (inherent); which is a consequence of fatigue, lapses memory and sometimes due to environmental pressure (noise, heat...etc.). As a matter of fact, we are absolutely interested in automatic diagnostics; which enables early detection about anomalies, which is one of the sure means of contributing to improve the productivity of the various sectors. For this purpose, the proposed research work deals with the co-simulation using FPGA configured soft processor of Artificial Neural Network based diagnostic of induction machine faults. Once the ANN architecture is chosen and an off-line training is applied which makes the ANN able to identify the different induction machine faults, a method is proposed to implement the sigmoid shaped activation function using system generator toolbox provided by Xilinx. The system generator allows downloading the obtained ANN algorithm in the Virtex4 FPGA chip. The results obtained by co-simulation of the induction motor drive in Matlab/Simulink and the ANN on the FPGA are satisfactory and very promising.

Résumé:
La détection automatique des défauts devient de plus en plus importante faiblesse de l'opérateur humain (inhérente) ; qui est une conséquence de la fatigue, des trous de mémoire et parfois due à la pression environnementale (bruit, chaleur...etc.). En fait, nous sommes absolument intéressés par les diagnostics automatiques ; qui permet une détection précoce des anomalies, ce qui est l'un des moyens sûrs de contribuer à améliorer la productivité des différents secteurs. À cette fin, le travail de recherche proposé porte sur la co-simulation à l'aide d'un processeur logiciel configuré sur FPGA du diagnostic basé sur un réseau de neurones artificiels des défauts de la machine à induction. Une fois l'architecture ANN choisie et une formation hors ligne appliquée permettant à l'ANN d'identifier les différents défauts de la machine à induction, une méthode est proposée pour implémenter la fonction d'activation en forme de sigmoïde à l'aide de la boîte à outils du générateur de système fournie par Xilinx. Le générateur de système permet de télécharger l'algorithme ANN obtenu dans le vaisseau Virtex4 FPGA. Les résultats obtenus par co-simulation de la commande du moteur à induction dans Matlab/Simulink et de l'ANN sur le FPGA sont satisfaisants et très prometteurs.

Keywords: ANN;FPGA;DIAGNOSIS

Praise be to **GOD** who gave me the opportunity to return to my studies after dropping out for a year.

I will never dare forget to thank my Soulmate my

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LIST OF SYMBOLS

$\boldsymbol{I_{sa}}$, $\boldsymbol{I_{sb}}$,$\boldsymbol{I_{sc}}$: stator's three phase currents **(A).**

$\boldsymbol{R_s}$: Resistance of stator's winding **(Ohm).**
$\boldsymbol{R_r}$: Resistance of rotor's winding **(Ohm).**
$\boldsymbol{L_s}$, $\boldsymbol{L_r}$: Stator's and rotor's self–inductances **(Henry).**

$\boldsymbol{M_s}$: Mutual inductance **(Henry).**

$\boldsymbol{\omega_r}$: Rotor's angular speed **(mechanical) (rad/sec).**

P: No. of poles pairs.

J: Moment of inertia **(Kg · m2).**

TL: Load torque **(Nm).**

s: Stator quantities.

r: Stator quantities.

$\boldsymbol{\phi_s \phi_r}$: Stator's and Rotor's fluxes **(Weber).**

$\boldsymbol{i_{sa}}$, $\boldsymbol{i_{sb}}$, $\boldsymbol{i_{sc}}$: Stator's three phase currents **(A).**

θ: Angular position in the frame of motor **(Deg).**

$\mathbf{F_S}$: Slip frequency.

$\mathbf{F_P}$:Pole pass frequency.

$\boldsymbol{F_{CC}}$: eccentric of rotor frequency.

$\boldsymbol{F_b}$: rotor bar frequency.

$\boldsymbol{F_L}$: Electrical line frequency.

$\boldsymbol{B_D}$: Ball Diameter.

$\boldsymbol{N_B}$:Numbers of Ball**.**

$\boldsymbol{P_D}$:Ball Pitch Diameter

LIST OF ABBREVEATION

AE: Acoustic Emission

AD: Analog Device

AC: Alternating Current

AI: Artificial Intelligence

ANN: Artificial Neural Network

BP: Back Propagation

BPFI: Ball Pass Frequency Inner

BPFO: Ball Pass Frequency Outer

BSF: Ball Spin Frequency

CM: Condition Monitoring

CSLDV: Continuous Scan Laser Doppler Vibrometry

DSP: Digital Signal Processor

EPRI: Electric Power Research Institute

FD: Fault Detection

FFT: Fast Fourier Transform

FODS: Fiber Optic Displacement

FPGA: Field Programable Gate Array

FTF: Fundamental Train Frequency

ICA: Independent Component Analysis

IEEE: Institute of Electrical and Electronic Engineers

IM: Induction Machine

LDV: Laser Doppler Vibrometry

MEMS: Microelectromechanical System

MMF: MagnitoMotiveForce

NN: Neural Network

ODS: Optic Displacement Sensor

PCA: Principal Component Analysis

PD: Partial Discharge

PMSM: Permanent Magnet Synchronous Motors

RMS: Root Mean Sequard

RBPF: Rotor Bar Pass Frequency

STFT: Short Term Fourier Transform

WPT: Wavelet Packet Transform

WT: Wavelet Transform

Induction machine are among the most widely used motors. Compared to other alternatives, they are cheaper and easier to maintain, and also a weak link due to their important role in the production chain [1]. Therefore, the control of motors has evolved a lot in the industry as the need to improve the reliability of these motors and their durability has become more and more important [2]. Due to its robustness and low cost, the squirrel cage induction motor is in a suitable position. In recent decades, the detection and early diagnosis of faults in induction motors has been the subject of numerous studies [3,4,5,6]. There are different types of detection and diagnostic techniques namely vibration analysis and thermal analysis, stator current analysis or MCSA (Motor Current Signature Analysis). Its feature is that the stator current contains information about almost all possible faults of the asynchronous motor without the need to add additional sensors of mechanical quantities or vibrations. Due to industry demands and the complexity of the system, the need to quickly troubleshoot the requires various diagnostic techniques that have different characteristics and can solve these problems. Artificial intelligence techniques culminate among the most important and widespread diagnostic techniques, including Neural Network, which is considered to be the most accurate and easiest to implement on electronic circuits such as FPGA and PSD [3,4,5,6,7,8,9,10,11]. In order to be able to cope with this work adequately, this work is structured as follows:

The first chapter is dedicated to the investigation of the fault's diagnosis of inductions machines. We will start first with an introduction to diagnostics, then we will present the different faults that can occur in asynchronous motors and we will end this chapter with an analysis of the different diagnostic techniques, making comparisons between diagnostic methods and talking about the maintenance classification and its main aspects important methods used in the industry.

The aim of the second chapter is to present a sufficient and suitable modeling framework to be used in the next derivation of the fault detection and isolation scheme. In general, three-phase induction motors can be modeled as three-phase models.

The objective of the third chapter is the implementation of neural network on an FPGA circuit. The purpose of this implementation is to study the contribution of hardware integration solutions (FPGA) in the diagnosis of asynchronous motor failures for a lack of phase fault case. In this study, we start with the adaptation of the neural network in order to allow an optimal implementation. This implementation must ensure efficiency, speed of execution and a minimum possible space on the FPGA circuit

Chapter I

State of the art of induction machine fault diagnosis

Chapter I

State of the art of induction machine fault diagnosis

I.1 Induction machine components :

Induction motors are complex electro-mechanical devices used worldwide in industrial processes to convert electrical energy into mechanical energy. Such motors are widespread because they are robust, easily installed, controlled, and adaptable for many industrial applications, including pumps, fans, air compressors, machine tools, mixers, and conveyor belts, as well as many other industrial applications. Moreover, induction motors may be supplied directly from a constant frequency sinusoidal power supply or by an ac variable frequency [1].

Due to the large range of types and applications of electric motors. In other words, the focus is on the three-phase squirrel cage induction motor, which is a type of asynchronous motor. As is common in the literature, a three-phase squirrel cage induction motor is referred to as an induction motor throughout this thesis. This type of induction motor is highlighted in Fig. 1[1].

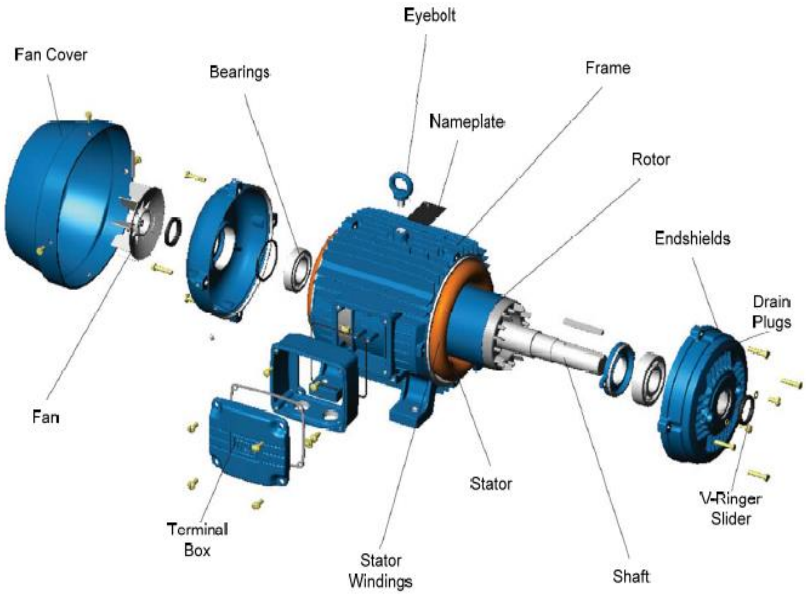


Figure.I.1 : THREE PHASE INDUCTION MOTOR

An induction machine consists of a stator and a rotor. The stator is a stationary part, and the rotor is the rotating part of the machine [2]. There are two types of rotor designs: 1) Squirrel cage rotor and 2) wound rotor. In this work, the squirrel-cage induction motor is considered. The design of an induction device strives for low maintenance, high reliability and good efficiency [3]. Figure 2 shows the internal structure of a three-phase asynchronous motor.

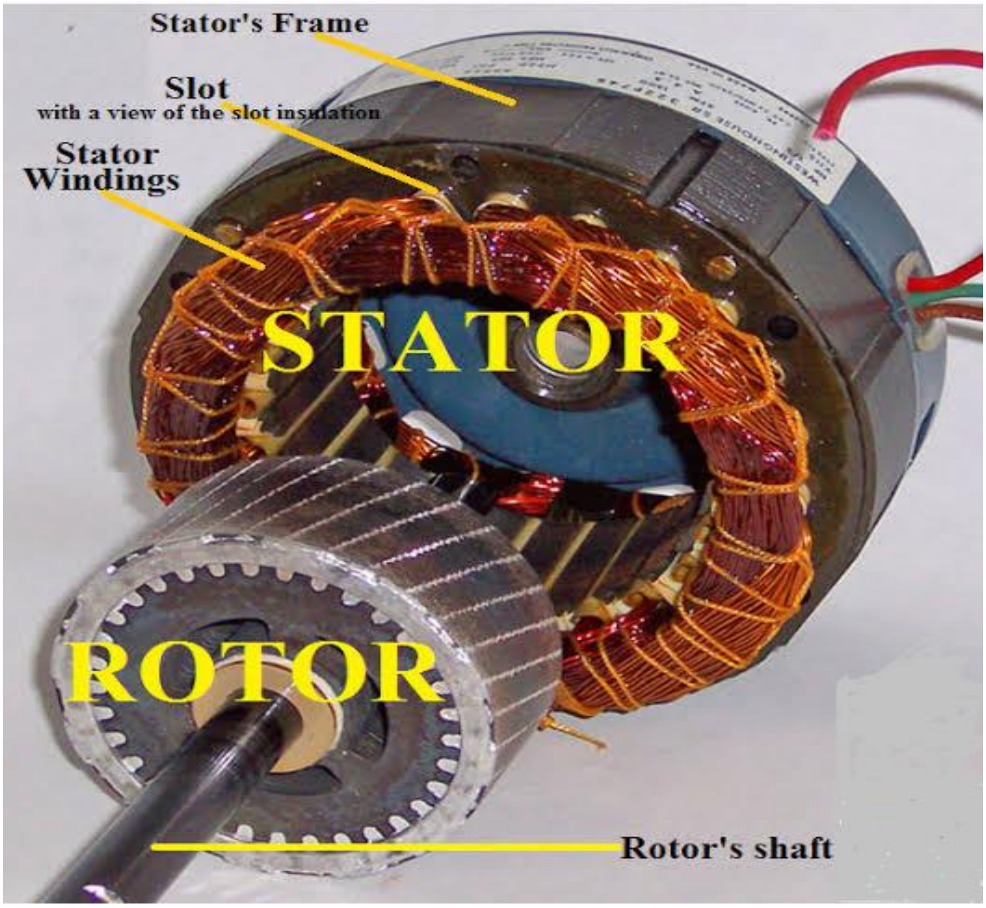


FIGURE.I.2. THE INTERNAL STRUCTURE OF A THREE-PHASE INDUCTION MOTOR.

I.1.1 The stator:

The stator is composed of three parts: frame, lamination core and windings show Figure 3.

The frame mechanically: supports the stator and the rotor shaft bearings. The windings are composed of three equally distributed coils along the stator lamination core, which are connected to the three-phase power supply. Only the stator is connected to the power supply. The energy for the rotor is delivered by induction by the synchronous rotation of the stator magnetic field. The name of the “induction motor” is thus derived from this phenomenon. It should be pointed out that there is a space between the stator and the rotor which is called the air gap [4].

lamination core: It consists of a series of slots of high-quality alloy steel laminations supported on the outer cylindrical stator frame. The magnetic path is laminated to reduce eddy current losses and heating.

One set of insulated electrical windings: In a three-phase motor, the stator circuit has three sets of coils, one for each phase, spaced 120° apart. These coils are inserted into the slots. of the laminated magnetic path.

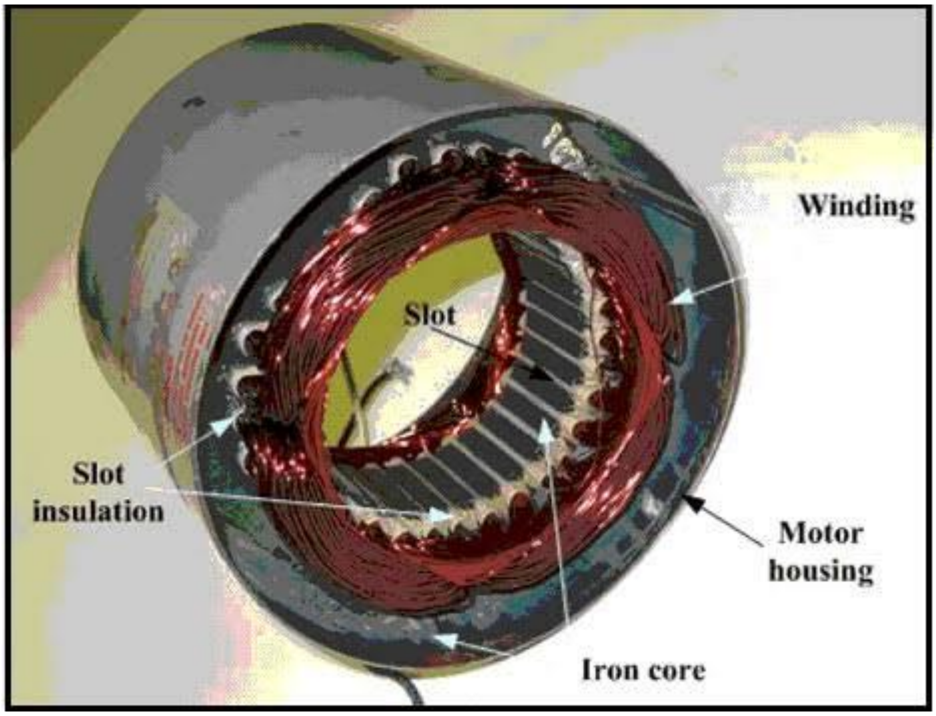


FIGURE.I.2: COMPENENTS OF THE STATOR IN INDUCTION MOTR

I.1.2 The rotor:

It is the rotating part of the engine. It is inserted into the stator hole and rotates coaxial to the stator. Like the stator, the rotor is made up of a series of thin slots. sheets, so-called laminations, pressed from electromagnetic substance (special core steel) [5]. together in the form of a cylinder. This insulates the thin metal sheets the slots consist of the electrical circuit and the cylinder electromagnetic substance acts as a magnetic path. Winding of the rotor of an induction. The motor can be of two types: **(B.1)** squirrel cage type and **(B.2)** wound type. Dependent in rotor-wound induction motors are divided into two groups [6]:

Squirrel cage induction motor: Here the rotor consists of a set of bars made of copper, aluminum or alloy as rotor conductors embedded in the rotor slots. This results in a very robust construction of the rotor. The rotor bars are connected at both ends with a last ring to form a narrow path. Figure 4 shows a squirrel cage rotor

FIGURE.I.3: SQUIRREL CAGE ROTOR

Wound rotor: In this case the rotor leads are insulated windings that are not short-circuited by the end rings but by the clamps turns are taken out to be connected to three isolated voucher numbers. rings mounted on the shaft as shown in Fig. 5. external electric the connections from the to the rotor are made by brushes placed on the slip rings. For Due to the presence of these slip rings, this type of motor is also referred to as a slip ring Induction motor

FIGURE.I.4: WOUND ROTOR TYPE

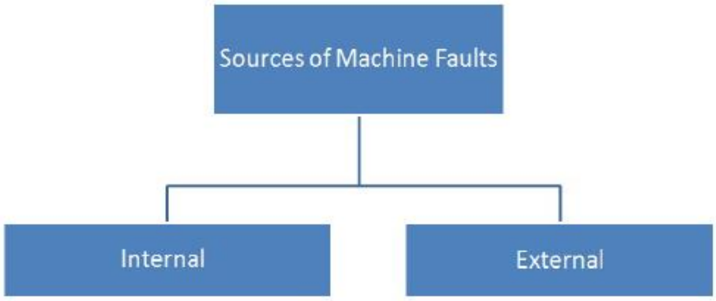
I.1.3 Mechanical elements

In addition to the two main parts mentioned above, an induction motor consists of other parts which are named as follows [4]:
End Flanges There are two end flanges used to support the two bearings at both ends of the motor
.

Bearings: There are two sets of bearings that will fit either end the rotor and are used to support the rotating shaft.
Shaft: It is made of steel and is used to transmit the torque generated to the load.
Cooling Fan: Normally located at the opposite end of the load side, called non-drive end of the motor, for forced cooling of the stator and rotor.
Terminal Box: Located on top or on either side of the outer cylindrical frame of the stator to accommodate external electrical connections.

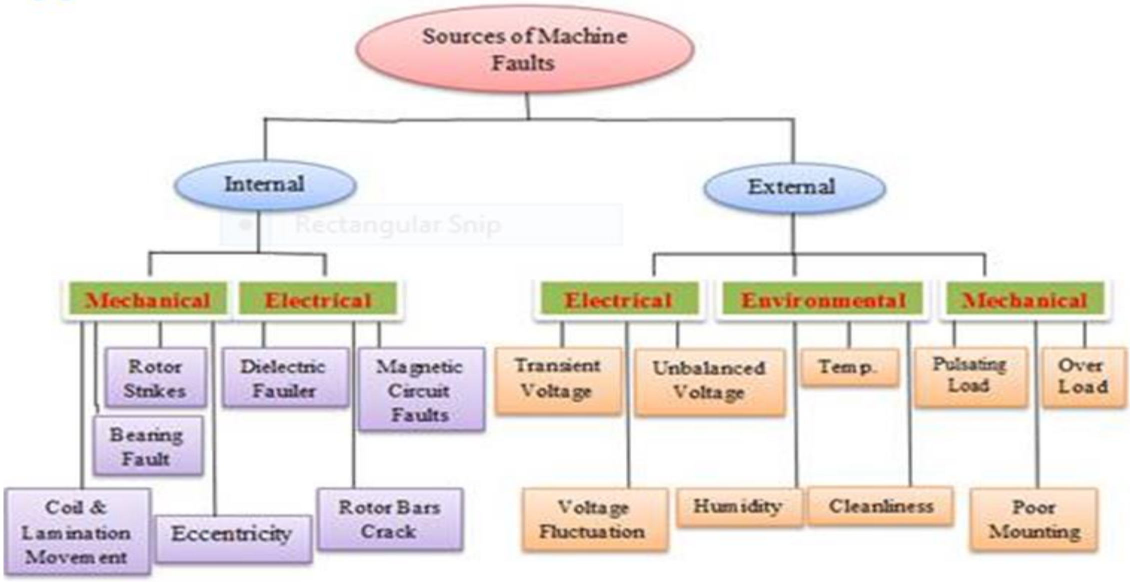
I.2 Types of faults in induction machine and their causes:

Fault diagnosis and protection of electrical machines an old concept. First manufacturer and operator of electrical machines hung simple and uncomplicated protection such as over-current, over-voltage, ground fault, etc. for guarantee safe and reliable operation. However, the work performance of the machines became more and more complicated, troubleshooting became very important. Currently has becomes very important for diagnosing errors on your startup Otherwise there may be unplanned machine downtimes, the draft of can lead to severe financial problems. casualties. Both primary and secondary error types are subjected to an induction machine. The various sources of failures in an induction motor are shown in Figure 6



FIGUREI.5: THE VARIOUS SOURCES OF FAILURES IN AN INDUCTION MOTOR

Classification of various internal and external faults of induction machine is shown in Figure.7 The sum of the fault in an induction motor is roughly classified by its or external condition. The error can be classified as mechanical or electrical faults according to their cause. Based on location, a fault can be classified as a rotor error [8] or stator error Figure 7. Failures in an induction machine can are generally classified as rotor failures, stator failures, air gap eccentricity error, mechanical vibration error, bearing error, etc [9].



FIGUREI.6: VARIOUS INTERNAL AND EXTERNAL ERRORS

Induction machines can encounter various fault conditions that can lead to maintenance costs and unplanned downtime, resulting in an overall loss of production and financial income. Over **80%** electromechanical conversion in industrial drives belongs to the induction motor (**IM). ** Also the total number of operational electrical equipment machines worldwide there were around **16.1** billion in **2011**, with a growth rate of around **50%** per year last five years **[5].** In general, several surveys investigating failures in induction machines have categorized the most common failure mechanisms. The more statistical results, based on statistics **IEEE** Industry Applications Society Motor Reliability Working Group Report, which examined **1,141** engines, and the Electric Power Research Institute **(EPRI),** the surveyed **6312** engines can be summarized in the results shown in Figure 8 **[10].**

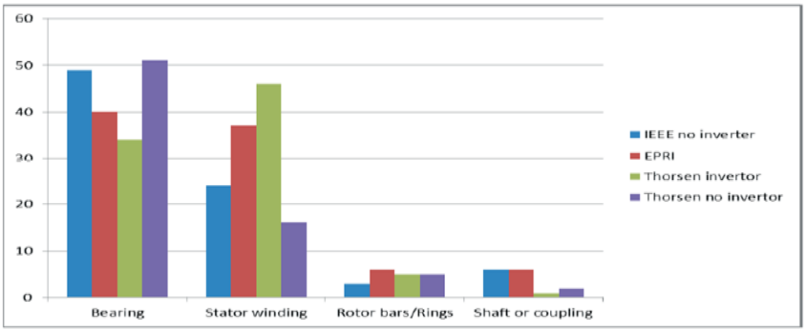
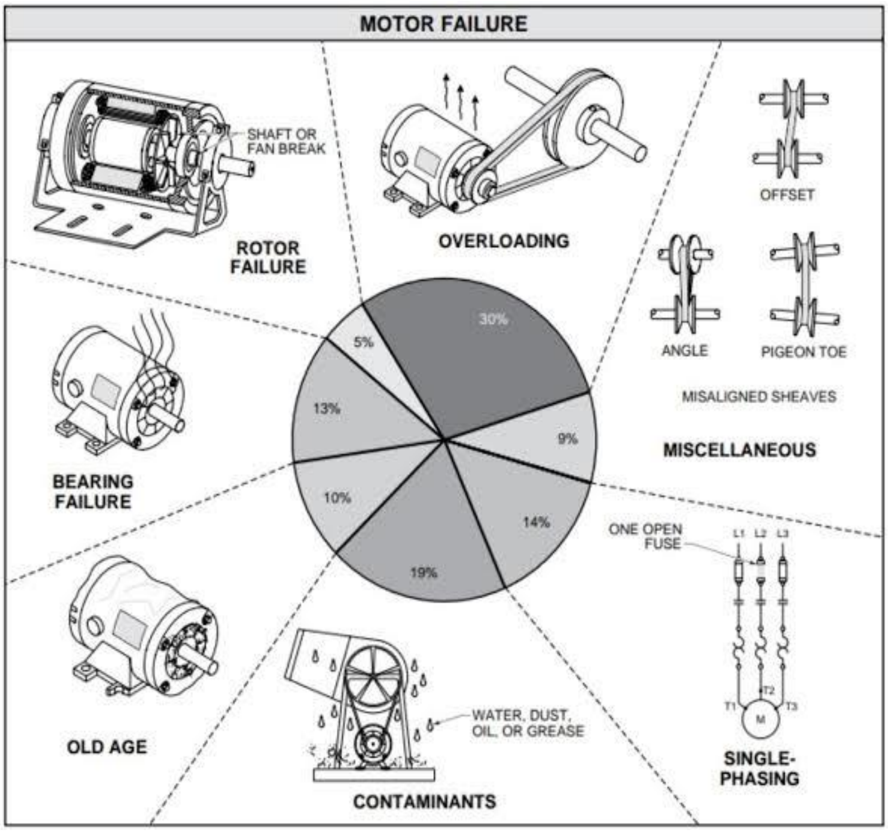


Figure.I.7 : The percentages of common faults in three phase induction machines

Induction motor failures can be classified as follows [11-12] Figure 9.

Electrical fault: Outages under this classification are unbalanced supply. voltage or current, single phase, under or over current voltage, reverse phase.

Mechanical fault: Failures under this classification are broken rotors bar, mass imbalance, air gap eccentricity, bearing damage, rotor winding Error and failure of the stator winding.



FIGUREI.8 : VARIOS OF MOTOR FAILURE.

I.2.1 Electrical fault:

Electrical faults are divided into stator and rotor faults. Stator failures and rotor failures mainly occur in the turns [2]:

I.2.1.1 Stator fault:

Stator failures are generally due to insulation faults. Several studies have shown that 30%− 40% of induction motor failures are due to stator winding faults. The stator winding consists of coils of insulated copper wire placed in slots in the stator, while stator winding faults are initiated due to insulation breakdown between two adjacent turns in a coil of the same phase; This fault is commonly referred to as a shorted turn or shorted turn. Therefore, this type of error generates additional heat and an imbalance in the machine's magnetic field. Additional heat residing between two or more shorted turns will cause further damage to the insulation of the adjacent up to the point of catastrophic failure such as B. phase error, phase-to-phase error, phase-to-earth error or earth error phase. phase against ground fault [10] show figure 10.

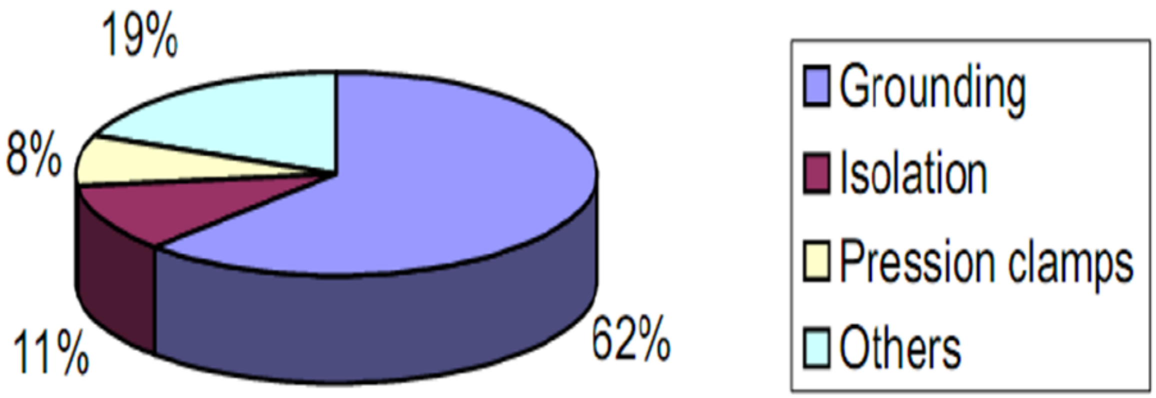


FIGURE.I.9 :THE PERCENTAGES OF COMMON FAULTS IN THE STATOR.

However, stator failures can be roughly divided into the following two categories [13-10]:

Laminated cores: (core overheating, core loosening, etc.) and skeletons (vibrations, circulating currents, refrigerant loss, ground fault, etc.) Defects

Faults in the stator windings: The most common faults detected in the stator windings relate to faults in the last winding part or in the slot part in the last part of the winding contains local insulation damage, isolation friction, moisture, oil or dirt contamination; Damaged connector, winding failure (while part-groove failures include insulation friction) and conductor shifting. In fact, most of these defects are due to a combination of different voltages being applied to the short circuits between turns shorted turns in stator windings is a category of faults more common in induction motors. In general, short circuits in stator windings occur between turns of one phase or between turns of two phases or between turns of all phases. In addition, short circuits between the winding lines and the stator core also occur.

The different types of winding faults are summarized below as follows [14]:

• Inter-turn short circuits between turns of the same phase (see Fig. 11a)
, short circuit in the winding (see Fig.11b),
short circuit between winding and stator core (see Fig. .11c and Fig..11d)
, short-circuits in the connections (see Fig. .11e) and short-circuits between the phases (see Fig.11f) are usually caused by stator voltage transients and abrasion.

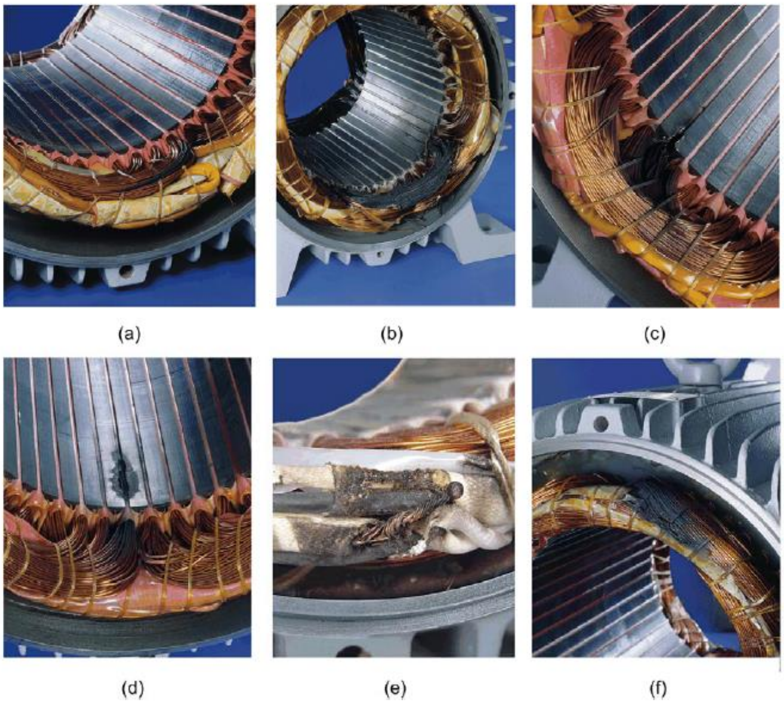


FIGURE.I.10: TYPICAL INSULATION DAMAGE LEADING TO INTER-TURN SHORT CIRCUIT OF THE STATOR
WINDINGS IN THREE-PHASE INDUCTION MOTORS.

(A) INTER-TURN SHORT CIRCUITS BETWEEN TURNS OF THE SAME PHASE.
(B) WINDING SHORT CIRCUITED.
(C) SHORT CIRCUITS BETWEEN WINDING AND STATOR CORE AT THE END OF THE STATOR SLOT.
(D) SHORT CIRCUITS BETWEEN WINDING AND STATOR CORE IN THE MIDDLE OF THE STATOR SLOT.
(E) SHORT CIRCUIT AT THE LEADS. (F) SHORT CIRCUIT BETWEEN PHASE

Sheathing of winding insulation and consequent full-winding short circuits of all phase windings, usually caused by motor overload and locked rotor and stator excitation from under voltage supplies - nominal and overvoltage. This type of failure can be caused by frequent starts and reversals. These errors are shown in Fig. 12Fig.12a and b.

• Interterm shorts are also due to voltage transients, as shown in Figure 2.17c, which can be caused by successive reflections resulting from the connection of cables between motors and frequency converters. Such AC drives create additional voltage stress in the stator windings due to the inherent pulse width modulation of the voltage applied to the stator windings. Again, long cable connections between a motor and a

VFD can induce over voltages in the motor. This effect is caused by consecutive reflections of transient voltages.

• A total short circuit of one or more phases can occur due to a phase failure caused by an open fuse, a contactor or circuit breaker failure, a connection fault, or a power failure. Such an error is shown in Fig.12figure. 12d and e.

• Short-circuits in one phase are usually due to an unbalanced stator voltage, as shown in Fig.12f. Unbalanced voltage is caused by an unbalanced load on the power line, poor motor terminal connection, or poor circuit connections. An unbalanced voltage also means that at least one of the three stator voltages is below or above the value of the other phase voltages.

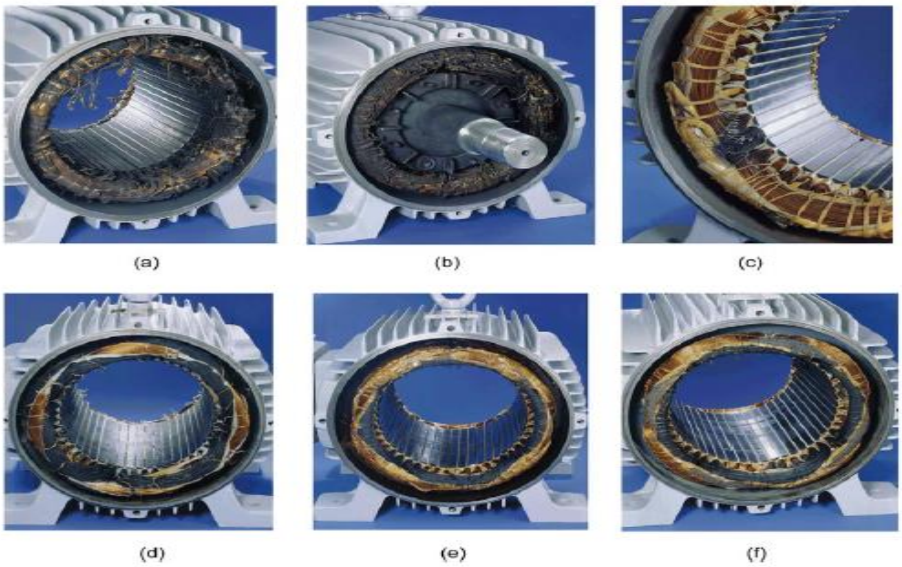


Figure.I.11: Inter-turn short circuit of the stator winding in three-phase induction motors.

(A) Short circuits in one phase due to motor overload
(B) Short circuits in one phase due to blocked rotor.
(C) Inter-turn short circuits are due to voltage transients.
(D) Short circuits in one phase due to a phase loss in a Y-connected motor.
(E) Short circuits in one phase due to a phase loss in a delta-connected motor.
(F) Short circuits in one phase due to an unbalanced stator voltage

I.2.1.2 Causes of stator faults:

a. **Mechanical stresses:** They are due to the movement of the stator coil and the rotor. hits the stator [15]. The movement of the coil caused by the stator current force is proportional to the square of the current can detach the tip sticks and can also damage the copper conductor and its insulation. The rotor may hit the stator due to rotor-stator misalignment or due to the shaft deflection or due to bearing damage and if it hits then the impact will be will cause the stator laminations to puncture the coil insulation, damaging the coil ground fault. High mechanical vibrations can separate the stator winding produces the open circuit fault [16].
b. **Electrical stresses:** These are mainly due to transient supply voltages. This transient occurs due to various faults (e.g. line-line, line-earth, or three-phase fault), by lightning, opening or closing of switches or by frequency converters. This transient voltage reduces the lifetime of stator winding and in severe cases can cause spin to spin or spin to ground fails [16].
c. **Thermal Stresses:** These are mainly due to thermal overload and are the main reason, among other possible causes, for the deterioration of Insulation of the stator winding. Thermal stress occurs due to overcurrent [16]. Flow due to sustained overload or failure, higher ambient temperature, obstructed ventilation, asymmetric supply voltage, etc.A rule of thumb is it says that the winding temperature will increase by 25% phase that has the highest current with a voltage imbalance of 3.5% phase . The winding temperature will also rise within a short time A series of starts and stops is performed in the engine times. What could that be Cause when the winding temperature increases and the motor is operated on it temperature limit can quickly fail even the best insulation. rule of thumb, states in this regard that for every 10 °C increase in temperature above the stator winding temperature limit, insulation life is reduced by 50% [17].

I.2.1.3 Rotor fault:

rotor failures account for approximately 5-10% of all induction motor failures today [17] show figure 13.

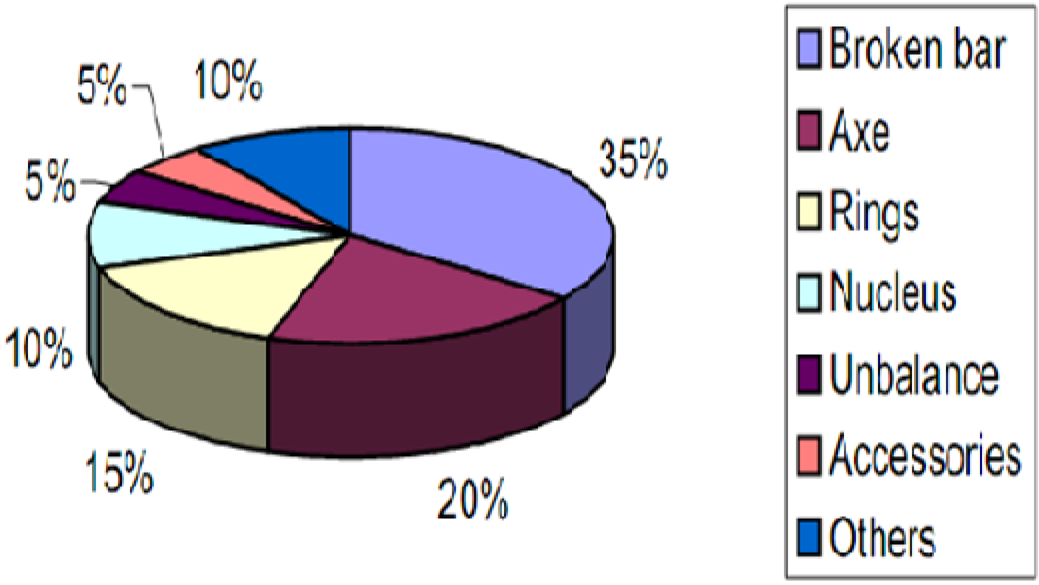
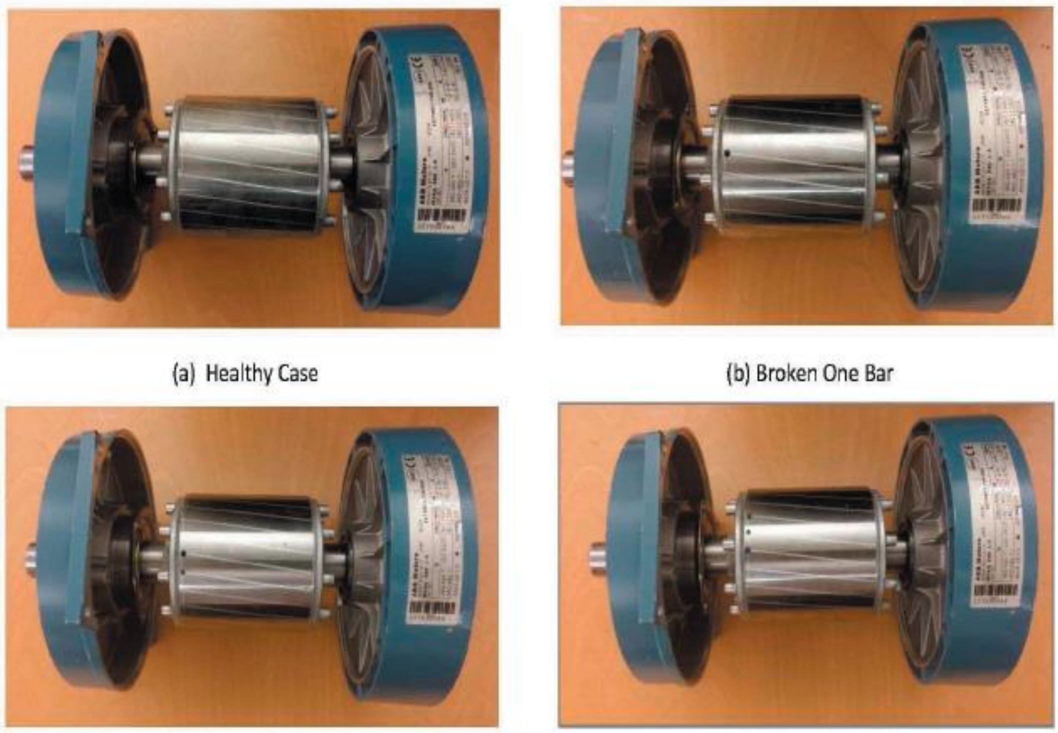


FIGURE.I.12: THE PERCENTAGES OF COMMON FAULTS IN THE ROTOR.

However, induction motor rotor failures generally fail assume a small fracture or a point of high resistivity in the rotor bar. This place heats up and worsens the damage until the rotor bar breaks completely. After the occurrence of A bus defective, rotor current is transferred to another bus and causes overcurrent and ultimately leads to a higher number of broken bars. Rotor cage failures can lead to shaft failures. vibrations and consequent bearing failures and air gap eccentricity etc., while breaking a rod leads to high current in the neighboring bars, which leads to possible further interruptions, as well as to stator failures. Therefore, early detection of rotor asymmetry is not only for the protection of the rotor, but also to reduce some other types of motor failures [4].



(a) Healthy Case (b) Broken One Bar

(c) Broken Two Bar (d) Broken Three Bar

FIGUREI.13 : INTERNAL OVERVIEW OF THE INDUCED FULL ONE, TWO AND THREE BROKEN BARS FAULTS ON THE ROTOR OF MOTOR

I.2.1.4 CAUSES OF ROTOR FAULTS [10]:

a. **Thermal stresses:** from overload and thermal imbalance; Hot spots or excessive losses or sparks (mainly fabricated rotors)
b. **Magnetic loads:** from electromagnetic forces, unbalanced magnetic attraction, electromagnetic noise and vibration
c. **Residual stresses:** due to manufacturing problems.
d. . **Dynamic stresses:** caused by paired shafts, centrifugal forces and alternating stresses
e. **Environmental pollution:** due to dirt and abrasion of the rotor material by chemicals or moisture

I.2.2 Mechanical fault:

The priority of the occurrence of mechanical failures is maximum for the induction motor. Mechanical failures are classified as bearing failure, eccentricity failure or load failure [4].

I.2.2.1 Bearing fault:

As shown in Figure 15, about 40% of induction machine failures come from bearings. failure. In general, the rolling bearing consists of an inner and an outer ring, while a set of rolling elements meets in the middle. Standard rolling element shapes include the ball, cylindrical roller, conical roller, needle roller, etc. rolling elements, a bearing is housed in a cage to ensure equal spacing between the elements to avoid mutual contact. The various failures that occur in a rolling bearing can be classified as bullet defect, inner ring defect, and defect in the outer race. The rolling bearing is one of the most critical components when turning induction motors, because that's where the vast majority of problems come from defective bearings. Therefore, both detection and diagnosis of mechanical breakdowns is in Bearings with elements are very important for the reliable operation of an induction motor [20]

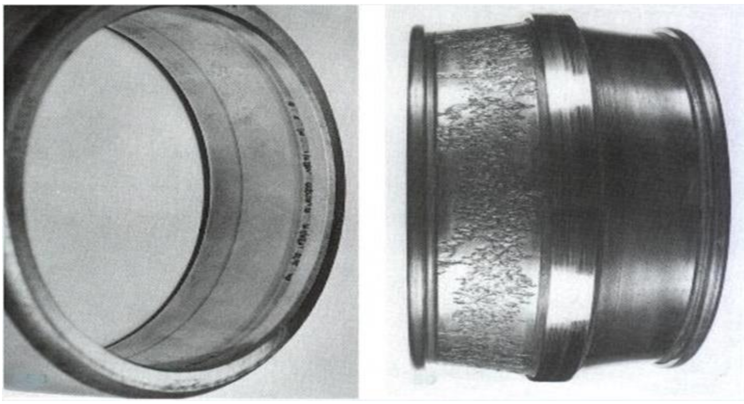


Figure.I.14: bearing in advanced state of deterioration

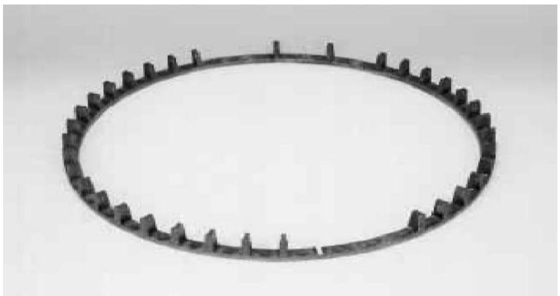


Figure.I.15: bearing cage damage

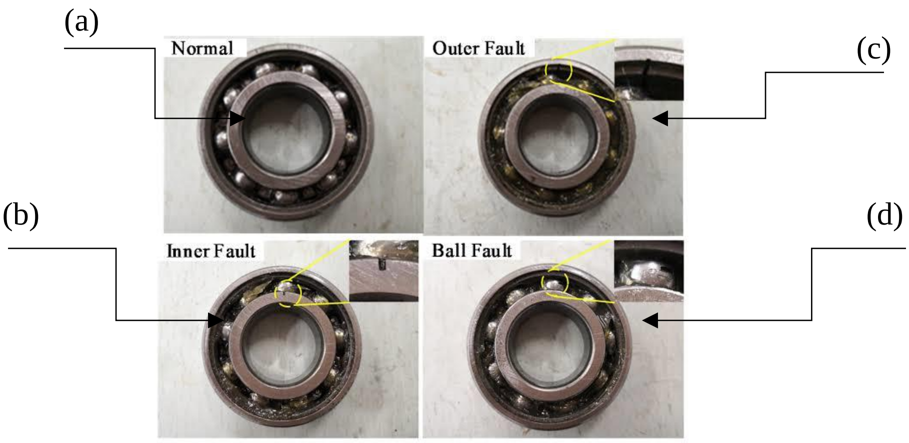


Figure.I.16:(a) BEARING HEALTHY STATE, (b) INNER FAULT, (c) OUTER FAULT, BALLFAULT

I.2.2.2 Causes of bearing faults [18-19]:

Excessive loads, tight fits, and excessive heating—all of which can anneal both race and ball materials. You can also break them down, even destroy them lubricant. If the load exceeds the elastic limit of the bearing material, corrugation will occur. occurs.

Fatigue failure - This is due to the long life of the bearings. Causes breakage and subsequent removal of small discrete particles of material from surfaces runs or balls. This type of bearing failure is progressive, that is, if once will be extended if the further operation of the camps takes place. For this Bearing damage increases the vibration and noise level of the motor.

Corrosion: Occurs when bearings are exposed to corrosive liquids (acids, etc.) or corrosive atmosphere. If the lubricants deteriorate or the bearings are handled careless when installing, it can also lead to bearing corrosion. Corrosion can cause premature fatigue failure.

Contamination: It is one of the main factors in bearing failure. Get the lubes contaminated by dirt and other foreign particles most commonly found in industrial environment. High vibration and wear are the effects of pollution.

Lubricant Error - If the lubricant flow is restricted or the temperature is too high takes place. It degrades the property of the lubricant, so excessive wear occurs balls and runs occur, causing overheating. If the storage temperature rises too high, the grease (lubricant) will melt and run out of the bearing. discolored balls and races are the symptoms of lubricant failure.

Bearing Misalignment: This requires wear on the ball and raceways. spot that causes the bearings to heat up. It is observed that with each bearing damage, the friction usually increases, which leads to an increase in the temperature of the bearings and an increase in the vibration of the machine in question. Temperature and vibration of the bearings can cause this Information on the condition of the bearings and thus on the condition of the machine.

I.2.2.3 The eccentricity fault:

which is an uneven air gap between the stator and the rotor. The presence of this defect causes an unbalanced magnetic attraction or an unbalanced radial force generated due to friction between a stator and a rotor. There are two types of eccentricities [10-4]:

a) Static Eccentricity
b) dynamic eccentricities.

a. **Static Eccentricity:** can be caused by the oval shape of the stator core or by incorrect positioning of the rotor or stator during start-up. If the rotor shaft is stiff enough, the magnitude of the static eccentricity does not change. This can cause the rotor shaft to bend or the bearings to wear out. It can also drive dynamic eccentricity to some extent. Static shock can occur when a rotor deviates from the center of the hole but still rotates about its center [10-4].

b. **Dynamic eccentricity:** in this case the center of the rotor is not in the center of rotation and the position of the minimum air gap rotates with the rotor. Static eccentricity can lead to some degree of dynamic eccentricity due to the presence of an unbalanced magnetic attraction force. Mechanical resonances at critical speeds can also lead to dynamic eccentricity. Ideal core conditions can never be assumed. Therefore, an inherent degree of eccentricity is implied for any real machine. The static and dynamic combination. The eccentricity is called mixed eccentricity [4].

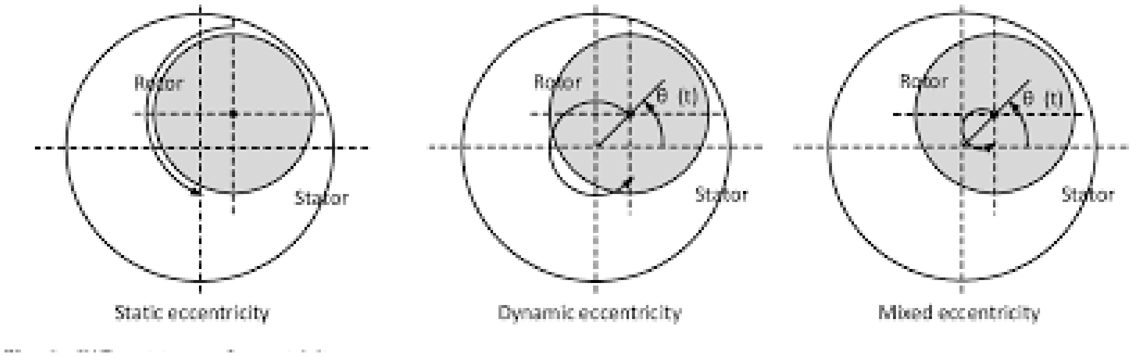


FIGURE.I.17 ECCENTRICITY DEFAULTS.

I.2.2.4 Causes of eccentricity fault [4]:

a. Manufacturing defects
b. internal shaft misalignment or bending
c. can occur after a longer period of operation with asymmetric addition or mass subtraction around the center of rotation of the rotor.

I.3 Health monitoring:

The continuous assessment of the condition of the equipment throughout its lifetime is known as health monitoring or condition monitoring. It is very important to detect faults while they are still developing. This is referred to as initial error detection[21-22]. This early detection of motor failures provides a totally safe environment. Induction Machine Condition Monitoring provides us with a continuous assessment of the electrical status of electric machines. By using condition monitoring it is possible to provide adequate warning of an imminent failure. The condition monitoring and fault diagnosis scheme allows the machine operator to have the required replacement parts before the machine is dismantled, reducing downtime. Hence the effective monitoring of the condition of electrical machines it can improve machine reliability, safety and productivity [23].

Health monitoring has a high priority in the corporate environment for the following reasons [21]:

- Reducing maintenance costs
- Predicting equipment failures

- Improving equipment and component reliability
- Optimizing equipment performance

I.3.1 Monitoring technique:

Many methods have been used over the past four decades to monitor the health of the machine, but the most common techniques are detailed below [24]:

a. **Thermal Monitoring:**
Thermal monitoring of electric machines can be completed by measuring the local temperature of the motor or by estimating the parameter. Due to the shorted turns in the stator winding, the value of the stator current will be very high and thus it will generate excessive heat if proper measures are not taken and lead to the destruction of the motor [25-26-27].

b. **Magnetic Flux Monitoring:**
The abnormal harmonics that occur in the stator current are functions of a number of variables due to the magnetomotive force (MMF) distribution. And the waveform of the air gap permeability. Hence any distortion in the flux density of the air gap due to a defect in the stator leads to an axial flow on the shaft. The axial magnetic flux leakage from the induction motor is easily measured with a circular search coil positioned at the non-powered (rear) end of the machine. Concentric to the axis. The search coil produces an output voltage that is proportional to the rate of change of the axial leakage flux
This signal contains many of the same frequency components that are present in the stator current.is especially useful for speed estimation as it contains a strong slip frequency component[28]**.**

c. **Vibration Monitoring:**
Vibration monitoring technique is the oldest health monitoring technique of induction motor. Commonly used to detect mechanical faults such as B. bearing damage or mechanical imbalance. A piezoelectric transducer is often used, which provides a voltage signal that is proportional to the acceleration. This acceleration signal can be integrated to give velocity or position. Almost all electrical machines generate noise and vibrations. Therefore, the researchers used this vibration for troubleshooting and successfully diagnosed several faults with this vibration parameter. Because a very small vibration amplitude in the machine can generate a high noise level. Noise and vibrations in electrical machines are caused by forces that are magnetic, mechanical and aerodynamic in origin. Vibrations can also occur due to a single phase. Faults in the windings between the turns and imbalances in the supply voltage. The radial forces of the air gap field are the main sources of vibration and noise in electrical machines. The air gap flux density distribution is the product of the resulting mmf wave and the total presence wave. The resulting mmf also includes the influence of possible asymmetries in the rotor or stator[29-30]**.**

d. **Partial Discharge Monitoring:** This method is used to detect stator insulation faults in higher voltage motors. It consists of ultra-fast low-amplitude detection pulses generated by electrical discharges in small holes in the insulation. Partial downloads also take place on working computers. However, an increase in PD activity may be accompanied by a worsening of insulation [31]**.**

e. **Noise Monitoring: by** measuring and analyzing the spectrum of acoustic noise, we can monitor noise. Because of the air gap eccentricity sounds are generated. This noise is used to detect faults in the induction motor. However, it is not the accurate way to detect the error by monitoring the noise due to background noise from other machines[32].

f. **Stator Voltage Monitoring:** This can be safely measured with a high frequency differential voltage probe or isolation amplifier. has been used calculates instantaneous power, instantaneous torque and negative sequence impedance. [33].

g. **Stator Current Monitoring**: Stator current is typically measured with a clip-on Hall Effect current probe. Contains frequency components. which can be related to a variety of faults such as mechanical and magnetic asymmetries, broken rotor bars and short circuits. turns in the stator windings. Most of the research published in recent years has dealt with the use of the stator power for health monitoring. In particular, using frequency analysis [34-35].

I.3.2. Fault diagnosis methods:

In general, the PMSM troubleshooting flowchart is as shown in Figure 1. All mistakes diagnostic methods to determine the nature of the failure of a real engine, it is necessary to capture its signal dates first. The detected signals include current, vibration and the like mentioned above used for analysis after pre-treatment such as noise reduction and gain. Some researchers have studied the information fusion method for data from multiple types of signals or multiple sensors [36-37]. However, there are also some methods that use raw data directly without requiring features. and information fusion. Finally, the different diagnostic methods to treat this data were identified. In summary, the common methods of engine fault diagnosis can be divided as follows three categories: Data Acquisition Methods **(**model-based) error diagnosis methods, [38]. Signal Processing **(**signal-based) error diagnosis methods, and AI-based fault diagnosis methods. These can include Data Acquisition methods get into the essence of error generation. Can predict signal power after various errors occur in the engine and by comparing the actual performance data with the engine model performance, can determine the nature of the error. Signal-Processing methods are most commonly used for processing and extraction different characteristics of engine signals, and these characteristics are then diagnosed manually Previous experience or application of knowledge-based methods. AI-based methods can automatically determine the error status based on expert knowledge, but based on research using artificial intelligence and machine learning, data-based intelligent diagnostic systems that do not build on it knowledge, have recently shown broad application perspectives. Engine data can be used to train a machine learning model [39]

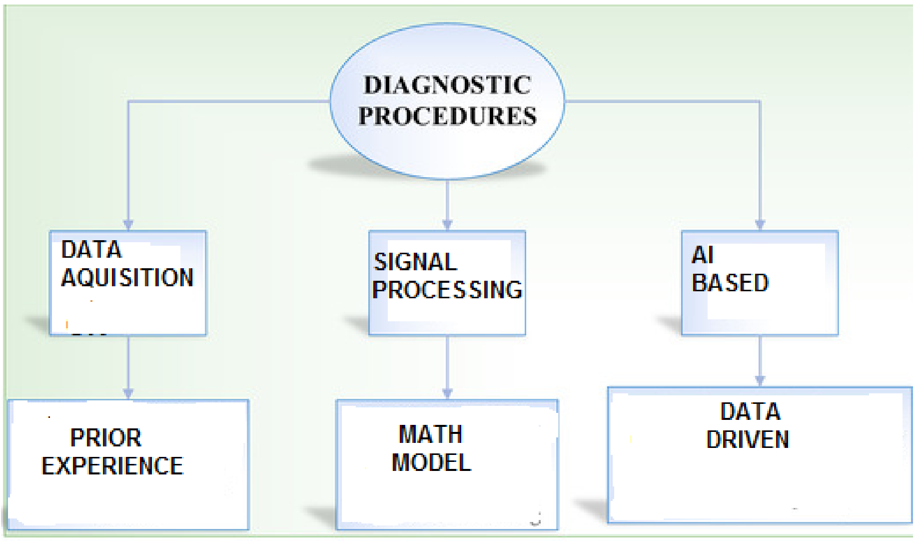


FIGURE.I.18 : DIAGNOSTIC PROCEDURES.

I.3.3 Data Acquisition Methods:

FD of MI using Data Acquisition techniques requires prior knowledge of the system Referring to Figure 2. A prior assumption about the initial conditions is also a prerequisite for the representation of the System in service. The signals generated by mathematical models help with this in detecting and identifying errors that have occurred in the IM. Also based on role models techniques are mainly based on and equipped with the precise dynamic model of the system detects unexpected errors. there are two tools that are crucial in data collection level which are analyzer and sensor. Vibration CM by MI. The most common standard approaches to analyze errors in IMs analyzer can be divided into standalone and computational methods. analyzer, while the vibration sensor consists of accelerometer, speed converter, displacement sensor and Doppler laser Vibrometer (LDV). the accelerometer can be further subdivided in piezoelectric and microelectromechanical systems ‘MEMS' accelerometer [40].

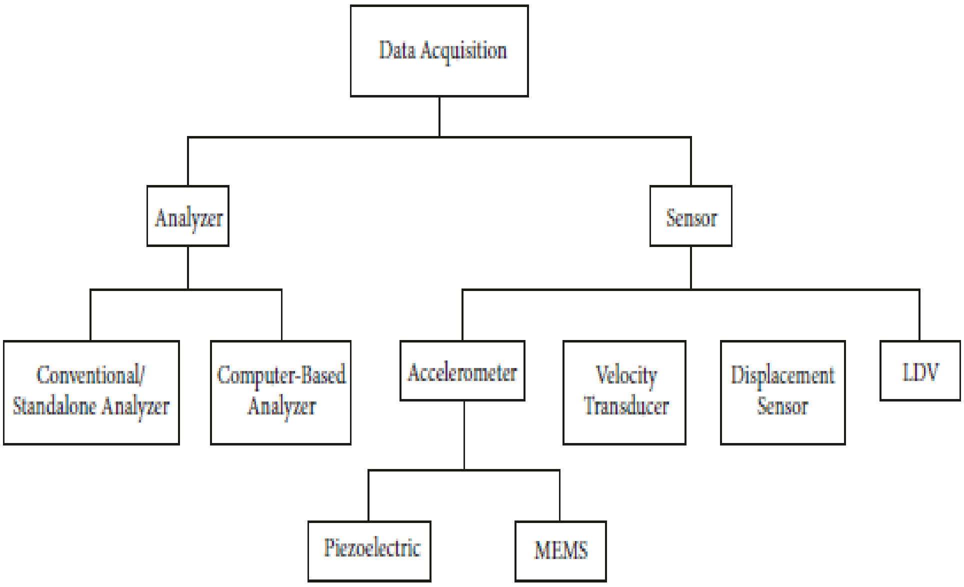


FIGURE.I.19 : THE DATA ACQUISITION METHODS.

a. Analyzer:

The analyzer is a tool for analyzing vibration data generated by machines. It consists of a sensor (which will be presented in the last part of this document), an amplifier, a filter and an AD converter. The signal from the vibration sensor is passed through an amplifier to increase resolution and signal-to-noise ratio. The amplified signal is then passed through a filter to prevent aliasing during the digitization phase. The signal is digitized in the AD converter and then passes through the processing unit, where it can be displayed as a time signal or further processed to record the frequency spectrum [41-42]. Vibration analyzers can be divided into conventional and computerized vibration analyzers. A traditional vibration analyzer is a standalone instrument specifically designed to measure vibration. It's a complicated and expensive tool. it is commonly used by vibration experts. This tool can help the user to determine the existence of the problem, its root cause and the time it takes for the machine to fail. One, two and four-channel analyzers are available on the market. A single-channel analyzer can only receive one accelerometer input at a time, while a dual-channel analyzer can simultaneously receive inputs from two differently positioned accelerometers [43]. the four-channel analyzer can receive multiple sensor inputs while providing horizontal, vertical, axial and bearing scanning. Typically used with a three-axis accelerometer. The main advantage of the four-channel analyzer is the ability to observe the machine's operating deviation form (ODS) [44]. used a four-channel vibration analyzer to monitor bearing condition, and the use of a two-channel analyzer to monitor machinery can be seen in Another cheaper alternative is a portable vibrometer. [45-46].

b. Sensor:

A sensor or transducer is a device that converts mechanical signals into electrical signals [47]. The type of sensors used is generally based on frequency range, sensitivity, design and operational limitations. Regardless of the sensor type used, the following applies: the more rigid the sensor connection, the larger the frequency range and the higher the measurement accuracy. There are three widely used sensors on the swing to detect the vibration signal., These sensors are accelerometer, speed and displacement sensor.[47].

I.3.3.1 Sensor Mounting Method:

sensor mounting method. Choosing a mounting method and implementing it correctly is an important factor in collecting vibration data. For continuous or online monitoring Depending on the condition of the machine, vibration sensors are usually permanently mounted in a specific location the machine. Mounting can be divided into four main methods, namely bolt mounting, with glue, with magnet and unassembled. Stud mounting is generally preferred for permanently mounted applications. The sensor is screwed into a stud and attached. This mounting technique is not only extremely reliable and safe, but also has the widest frequency response compared to other methods. Make sure where the sensor is located to be mounted is clean and free of paint, since irregularities on the mounting surface will lead to incorrect measurements or worse, damage the sensor itself. For adhesive mount, no complex machining required as epoxy, glue or wax is applied. If the machine cannot be drilled for stud mounting, adhesive mounting is generally the best option. best alternative. Although this assembly technique is easy to use, the measurement accuracy is reduced by the damping present in the adhesive [49].

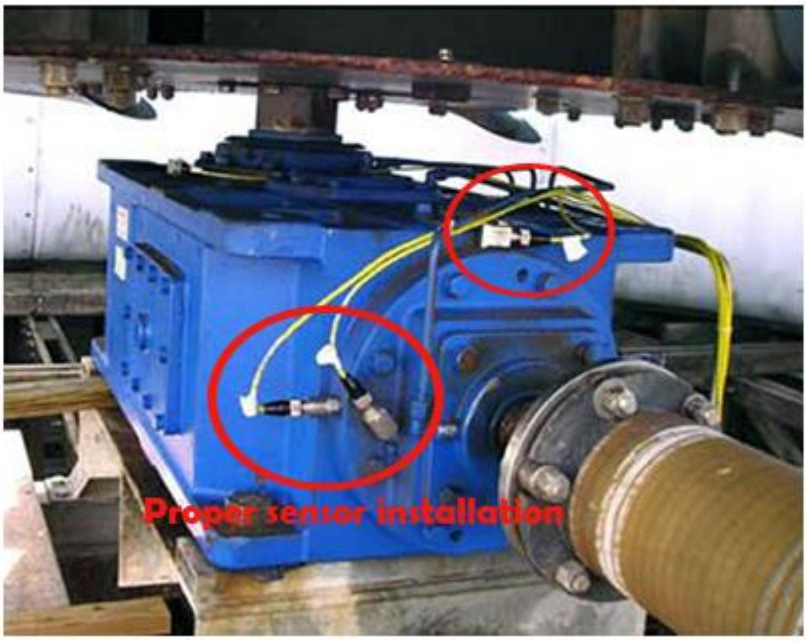
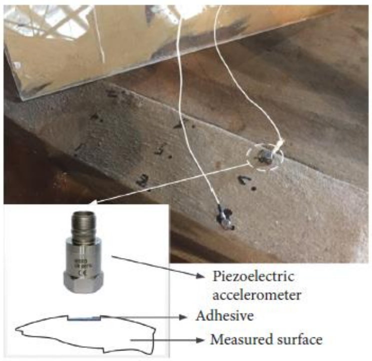


FIGURE.I.20 : PROPER SENSOR INSTALLATION.

I.3.3.2 Type of sensors:

a. **Accelerometer**: An accelerometer is a device used to measure the vibration or acceleration of a structure in the SI unit g (m/s). The working mechanism is that when the piezoelectric material in the accelerometer is subjected to a force, it generates a charge equal to the force exerted. Since force is directly proportional to acceleration, any change in this factor will result in a change in the charge generated, which will then be amplified [50]. uniaxial the accelerometer can only detect motion in one plane, while the three-axis accelerometer covers all three dimensions. Compared to the uniaxial accelerometer, the triaxle accelerometer has larger storage capacity but is much more expensive. The accelerometer is a widely used sensor due to its characteristics its reliability, simplicity and robustness. It can be further divided into a piezoelectric accelerometer and MEMS [51].

b. T**he piezoelectric accelerometer**: relies on the piezoelectric effect of quartz or ceramic crystals, which are usually pre-charged to produce an electrical output proportional to the acceleration applied. Changes in the generated charge depend on this acceleration. The piezoelectric accelerometer has several advantages, such as better frequency and dynamic range, light weight and high sensitivity. However, it is susceptible to interference from the external environment. It also requires electronic integration to obtain velocity and displacement data as it is AC coupled. demonstrated the application from LabVIEW to monitor and analyze vibration signals, using a piezoelectric accelerometer in his study. . installed the piezoelectric accelerometer on the operating turbines to obtain vibration data for time-domain analysis. used the piezoelectric accelerometer to obtain vibration data from rotating machinery for analysis defective bearings. Figure 3(a) shows the measurement of vibration [52].



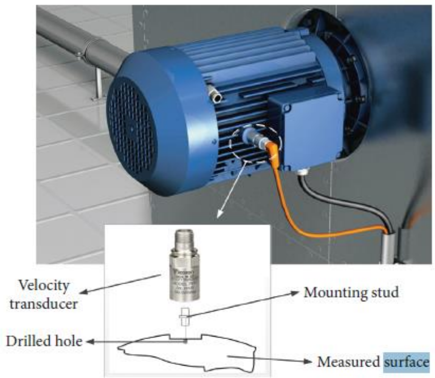


FIGURE.I.21 VIBRATION MEASUREMENT USING (A) PIEZOELECTRIC ACCELEROMETER BY MEANS OF ADHESIVE MOUNTING AND (B) VELOCITY TRANSDUCER, STUDMOUNTED ON THE MACHINE'S SURFACE

c. **speed converter**: A velocity transducer measures the voltage generated by the relative movement of an object, usually in m/s or cm/s. It works on the concept of electromagnetic induction and can work without an external device [53]. The movement of the magnet in the coil, like the surface on which it is mounted, creates a voltage proportional to the vibration speed. This voltage signal represents the vibrations generated and thus supplies the measuring device or analyzer. Speed sensors are not recommended when diagnosing high-speed machinery because the operating frequency range is limited from 10 Hz to 2 kHz [51]. The speed sensor generally costs less than other sensors and thanks to its characteristics it is easy to install and advantageous for vibration monitoring of rotating machines. However, it is large, heavy and most tachometers have reliability problems at operating temperatures above 121 °C [54].

d. **Displacement Sensor:** displacement sensor, sometimes referred to as a proximity or eddy current sensor, measures both relative vibration and shaft position. the path unit can be specified in m, cm or mm. Typically used to measure low frequency vibrations below 10 Hz; However, it can also measure vibrations up to 300 Hz [50]. However, they are not characterized by measuring an axis that is bent away from the probe position [51]. Imbalance and misalignment problems are the types of problems that the displacement probe can detect. With measured vibration frequencies above 1 kHz, the amplitude is often lost in the background noise [51]. It has the advantages of good dynamic range within a given frequency range,reasonable sensitivity, and simple post-processing circuitry with negligible maintenance. However, it's difficult to install, prone to shock, and some traditional displacement sensors aren't calibrated for strangers. metallic materials [55]. used the displacement sensor to monitor the cutting forces of the machining center under different cutting conditions. developed a low-cost fiber optic displacement sensor (FODS) for industrial applications that is immune to electromagnetic interference. investigated the ability of a fiber optic displacement sensor to detect vibration amplitude and frequency and according to the results, this sensor can solve many detection problems in aircraft [56].

e. **LDV:** is a non-contact optical measuring device that can be used to determine the vibration velocities of any point on the surface of a given machine [57,58]. The LDV working mechanism is based on the laser Doppler concept in which a coherent frequency modulated laser beam is reflected off a vibrating surface and the Doppler shift of the reflected beam is compared to this reference beam. Currently, higher power infrared (invisible) fiber lasers are more popular in LDV compared to He-Ne lasers. The introduction of this technology has achieved the goal of achieving long-range measurements without compromising signal quality . Continuous Laser Doppler Vibrometer (CSLDV) has accelerated measurement in many places. The laser beam scans continuously along a defined path through a structure according to the desired scanning frequencies. One of the main advantages of the LDV is the easy measuring point change, which can be done simply by deflecting the laser beam. Despite this, the application of LDV in machine monitoring and diagnostics is limited by factors such as price and portability[59].

I.3.3.3 Signal Processing/Feature Extraction Methods:

Signal processing methods the motor integrates electrical and mechanical components. Therefore, when errors occur, some complicated error phenomena may occur . There are electrical quantities such as voltage, frequency, electricity, power, etc., and non-electrical quantities such as heat, sound, light, gas, radiation, vibration, etc. Processing signals received from the motor is one of the commonly used methods. Error detection methods. These methods can identify error performance and extract errors. of signals mainly consisting of current, vibration etc. Motor Current Signal Analysis (MCSA) has been extensively studied and some researchers have also combined different signals to build a PMSM fault diagnosis system [60,61].

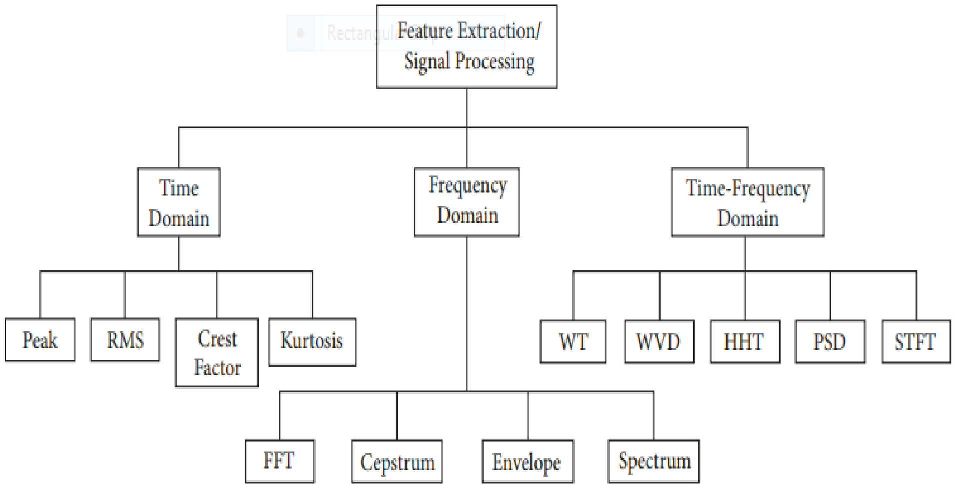


FIGURE.I.23: THE FEATURE EXTRACTION/SIGNAL PROCESSING STAGE.

a. Frequency Domain Methods:

In general, signal processing methods usually include time domain methods, frequency domain methods and methods of time-frequency analysis. Statistical indicators in the time domain are used as errors. features in the early development period of fault diagnosis technology, such as mean value, peak, root mean squares (**RMS**), kurtosis values, etc show figure. ; however, they are not precise enough. The classic method of frequency domain analysis is the Fast Fourier Transform (**FFT**). The Fourier transform represents a signal as a superposition of several sine or cosine functions. It can show the frequency distribution of clearly signal, where amplitude and frequency of the harmonic components can be used as characteristics different failures [62].

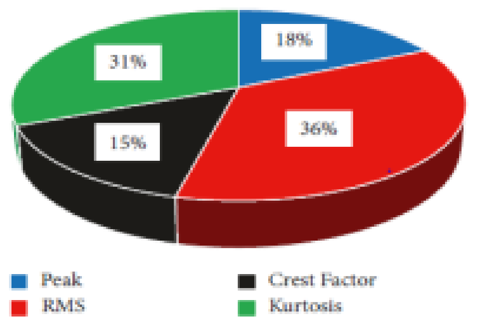


FIGURE.I.22: THE PERCENTAGE DIFFERENCE BETWEEN FREQUANCY DOMAIN APPROACHES.

b. Wavelet Transform:

used the wavelet Packet Band Energy Analysis Method to extract interterm short circuit characteristics from PMSM error which consists in exactly dividing the frequency band of the current signal by WPT and considering it the signal energy of the corresponding frequency bands as a characteristic vector of the interference. A fitting one The mother wave function makes the WT more sensitive to surge transients, which also presents a limit: the results of the analysis are strongly related to the choice of the mother wavelet function. As well as STFT, it is also impossible to achieve both time and frequency with high accuracy in a given frequency band [63],

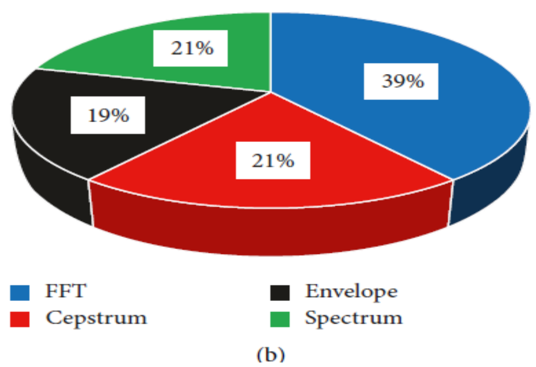


FIGURE.I.23: THE PERCENTAGE DIFFERENCE BETWEEN CONVENTIONAL APPROACHES.

c. AI-based technology:

Artificial intelligence algorithms are based on prior knowledge. The application of AI in vibration analysis for machine monitoring and diagnostics is growing in popularity, AI-based techniques are helping about 57% of the general method of vibration analysis in the diagnostics and monitoring of machines, show the figure because most of the above techniques require a lot of experience for a successful implementation, which makes them not suitable for the ordinary user[64],. Due to the research on artificial intelligence and machine learning, many data-based intelligent diagnosis algorithms have been proposed lately. Basic data-driven approaches include some statistical methods, the principal component analysis (PCA) [65],. and the independent component analysis (ICA) are also used in the feature request for error diagnosis, but with data-driven smart diagnostic algorithms, they can be used to automatically detect the type and severity of engine failure based on input data based on the training data provided. These methods mainly include, show the figure Neural Networks, Support Vector Machine, Sparse Rendering, Deep Learning, Fuzzy logic etc [66].

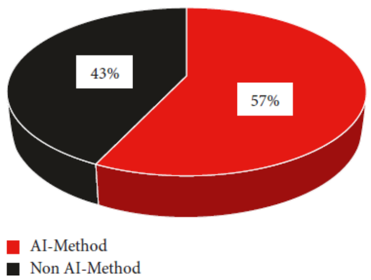


FIGURE.I.24 : THE PERCENTAGE DIFFERENCE BETWEEN AI AND NON-AI METHODS IN VIBRATION ANALYSIS FOR MACHINE DIAGNOSIS AND MONITORING.

d. Neural networks (NN):

artificial neural networks (ANN) have also been proposed development of artificial intelligence, widely used in the fields of pattern recognition, automatic control etc. as well as error diagnosis [67]. NN can simulate the human brain and automatically identifies the nature of the error. Traditional neural network models generally consist of one input layer, a hidden layer and an output layer; each layer contains many nodes. the output is obtained from activation function after computation of multilayer fully connected nodes. The goal of NN is to minimize classification errors in the training set and to respond appropriately responds to new inputs, which requires adjustment of the initial parameter values and training of the network several times. Therefore, different training algorithms and network models are used in error diagnosis. studies such as Backpropagation Network (BP), dynamically recurrent NN etc. needed the third harmonic in the PMSM current as an input for the ANN to get a good diagnostic result short circuit between turns. However, it also has the disadvantage of being dependent on large numbers input data, simple overfitting, "black box" etc [68].

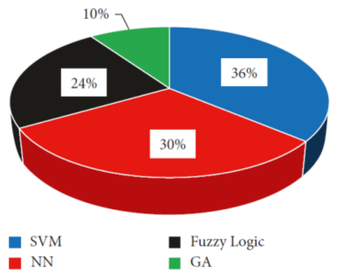


FIGURE.I.25: THE PERCENTAGE DIFFERENCE BETWEEN AI-BASED APPROACHES,

In addition, especially the deep transfer learning method, is beginning to be applied in vibration for machine monitoring and diagnostics as it helps minimize the need for experts' knowledge in the complicated feature extraction step. Traditional AI methods such as ANN and Fuzzy Logic still requires expert knowledge in the phase of extracting features from newly fed data sets. Traditional time domain functions such as RMS and crest factor will remain relevant and the AI application will continue to grow [69].

I.4 Consideration about maintenance:

Condition Monitoring and its Necessity induction motors are the main workhorse of industrial prime movers because of their characteristics robust, inexpensive, low maintenance, relatively small, relatively high and powered by a readily available power supply. About 50% of the These induction motors consume % of a nation's total generated energy [9]. The However, the statistics give an idea about the use of a large number of induction motors have some limitations in their operating conditions. If these conditions are exceeded, then premature failure of the stator and/or rotor may occur. This failure, in many industrial applications, it can even paralyze the entire resulting industrial process waste of production time and money. Therefore, it is important to avoid them Type of induction motor error. Induction motor operators and technicians 2.10 Crawl 25 are under constant pressure to prevent and reduce unplanned downtime engine maintenance costs. Maintenance of electric motors can be done in three ways: Failure maintenance, fixed-term maintenance, and Scheduled maintenance [70],

I.4.1 Classification of maintenance activities [9]:

a. **Scheduled maintenance**: This type of maintenance includes maintenance according to the manufacturer's specifications or according to a planned schedule determined based on the accumulated hours of operation of the machine. This is one of the most common maintenance methods in the industry, but it does not prevent an emergency engine failure.
b. **Servicing breakdowns**: This method is intended to keep the engine running to tolerance until failure, so this is usually the least preferred maintenance technique. Due to breakdown, the engine may not be replaceable, only suitable for replacement. This method is therefore rarely used in industry today.

c. **Maintenance depending on condition**:This is the most viable technique on the rise in industrial and commercial industries today. In most cases, it is real time monitoring, observing the state of the system during operation and detecting any anomalies that occur during the system's operational mode. Indication of system deviation from normal operation could be provided by an alarm system or other means which can inform the system to shut down for analysis and reinstallation. Real-time condition monitoring technique consists of a system that continuously monitors the working conditions of the systems over time and is able to detect deviations or anomalies that occur. This technique is more practical and effective as it is able to prevent serious damage to the machine and avoid continuous machine failures.

I.5 Position of Problem:

Given the state of the art of an electric propulsion system, the asynchronous machine seems to be very important in this system due to its role in electromechanical conversion as well as its availability in factories. According to previous statistical research, stator failures in windings are more common in all power ranges, especially at high powers, and short circuits between turns of the same phase of the stator (winding) are among them. stator failures in order to study this problem, it is necessary to create a mathematical model that models the asynchronous machine and also the inter-turn short-circuit fault. The simulation of this model can provide an insight into the behavior of the machine in the event of a fault and also generate signatures of certain faults. Business continuity requirements enforce the presence of predictive maintenance without service interruption and the use of automatic diagnostics. The system flags the fault if it exists to warn the operator and force the maintenance manager to intervene

I.6 CONCLUSION:

In this chapter we recalled the structure and principle of operation of an electric system, naming the main elements of the system according to their composition. Then we present the main faults at the level of the different parts of an electric propulsion system. These faults can be of electrical or mechanical origin and can be found in different places of the element or part of the system. To do this, we have indicated all the defaults that can appear in each of the components that make up each element of a system. 'Education. In fact, for each type of default, we have listed the main causes and symptoms encountered. Then the established bibliographic synthesis allowed us to mention a non-exhaustive list of commonly used diagnostic methods. Three main families of methods were reviewed: those data acquisition. based on data analysis and those based on an AI model of the machine under study, with particular attention to model-based diagnostic techniques. It is therefore important to have mathematical models that are truly representative of the behavior of the system, in order to better understand the phenomena to be considered before developing in detail the diagnostic method chosen and discussing its implementation for fault detection. As a basic for the development of the thesis, a positional problem was raised, containing the defective element and the nature of the failures, as well as the diagnostic procedure applied to the propulsion system. The next chapter is devoted to the develop the indicatives signature of IM working in a healthy regime and in a failed regime, followed by validation of this model by simulation in MATLAB.

Chapter II

Development of signature indicative of IM fault

II.1 Introduction:

Spectrum analysis provides a wealth of information about the condition of rotating machinery. However, you should consider the spectrum as a summary of the vibrations inside the machine. Fast Fourier Transform takes the time waveform and calculates how much of each frequency is there and displays it as a line in the spectrum (in short, but that's basically the case). So, if the vibration of the machine is generated by a smooth periodic movement, the spectrum gives a very good representation of what is happening inside the machine. The rolling elements ride over damaged areas in the bearing race, the vibration produced is neither smooth nor periodic. And there are many other fault conditions that also do not produce smooth, periodic oscillations. Therefore, the only way to truly understand what is going on inside the machine is to examine the time waveform. The time waveform is a record of what is happening from one moment to the next as the shaft rotates, and the rollers rotate about the bearing. Every smallest change caused by bumps, scrapes, scratches, rattling, overvoltage and much more is recorded over time and summarized in the spectrum. Therefore, it is important to properly record and analyze the timing waveform when you suspect an error condition [71] [72].

II.2 Mechanical Problems:

II.2.1 Spectral identification of bearing errors

Bearing is a machine element consisting of two rings called inner and outer rings. while in these rings rotates a set of balls or rolling elements arranged in raceways . standard shapes of rolling elements are ball, cylindrical roller, tapered roller, needle roller etc . Bearing failures can result in excessive audible noise, reduced working accuracy, and the development of mechanical vibrations, which lead to increased wear . From others from the point of view of the ball bearing defects are to be classified as external defects due to their location[73].

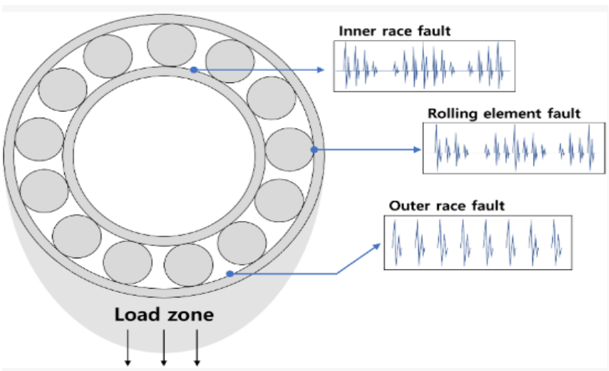


FIGURE.II.1. :BEARING DEFECTS

Most bearing-related condition monitoring programs focus on these four characteristics failure frequencies. These frequencies are [73].

a. **BPFO (Ball Pass Frequency Outer)**: or frequency of leaving the outer lane. In physical terms, it corresponds to the number of balls or rollers that pass through a certain point on the outer ring for each complete revolution of the shaft.
b. **BPFI (Ball Pass Frequency Inner):** or inner ring failure rate. Physically, it corresponds to the number of balls or rollers that pass through a certain point of the inner ring during each complete revolution of the shaft.

c. **BSF (Ball Spin Frequency):** or rolling element failure rate. In physical terms, it corresponds to the number of revolutions that a ball or roller bearing makes for each complete revolution of the shaft.
d. **FTF (Fundamental Train Frequency):** or cage failure frequency. Physically, it corresponds to the number of revolutions that the bearing cage makes for each complete revolution of the shaft.

- **Formulas for calculating bearing failure rates**

. The four characteristic default frequencies are defined in**(1)- (2)** [73].**:**

$$\textbf{BPFO}= \frac{N_B}{2}\left(1-\frac{B_D(\cos\beta)}{P_D}\right)\times RPM \qquad (1)$$

$$\textbf{BPFI}= \frac{N_B}{2}\left(1+\frac{B_D(\cos\beta)}{P_D}\right)\times RPM \qquad (2)$$

$$\textbf{BSF} = \frac{D_P}{2}\left(1-\frac{{B_D}^2(\cos\beta)^2}{{P_D}^2}\right)\times RPM \qquad (3)$$

$$\textbf{FTF} = \frac{1}{2}\left(1-\frac{B_D(\cos\beta)}{P_D}\right)\times RPM \qquad (4)$$

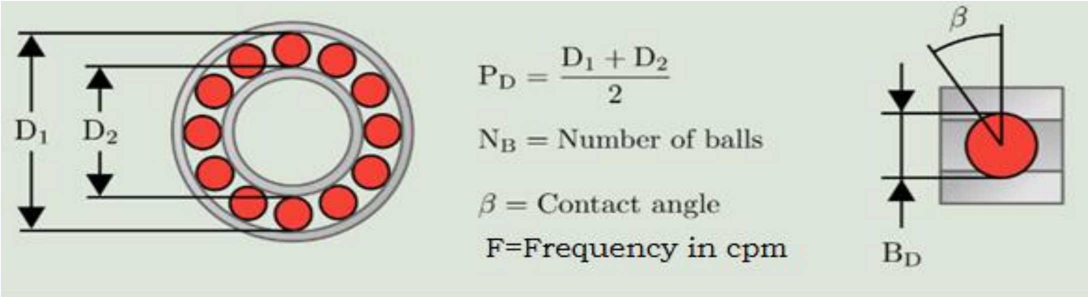


FIGURE.II.2:ILLSTRATION OF BEARING COASTER.

II.2.2 Spectrum of Outer ring failure:

The spectrum is characterized by the presence of harmonic peaks in the outer ring failure frequency (between the **8th** and **10th** harmonics of the **BPFO**).

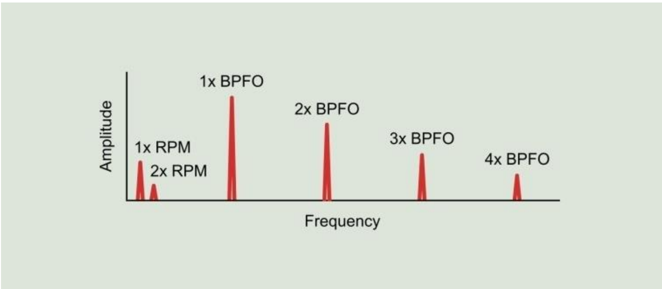
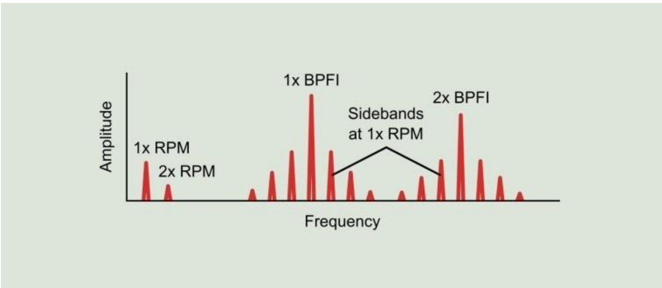


Figure.II.3 : Outer ring failure.

II.2.3 Spectrum of Inner ring failures:

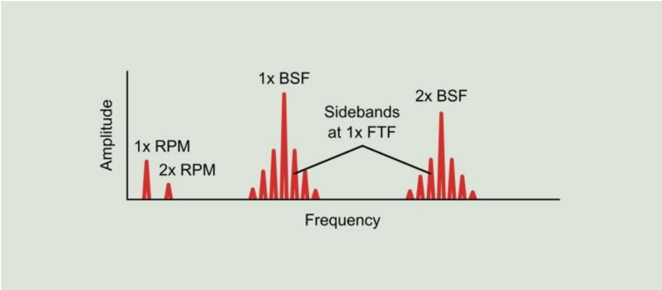
The spectrum shows multiple harmonic peaks of the inner ring failure frequency (typically between the **8th** and **10th** harmonics of the **BPFI**) modulated by sidebands at 1x **RPM**.



FigureII.4*:* Inner ring failures.

II.3.4 Spectrum of Ball or roller failures:

Due to the presence of wear frequency harmonics, rolling elements **(BSF)** marked in the spectrum. In most cases, the harmonic with the highest amplitude indicates the number of broken balls or rollers. They are usually accompanied by mishaps in the race.



FigureII.5*:* Ball or roller defects.

II.2.5 Spectrum of Frame failures:

Characterized by the presence of a Frame Interrupting Frequency (FTF) and its harmonics in the spectrum. Cage failures are usually accompanied by track failures, and the (FTF) typically modulates one of these failure frequencies during races, resulting in frequency sums and/or differences.

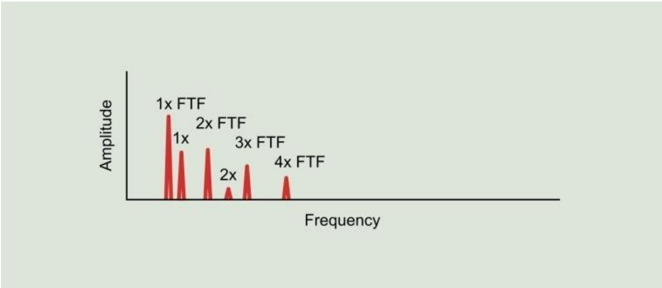


Figure.II.6*:* Frame failures.

II.2.6 Spectral identification of eccentricity fault:

The rotor is assumed to be concentric with respect to the stator coils. Otherwise, an unbalanced magnetic force will be generated, which is given by the formula:

$$\boldsymbol{F_{CC}} = \left[\frac{KI^2}{g^2}\left(\frac{4e}{(1-e)^2}\right)\right] \quad (5)$$

Where:
I*:* stator current,
g*: average* gap between stator and rotor,
e*:* eccentricity.
K: 1, 2, 3, . . . is a positive integer,
$\boldsymbol{F_{CC}}$:is eccentric of rotor frequency

From this equation it can be seen that current and eccentricity can increase and create high unbalanced magnetic forces. It is assumed that the eccentricity of the rotor aligns with the magnetic field. The nearest side of the rotor is attracted to the positive and negative poles respectively; hence the force changes twice during a single power cycle can also be found in the low spectrum by analyzing the rotational frequency sidebands. Generally located between $\mathbf{2 \times F_L}$ and the nearest operating speed harmonic, it is necessary to "zoom in" on the spectrum to separate $\mathbf{2 \times F_L}$ from the operating speed harmonic. The eccentricity of the rotor creates a $\mathbf{2 \times F_L}$ oscillation surrounded by the $\mathbf{F_P}$ sidebands as well as the$\mathbf{F_P}$ sidebands around the operating speed, $\mathbf{F_P}$ appears at low frequency as Typical $\mathbf{F_P}$ values vary from about **20** to **120 CPM (0 .3** to **2Hz)** is sufficient[74].

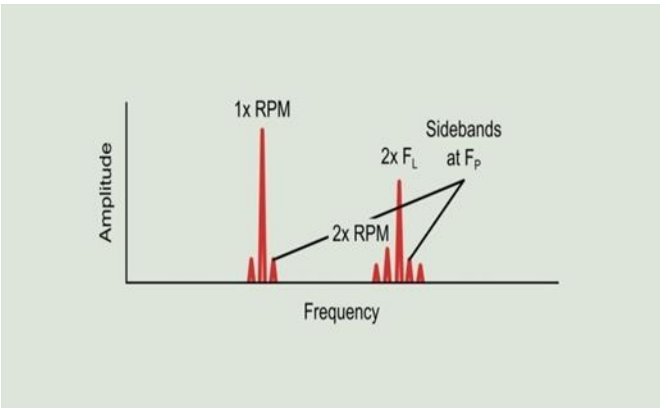


FIGURE.II.7: ECCENTRIC FAULT.

II.3 Electrical Problems:

Along with the stator is a rotor, which is basically an iron that follows the rotating magnetic field. As the magnetic field travels through the conductor, it creates a voltage across the rotor bar. When the bus is open, there are no current flows or forces. If the rod is shorted, a current will flow. this current is proportional to the speed at which the field flows through the conductor and to the field strength. The field interacts with the stator field to create more force on the rotor bar. All else being equal, an equal and opposite force will be developed on the opposite side of the rotor. These two forces create the torque that drives the load. If something interrupts the current or magnetic fields on either side of the rotor, the two forces become unequal. This creates a radial force that is the cause of the vibration [73-75].

II.3.1 Spectral identification of Broken rotor fault:

A broken rotor bar causes various effects in induction motors. A well-known effect of a broken bar is the occurrence of so-called sideband components [9]. The reference frequencies are determined by applying

$$F_b = (1 \pm KS)F_L \qquad \textbf{(6)}$$

(where s represents the slip,

$\boldsymbol{F_b}$: rotor bar frequency

$\boldsymbol{F_L}$: frequency

k=(1,2,3...).

Broken or cracked rotor bars Generates high vibration at **1x RPM** operating speed with$\mathbf{F_P}$ sidebands. In addition, these problems often create $\mathbf{F_P}$ sidebands around the **2nd, 3rd, 4th,** and 5th harmonics of the operating speed. Open rotor bars are indicated by sidebands at twice the mains.

frequency **(2x F_L)** around the rotor bar transition frequency **(RBPF)** and/or its harmonics. It often causes high levels at **2x RBPF** with only a small amplitude of at

1x RBPF. Electrically induced arcing between broken rotor bars and end rings often shows high levels at **2x RBPF** (with **2x F_L** sidebands); but little to no amplitude increase at **1x RBPF**[75].

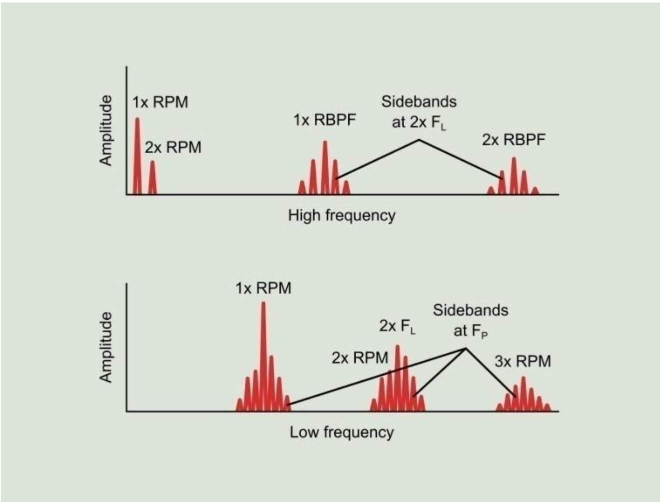


Figure.II.8**: Broken bar**

II.3.2 Spectral identification of Loose stator coil's fault:

An induction motor consists of a series of stator coils that produce magnetic rotation Field. The magnetic field causes alternating forces in the stator. If there is a slack or a weak support on the stator, each step of the pole gives it a jolt. This creates a high vibration at twice the line frequency **($2 \times F_L$).** also known as loose iron.

The line frequency of the coils is surrounded by $\mathbf{1 \times RPM}$ speed sidebands.

Cause short-circuited stator laminations localized warming that can increase significantly over time [75].

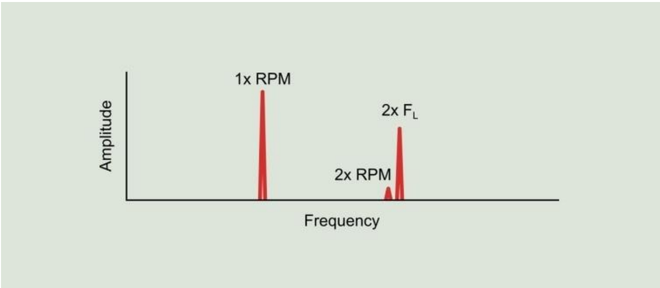


FIGURE.II.9: SHORT-CIRCUITED STATOR LAMINATION.

II.3.3 Spectral identification of Phasing fault:

Phase issues due to lose or broken connectors can cause excessive vibration at twice the line frequency **(2x FL)** having sidebands spaced 1/**3** the line frequency **(1/3 FL)** around them. . Levels at **2x FL** can increase significantly if left uncorrected. However, there may be cases where the only symptom is an increase in amplitude at **2x FL**. This is a problem in particular if the defective connector only makes sporadic contact. Poor or defective connectors must be repaired to prevent catastrophic failure [75].

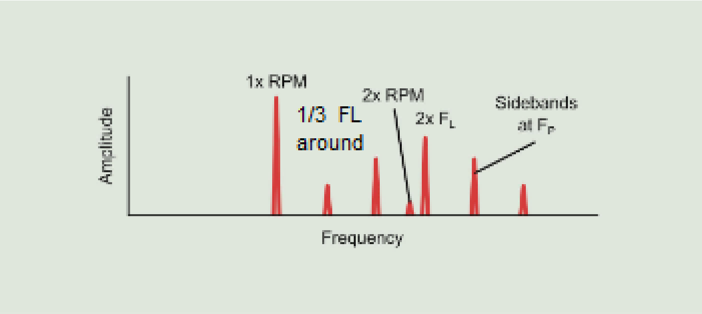


FIGURE.II.10: PHASING PROBLEM.

II.4 Three phase model of Induction machine:

The first mathematical model for the dynamic analysis of the asynchronous machine was based on the true two-axis reference system first developed by Park (1929) for the synchronous machine. Kovacs and Racz (1959) used the symmetrical configuration of the induction machine worked out the space complex vector theory and received a model for the stationary analysis of the machine. Both theories are used to model the three-phase induction machine. He The following assumptions are made when writing a complete system of equations for description Time-continuous linear model of the induction machine [10]:

- The geometric and electrical structure of the machine is symmetrical; ·
- The spatial harmonics of the stator and rotor magnetic flux are negligible;
- Infinitely Transmissivity Iron;
- The stator and rotor windings are distributed in space in a sinusoidal manner and are replaced by an equivalent concentrated winding;
- Prominence effects, grooving effects are neglected;
- Magnetic saturation, anisotropy effect, core loss and skin effect are negligible;
- The resistance and reactance of the windings do not change with temperature; ·
- Currents and voltages are sinusoidal quantities.
- Final and edge effects are neglected All these assumptions do not seriously change the end result for a wide range of inductions machines.

The three-phase induction motor has a three-phase symmetrical stator winding, staggered for 120o with Ns equivalent revolutions. The rotor winding also contains a three-phase motor. Winding of offset by 120o with Nr equivalent turns. The three-phase shaft of the stator u the rotors are separated by the rotor angle θr as shown in Figure 5.1 [76].

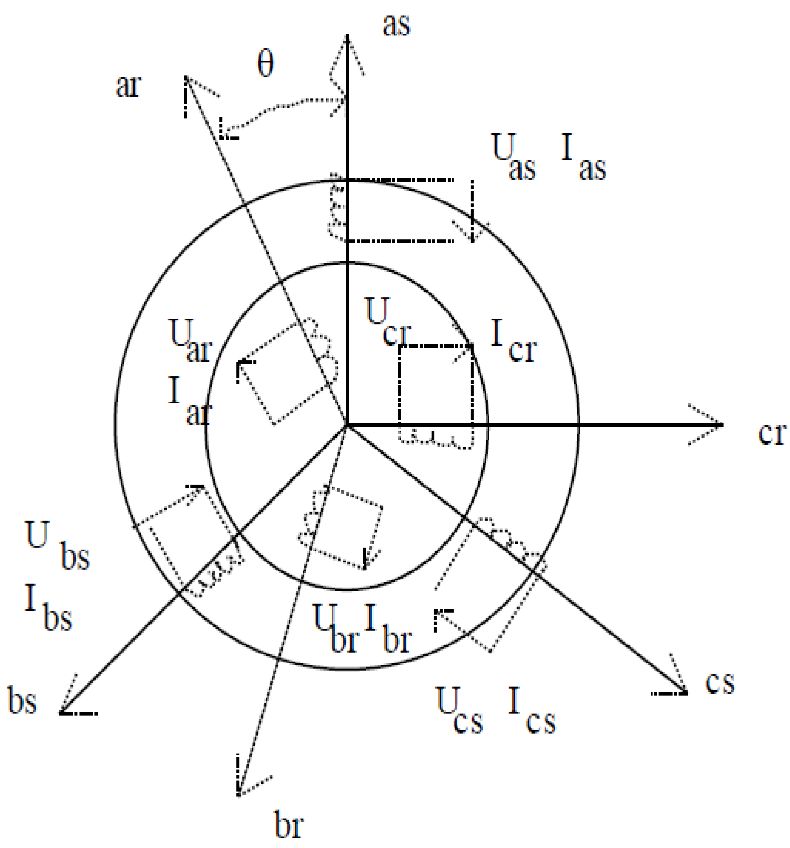


FIGURE.II.11: SYMMETRICAL INDUCTION MOTOR SIMPLIFIED SCHEME.

II.4.1 General equation:

The behavior of the asynchronous machine is entirely defined by three types of equations, namely [10]:

• Electrical equations.

• Magnetic equations.

• Mechanical equations

II.4.1.1 **Electrical equations:**

For all stator phases [10]:

$$\begin{bmatrix} U_{sa} \\ U_{sb} \\ U_{sc} \end{bmatrix} = \begin{bmatrix} R_s & 0 & 0 \\ 0 & R_s & 0 \\ 0 & 0 & R_s \end{bmatrix} \begin{bmatrix} I_{sa} \\ I_{sb} \\ I_{sc} \end{bmatrix} + \frac{d}{dt} \begin{bmatrix} \phi_{sa} \\ \phi_{sb} \\ \phi_{sc} \end{bmatrix} \text{(I)}$$

$$\begin{bmatrix} U_{sa} \\ U_{sb} \\ U_{sc} \end{bmatrix} = R_s \begin{bmatrix} I_{sa} \\ I_{sb} \\ I_{sc} \end{bmatrix} + \frac{d}{dt} \begin{bmatrix} \phi_{sa} \\ \phi_{sb} \\ \phi_{sc} \end{bmatrix} (8)$$

The stator resistance being the same for the three phases, there is no need to write a matrix of resistors.

$$\text{OR:} [U_{sabc}] = [R_s][I_{sabc}] + \frac{d}{dt}[\phi_{sabc}] (9)$$

Similarly, to the rotor

$$\begin{bmatrix} U_{ra} \\ U_{rb} \\ U_{rc} \end{bmatrix} = \begin{bmatrix} R_r & 0 & 0 \\ 0 & R_r & 0 \\ 0 & 0 & R_r \end{bmatrix} \begin{bmatrix} I_{ra} \\ I_{rb} \\ I_{rc} \end{bmatrix} + \frac{d}{dt} \begin{bmatrix} \phi_{ra} \\ \phi_{rb} \\ \phi_{rc} \end{bmatrix} (10)$$

$$\begin{bmatrix} U_{ra} \\ U_{rb} \\ U_{rc} \end{bmatrix} = R_s \begin{bmatrix} I_{ra} \\ I_{rb} \\ I_{rc} \end{bmatrix} + \frac{d}{dt} \begin{bmatrix} \phi_{ra} \\ \phi_{rb} \\ \phi_{rc} \end{bmatrix} (11)$$

$$[\boldsymbol{U_{rabc}}] = [\boldsymbol{R_r}][\boldsymbol{I_{rabc}}] + \frac{\boldsymbol{d}}{\boldsymbol{dt}}[\boldsymbol{\phi_{rabc}}] \quad (\mathbf{12})$$

II.4.1.2 **Magnetic equations:**

Each flow has an interaction with the currents of all phases including its own

(Concept of flux/self-inductance).

Stator side:

$$\begin{bmatrix} \boldsymbol{\phi_{sa}} \\ \boldsymbol{\phi_{sb}} \\ \boldsymbol{\phi_{sc}} \end{bmatrix} = [\boldsymbol{L_s}] \begin{bmatrix} \boldsymbol{i_{sa}} \\ \boldsymbol{i_{sb}} \\ \boldsymbol{i_{sc}} \end{bmatrix} + [\boldsymbol{M_{sr}}] \begin{bmatrix} \boldsymbol{i_{ra}} \\ \boldsymbol{i_{rb}} \\ \boldsymbol{i_{rc}} \end{bmatrix} \quad (\mathbf{13})$$

$$[\boldsymbol{\phi_{sabc}}] = [\boldsymbol{L_s}][\boldsymbol{I_{sabc}}] + [\boldsymbol{M_{sr}}][\boldsymbol{I_{rabc}}] \quad (\mathbf{14})$$

Side the rotor:

$$\begin{bmatrix} \boldsymbol{\phi_{ra}} \\ \boldsymbol{\phi_{rb}} \\ \boldsymbol{\phi_{rc}} \end{bmatrix} = [\boldsymbol{M_{rs}}] \begin{bmatrix} \boldsymbol{i_{sa}} \\ \boldsymbol{i_{sb}} \\ \boldsymbol{i_{sc}} \end{bmatrix} + [\boldsymbol{L_r}] \begin{bmatrix} \boldsymbol{i_{ra}} \\ \boldsymbol{i_{rb}} \\ \boldsymbol{i_{rc}} \end{bmatrix} \quad (\mathbf{15})$$

$$[\boldsymbol{\phi_{rabc}}] = [\boldsymbol{M_{rs}}][\boldsymbol{I_{sabc}}] + [\boldsymbol{L_r}][\boldsymbol{I_{rabc}}] \quad (\mathbf{16})$$

WITH:

$$[\mathrm{L_S}] = \begin{bmatrix} \mathrm{L_S} & M_S & M_S \\ M_S & L_S & M_S \\ M_S & M_S & L_S \end{bmatrix}$$ Matrix of the windings (inductors) to the stator

$$[\mathrm{L_r}] = \begin{bmatrix} \mathrm{L_r} & M_r & M_r \\ M_r & L_r & M_r \\ M_r & M_r & L_r \end{bmatrix}$$ Matrix of the windings (inductors) to the rotor

$$[M_{sr}] = [M_{rs}]^t = M_{sr}\begin{bmatrix} \cos\theta & \cos(\theta+\frac{2\pi}{3}) & \cos(\theta-\frac{2\pi}{3}) \\ \cos(\theta-\frac{2\pi}{3}) & \cos\theta & \cos(\theta+\frac{2\pi}{3}) \\ \cos(\theta+\frac{2\pi}{3}) & \cos(\theta-\frac{2\pi}{3}) & \cos\theta \end{bmatrix} (17)$$

$$[U_{sabc}] = [R_s][I_{sabc}] + \frac{d}{dt}([L_s][I_{sabc}] + [M_{sr}][I_{rabc}])$$

$$[U_{rabc}] = [R_s][I_{rabc}] + \frac{d}{dt}([L_r][I_{rabc}] + [M_{sr}][I_{sabc}]) (18)$$

II.4.1.3 Mechanical equation:

$$j\frac{d\omega r}{dt} = T_e - T_l - T_f (19)$$

whereT_l is the load torque, T_f is the friction torque loss and **ωr** is the angular velocity of the rotor The main advantage of this model is that it can be used to simulate special cases, such as. Failures in a broken rotor bar and voltage imbalance between power phases [10].

II.4.2 The Park transformation :

$$[X_{dq}] = T(\theta)[X_{abc}] (20)$$

With:

$$T(\theta) = \sqrt{\frac{2}{3}}\begin{bmatrix} \cos\theta & \cos(\theta+\frac{2\pi}{3}) & \cos(\theta-\frac{2\pi}{3}) \\ \cos(\theta-\frac{2\pi}{3}) & \cos\theta & \cos(\theta+\frac{2\pi}{3}) \\ \cos(\theta+\frac{2\pi}{3}) & \cos(\theta-\frac{2\pi}{3}) & \cos\theta \end{bmatrix} (21)$$

- **Choice of UV marker:**

1. **Space fixed frame over stator:**

$$\dot{\theta}_s = 0; \dot{\theta}_r = -\dot{\theta}; \omega_r = -\omega$$

a. Electrical equation:

$$U_{s\alpha} = R_s i_{s\alpha} + \frac{d\phi_{s\alpha}}{dt}$$

$$\boldsymbol{U_{s\beta} = R_s i_{s\beta} + \frac{d\phi_{s\beta}}{dt}} \qquad \textbf{(22)}$$

$$U_{r\alpha} = R_r i_{r\alpha} + \omega_r \phi_{r\beta} + \frac{d\phi_{r\alpha}}{dt}$$

$$U_{r\beta} = R_r i_{r\beta} - \omega_r \phi_{r\alpha} + \frac{d\phi_{r\beta}}{dt}$$

b. Magnetically equation:

$$\phi_{s\alpha} = L_s i_{s\alpha} + M i_{r\alpha}$$

$$\phi_{s\beta} = L_s i_{s\beta} + M i_{r\beta}$$

$$\boldsymbol{\phi_{r\alpha} = M i_{s\alpha} + L_r i_{r\alpha}} \qquad \textbf{(23)}$$

$$\phi_{r\beta} = M i_{s\beta} + L_r i_{r\beta}$$

c. Mechanical equation

$$\boldsymbol{C_{em} = p(\phi_{s\alpha} i_{s\beta} - \phi_{s\beta} i_{s\alpha})} \qquad \textbf{(24)}$$

2. **Space fixed frame over rotor:**

$$\dot{\theta}_s = \dot{\theta} = \omega; \dot{\theta}_r = \omega_r = 0$$

a. Electrical equation:

$$U_{sx} = R_s i_{sx} - \omega_s \phi_{sy} + \frac{d\phi_{sx}}{dt}$$

$$U_{s\beta} = R_s i_{sy} + \omega_s \phi_{sx} + \frac{d\phi_{sy}}{dt}$$

$$\boldsymbol{U_{rx} = R_r i_{rx} + \frac{d\phi_{rx}}{dt}} \quad (25)$$

$$U_{s\beta} = R_r i_{ry} + \frac{d\phi_{ry}}{dt}$$

b. Magnetically equation:

$$\phi_{s\alpha} = L_s i_{sx} + M i_{rx}$$

$$\boldsymbol{\phi_{sy} = L_s i_{sy} + M i_{ry}} \quad (26)$$

$$\phi_{rx} = M i_{sx} + L_r i_{rx}$$

$$\phi_{ry} = M i_{sy} + L_r i_{ry}$$

c. Mechanical equation:

$$\boldsymbol{C_{em} = p(\phi_{sx} i_{sy} - \phi_{sy} i_{sx})} \quad (27)$$

3. Space fixed frame over flux:

a. Electrical equation:

$$\boldsymbol{U_{sd} = R_s i_{sd} - \omega_s \phi_{sq} + \frac{d\phi_{sd}}{dt}} \quad (28)$$

$$U_{sq} = R_s i_{sq} + \omega_s \phi_{sd} + \frac{d\phi_{sq}}{dt}$$

$$U_{rd} = R_r i_{rd} - \omega_r \phi_{rq} + \frac{d\phi_{rd}}{dt}$$

$$\boldsymbol{U_{sq} = R_r i_{rq} + \omega_r \phi_{rd} + \frac{d\phi_{rq}}{dt}}$$

b. Magnetically equation:

$$\phi_{sd} = L_s i_{sd} + M i_{rd}$$

$$\boldsymbol{\phi_{sq} = L_s i_{sq} + M i_{rq}} \quad (29II)$$

$$\phi_{rd} = M i_{sd} + L_r i_{rd}$$

$$\phi_{rq} = M i_{sq} + L_r i_{rq}$$

c. Mechanical equation:

$$\boldsymbol{C_{em} = p(\phi_{sd} i_{sq} - \phi_{sd} i_{sq})} \qquad \mathbf{(30)}$$

II.4.3 MAS state representation:

In writing the system of equations in the form of state representation in the fixed frame with respect to the stator:

$$\left[\frac{dX}{dY}\right] = AX + BV$$

$$[X] = \left[\phi_{s\alpha} \quad \phi_{s\beta} \quad i_{s\alpha} i_{s\beta}\right]^T$$

$$[V] = \left[U_{s\alpha} \quad U_{s\beta} \ \right]^T$$

$$\boldsymbol{A} = \begin{bmatrix} \mathbf{0} & \mathbf{0} & -\boldsymbol{R_s} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & -\boldsymbol{R_s} \\ \frac{\mathbf{1}}{(\boldsymbol{T_r L_s \sigma})} & \frac{\boldsymbol{\omega}}{\boldsymbol{L_s \sigma}} & -\frac{\mathbf{1}/\boldsymbol{T_S}+\mathbf{1}/\boldsymbol{T_r}}{\boldsymbol{\sigma}} & \boldsymbol{\omega} \\ \frac{-\boldsymbol{\omega}}{\boldsymbol{L_s \sigma}} & \frac{\mathbf{1}}{(\boldsymbol{T_r L_s \sigma})} & \boldsymbol{\omega} & -\frac{\mathbf{1}/\boldsymbol{T_S}+\mathbf{1}/\boldsymbol{T_r}}{\boldsymbol{\sigma}} \end{bmatrix} \mathbf{(31)}$$

$$\boldsymbol{B} = \begin{bmatrix} \mathbf{1} & \mathbf{0} \\ \mathbf{0} & \mathbf{1} \\ [\frac{\mathbf{1}}{\boldsymbol{L_s \sigma}} & \mathbf{0}\ ] \\ \mathbf{0} & \frac{\mathbf{1}}{\boldsymbol{L_s \sigma}} \end{bmatrix} \mathbf{(32)}$$

$$\boldsymbol{A_{11}} = \begin{bmatrix} \mathbf{0} & \mathbf{0} & -\boldsymbol{R_s} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & -\boldsymbol{R_s} \\ \frac{\mathbf{1}}{(\boldsymbol{T_r L_s \sigma})} & \mathbf{0} & -\frac{\mathbf{1}/\boldsymbol{T_S}+\mathbf{1}/\boldsymbol{T_r}}{\boldsymbol{\sigma}} & \mathbf{0} \\ \mathbf{0} & \frac{\mathbf{1}}{(\boldsymbol{T_r L_s \sigma})} & \mathbf{0} & -\frac{\mathbf{1}/\boldsymbol{T_S}+\mathbf{1}/\boldsymbol{T_r}}{\boldsymbol{\sigma}} \end{bmatrix} \mathbf{(32)}$$

$$\begin{bmatrix} \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \frac{-\mathbf{1}}{(\boldsymbol{L_s \sigma})} & \mathbf{0} & -\mathbf{1} \\ \frac{-\mathbf{1}}{(\boldsymbol{L_s \sigma})} & \mathbf{0} & \mathbf{1} & \mathbf{0} \end{bmatrix} \mathbf{(33)}$$

II.5 Simulation of the machine in the normal mode:

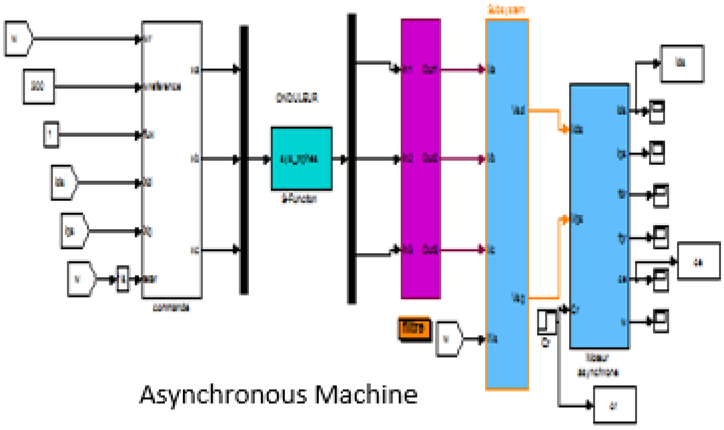


Figure.II.10 : Simulation bloc of Induction Machine.

II.6 Simulation results:

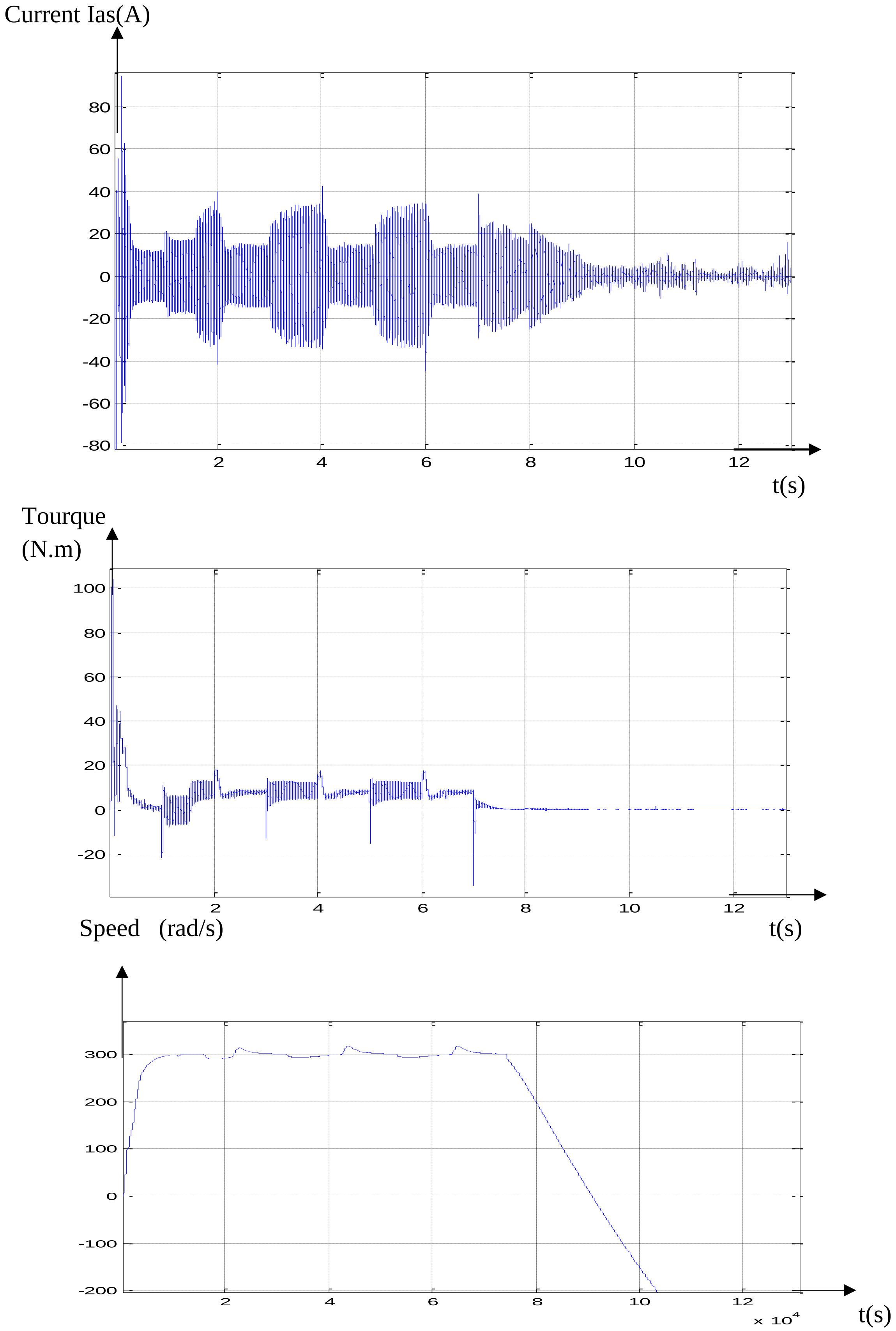


FIGURE.II.11Simulation results of Asyncrounous machine in presence of defaults

II.7 CONCLUSION:

In this chapter firstly, we discuss the spectral analysis of mechanical problems and electrical problems, in addition we modeled the three-phase asynchronous motor in the three-phase reference next Apply the park transformation and extract the engine state representation, then we have the Simulation of an asynchronous motor powered by a three-phase network.in conclusion discussed the results of indicatives signatures of induction machine variables.

Chapter III

Implementation of a fault diagnosis system based on a neural network on an FPGA circuit

Chapter III Implementation of a fault diagnosis system based on a neural network on an FPGA circuit

III.1 Introduction:

The monitoring of asynchronous motors is very important to ensure the continuity of production and not to block other tasks in the production chain. Because the asynchronous machine is the main element in industry and always put to work. Early detection can reduce the severity of faults and their impact on the machine, as well as rapid localization has advantages on the maintenance side, because after diagnosis, maintenance is carried out to correct the fault that has appeared. This is why continuous monitoring and real-time diagnosis are very important. In this chapter, we will make an automatic diagnosis by one of the tools of artificial intelligence, it is the neural network which will monitor the system in the event of failure which would occur. The neural network will automatically detect the phase failure fault and unbalance the three phases and also short-circuit between the turns as soon as it appears on the asynchronous motor. The RMS signal of the stator phase current of the squirrel cage induction motor is used as a fault indicating signal. The objective of this chapter is the implementation of neural network on an FPGA circuit. The purpose of this implementation is to study the contribution of hardware integration solutions (FPGA) in the diagnosis of asynchronous motor failures for a lack of phase fault case. In this study, we start with the adaptation of the neural network in order to allow an optimal implementation. This implementation must ensure efficiency, speed of execution and a minimum possible space on the FPGA circuit. Then we program this neural system on the System Generator. The Generator system is used to generate the VHDL code. This code is verified and implemented on a VIERTEX type FPGA circuit by the ISE foundation software from Xilinx.

III.2 FPGA Hardwar in the Loop:

FPGAs are integrated circuits made up of an array of identical logic cells interconnected by programming (linked by configurable communication buses). The principle basic is simple: in order to implement a logic function in an FPGA, it suffices to configure the logic cells and to link them correctly using the internal buses. Indeed, FPGAs are the descendants of CPLD, they are simply much more complex and powerful. There are all of them sizes, from a few thousand logic gates to a few million, which makes it possible to implement complex circuits without having to design an ASIC. In addition to configurable cells, many FPGAs have more complex memories and modules like multipliers. Some manufacturers even go so far as to implement microprocessor cores [78]. In addition, they are fully tested after production, so the designs do not require the generation of component test programs, no the automatic generation of test vectors (or design for testability). They only require functional type testing. As far as speed is concerned, FPGAs offer units that operate at speeds exceeding 400MHz in many applications. The speed of FPGAs is adequate for most applications. In critical cases, applications can be speeded up simply by using faster units, often without changing the circuit design. With dedicated circuits, the situation is completely different. Indeed, new manufacturing processes require the production of masks and increase the overall cost and production time. The development of FPGAs is accompanied by a constant evolution of design tools. These high-level tools remain affordable even by small design companies. The development time is made up solely of the time for simulation and production of the prototype, while the time for the other phases necessary for the dedicated circuits: generation of test vectors / production of masks, manufacture of waffles, packaging and testing final in manufacture, are avoided. This leads to a development time for FPGAs measured in days or weeks. While for dedicated circuits the durations are calculated in months

FPGAs have several advantages compared to other technologies, mainly [76]:
• Given their structure, all functions can be implemented, even the most complex, including including microprocessors or DSPs
• Can be reconfigured indefinitely;
• Parallel operation;
The legs of an FPGA are generally configurable and can adapt to several protocols communication (TTL, PC, etc.);
• Their programming is done by advanced languages, such as VHDL, Verilog, System generator. The FPGA has some disadvantages (which are not very important) such as:
• Programming these circuits requires learning the programming language, although that several studies have contributed to generate the VHDL language by more advanced languages, tonamely:
the C or MATLAB language;
• Since FPGAs are not dedicated circuits, the functions implemented are more slow and take up more space compared to a dedicated circuit, such as the DSP;
• Floating point representation is nearly impossible.

III.3. Application of neural network:

To apply neural networks to solve the problem the diagnosis of failures of an electromechanical system, two main steps must be applied [1,3,4,5,6,8]:

- The first is to examine the problem to be solved in order to Validate its adaptability with neural network resolution and set the goals to be achieved control the quality of the chosen solution.
- The second focus is on the technology of neural networks; includes the choice of network type and its implementation (the type of learning and the number of hidden). layers) depending on the characteristics of the problem under study and the goals.

The proposed neural network is to identify the induction motor faults. this artificial network consists of three layers, namely: the input layer consists of three neurons, whose function is to transmit the input values that correspond to the input variables (V_{eff1}, V_{eff2} and V_{eff3}) to the next layer called hidden layer. V_{effi} stands for the effective value of the *i-th* voltage ($i=1,2$ or 3). The output layer is composed of three neurons whose output is either 0 or 1. The RMS voltages V_{eff1}, V_{eff2} and V_{eff3} are calculated by using the RMS block which is available in Simulink library. The second stage in designing the ANN is the learning process which requires a data base defining the ANN input-output mapping. This data base is mostly given under matrix form as to clarify the inputs and the desired outputs. In our application, the matrix consists of three inputs (lines) corresponding to the three RMS voltages (V_{eff1}, V_{eff2}, V_{eff3}) and three digits (outputs) giving a code which corresponds to the appropriate fault. An optimal learning stage requires that the database must be very rich and cover different types of faults. For this purpose, the following tasks are completed:
- The machine is simulated in normal (healthy) state;

- The machine is simulated in abnormal regime (in the presence of faults: single phase, two-phase,..etc.);
The RMS values have been taken in each case including the healthy state.
This can be summarized by a classification of different states as shown in table 1

Table.III.1. Classification of different faults of IM.

TYPES OF FAULTS	SYMBOLES	CODES		
		S1	S2	S3
HEALTHY STATE	HS	0	0	0
SINGL_PHASE CUT **A** OFF	SPDA	1	0	0
SINGL_PHASE CUT **B** OFF	SPDB	0	1	0
SINGL_PHASE CUT **A** OFF	SPDC	0	0	1
TOW_PHASE CUT **AB** OFF	DPDAB	1	1	0
TOW_PHASE CUT **AC** OFF	DPDAC	1	0	1
TOW_PHASE CUT **BC** OFF	DPDBC	0	1	1

II.3.1. **Network test:**

For artificial neural network (ANN) building blocks. The use of multilayer perceptrons has proven effective for classifying shapes. The neural network we tested is multilayer network using the backpropagation algorithm for his learning. The purpose of this algorithm is to adjust the synaptic weights to minimize the average value of quadratic mean error. It requires the use of a layered neural system to solve the problem. The networks multi-layer networks are used, which include an input layer corresponds to the indicated values, an output layer that corresponds to the decision and a series of so-called hidden layers. These hidden layers make up the internal display variables of the problems. The network building steps can be divided as follows:

• Choice of network tickets, we use cash values of variables (Va, Vb, Vc) for Determine the number of network inputs (count).   hidden layer neurons), indicating the number of inputs in this network corresponds to 3 variables [3].
• Choice of outputs, in determination of the number editions and their manner, to facilitate the interpretation of the results of network output by expert system, our choice was based on the binary numbers (0,1) as outputs are binary and real inputs, the output function is a linear function and the activation function a sigmoid function.
• Determination of the number of hidden neurons and the Number of hidden layers: They are determined by testing and Error of a learning algorithm. As shown below Figure.III.1:

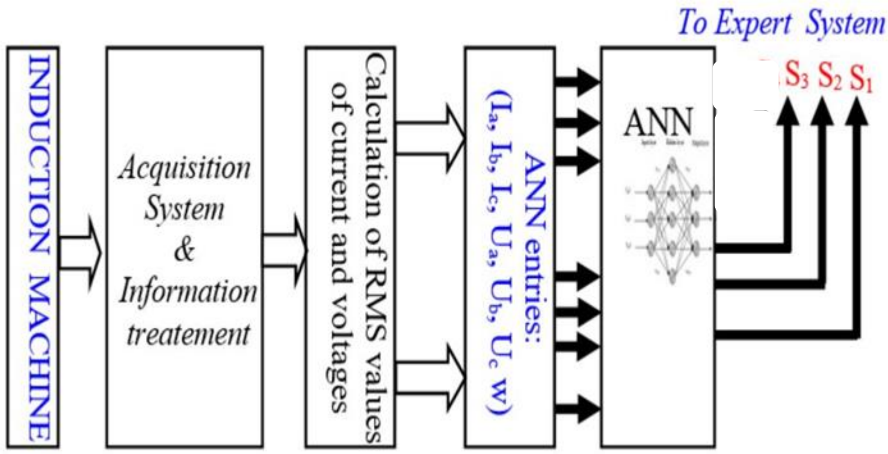


Figure.III.1. Acquisition and fault detection system based ANN

III.3.2. Signal processing by RMS

Root Mean square or the effective value of a signal is the square root of the mean constant squared values of this signal quantity, over a given time interval [77]:

For a signal sampled by a sampling step T $u(t)^2$ will be is only known at the sampling times: $\int_0^t u(t)^2 \cdot dt$ and can be approximated by the area between discretized $u(t)^2$and the timeline:

The RMS transform is applied for the “abc” stator current signals where the lack of phase or three unbalanced phases will therefore be visible the current signals which are signal’s fault indicators.

III.3.3 Interpretation of the results:

In order to detect errors in a system, a diagnosis is carried out by neural networks must have a sufficient number of examples during the operation in healthy cases and in the case of defects learning, through the learning function there are examples is displayed to the input network with the diagnosis according to the output. After learning, the network does not work only recognizes learned examples, but also models is similar to them, which equates to a certain robustness compared to standard signal distortion Upon detecting a defect.

for ANN, at time t=1s, it introduces the first error outputs: S1, S2, S3 each show the values: (1, 0, 0) so the single phase cut off is the same as the other cases Outputs S1, S2, S3, respectively see FigureIII.2.

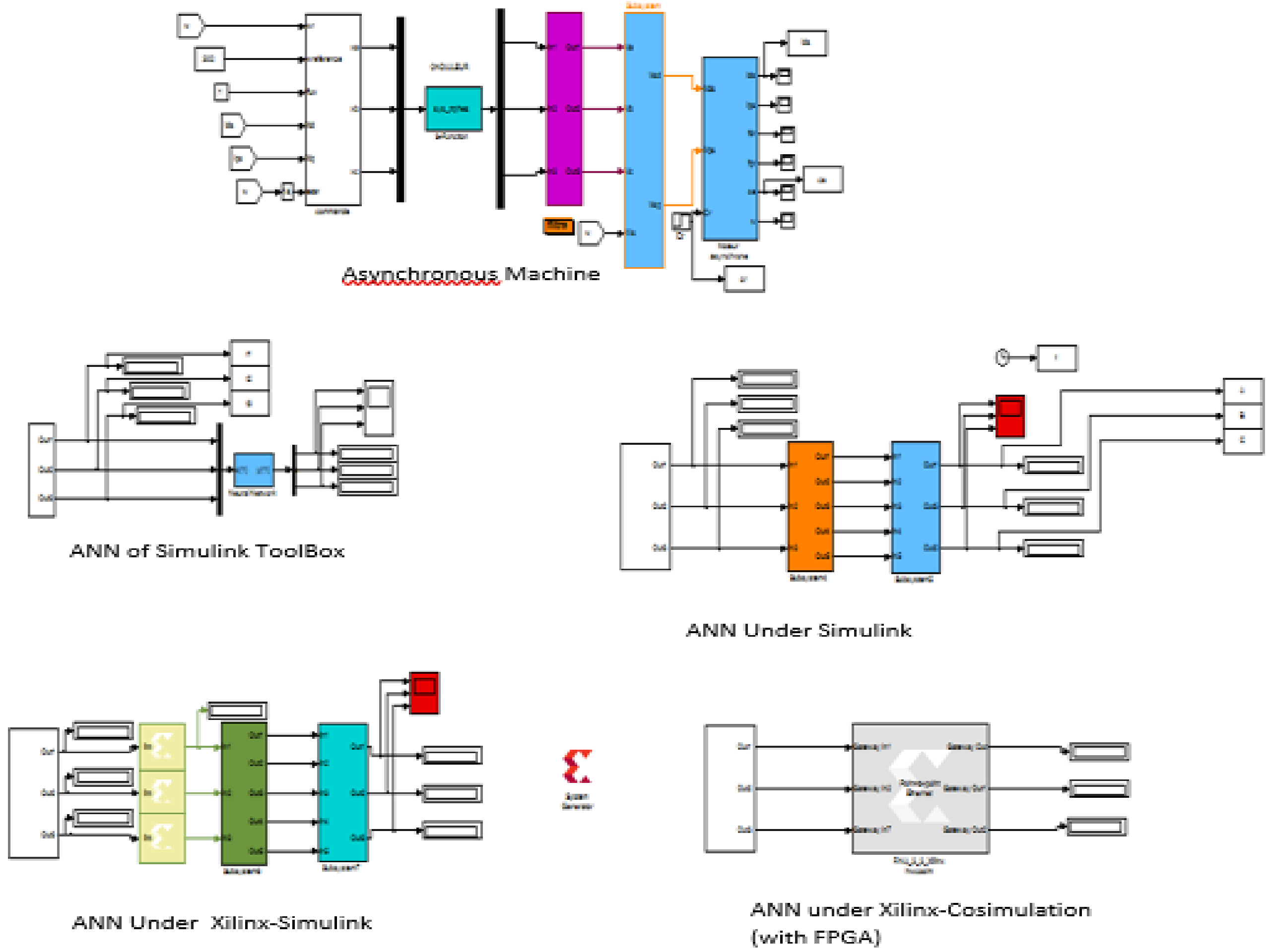


Figure.III.2. ANN based simulation with several tools (Simulink, Xilinx, Cosimulation).

III.4 ANN testing by co-simulation

Once the ANN code is dowloaded on the FPGA board, simultion of the whole system will be ready carry on see FigureIII.3. To check the performance of the prposed ANN as well as the approximated activation sigmoid function, the same scenario used to validate the ANN, has been coducted for this test. The results shown in figureIII.4 show respectively the instatanous stator current, the RMS stator current and the three ANN binnary outputs that identify the fault type. One can notice that the implemented ANN has generated the right binarry code according to fault applied to the motor. It is easy to filter or eliminate the ANN ouput during the motor starting otherwise it does not matter as the signal do not last long as to be confused with consequential one.

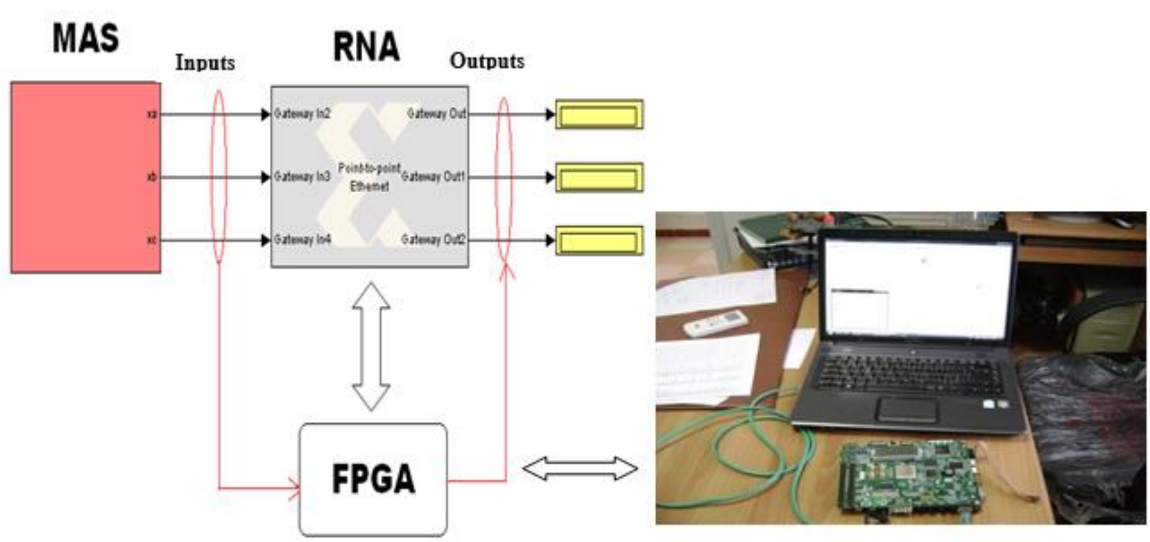


Figure.III.3. Principle of implementation of ANN block on FPGA using Co-simulation

(Co-simulation of ANN block with Virtex4 Device)

Finally, the figure.III.3 shows the association of the induction motor Simulink model with the artificial neural network system Xilinx model. The System Generator is used to convert the Xilinx model (ANN), generate the equivalent VHDL code and download it into the FPGA processor board (Virtex4 XC4VSX35-1011668). The system will look like that shown in figure 12. The connection of the FPGA to Matlab / Simulink in the PC is made through a Ethernet cable.

Table.III.2 Times of faults application

Time of application	**Fault type**	**Code**
t =1s	Single-phase cut A	SPDA
t = 2s	Healthy State	HS
t = 3s	Single-phase cut B	SPDB
t = 4s	Healthy State	HS
t = 5s	Single-phase cut C	SPDC
t = 6s	Healthy State	HS
t =7s	Unbalance single-phase2	DPDAB
t = 8s	Healthy State	HS
t =9s	Unbalance single-phase2	DPDAC

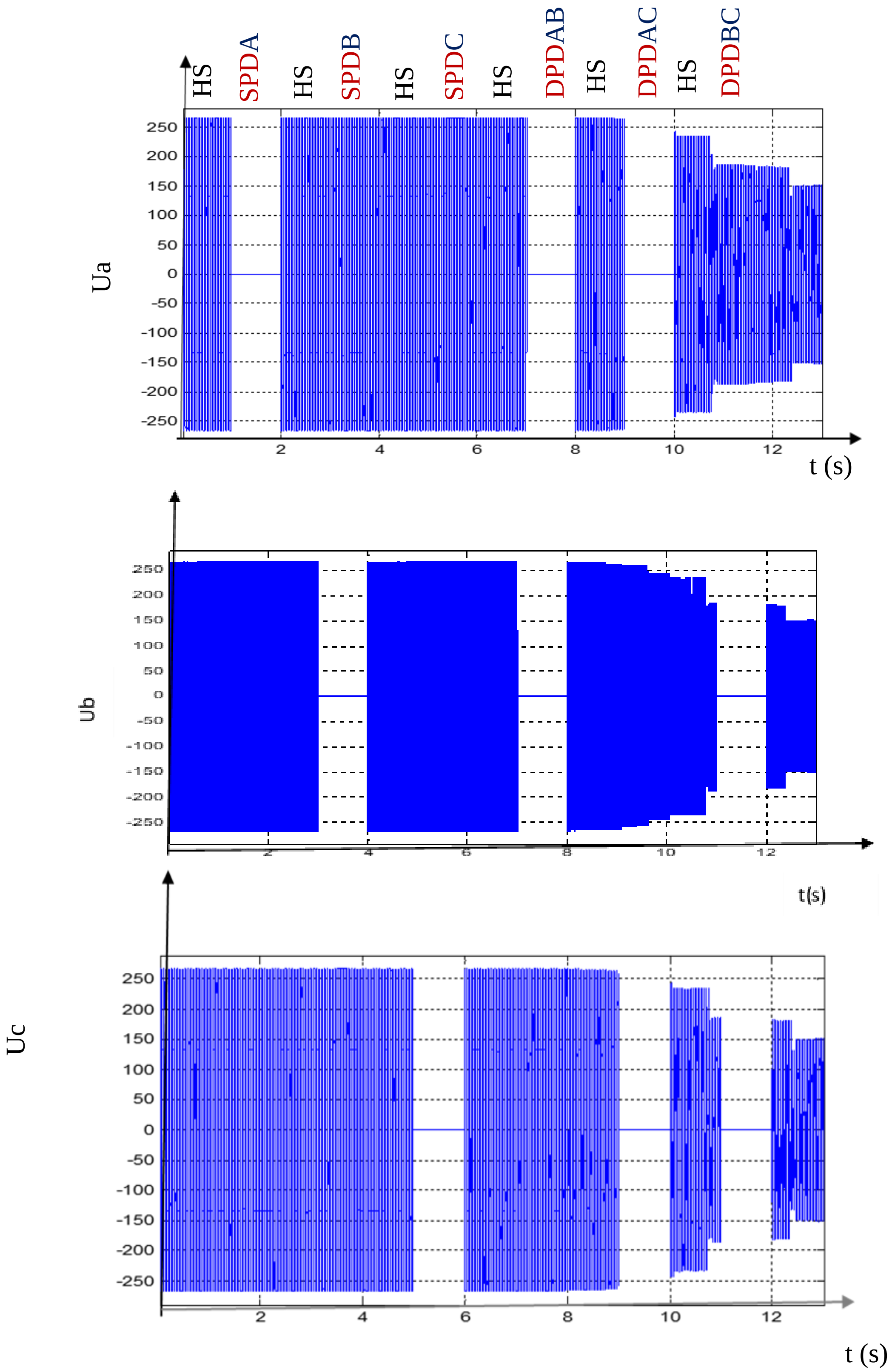


Figure.III.4 The stator voltages with different faults application

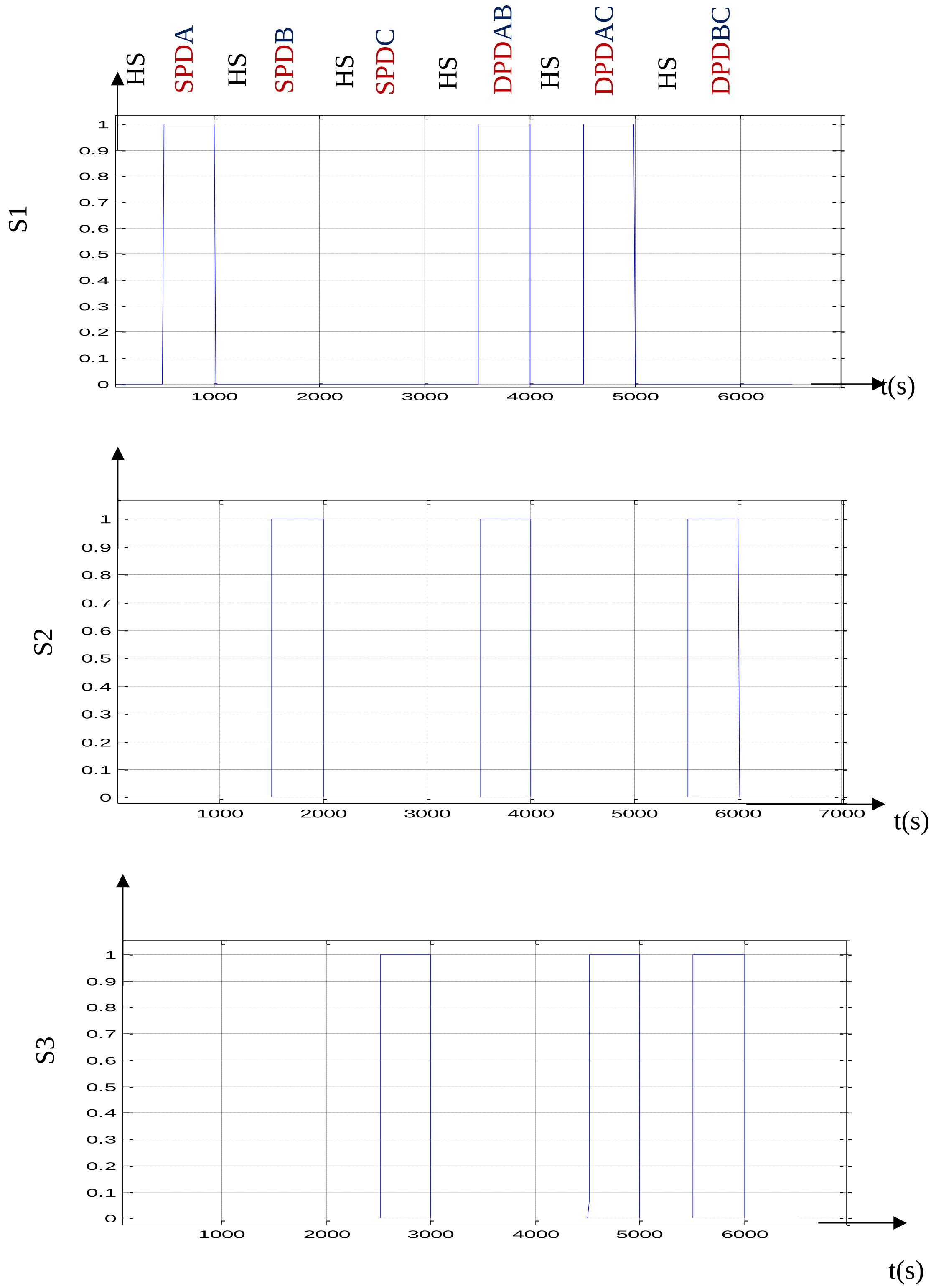


Figure.III.5. The stator voltages with different faults and the ANN outputs

Table.III.3: R**esults of synthesis of obtained ANN Block under Xilinx.**

Device utilization summary: Selected Device : 4vsx35ff668-10		
Number of Slices	113 out of 15360	0%
Number of Slices Flip Flops	113 out of 30720	0%
Number of 4 Inputs LUTs	206 out of 30720	0%
Number of Bonded IOBs	60 out of 448	13%
Number of GCLKs	6 out of 32	18%

From the results obtained on the table.3 reveals that the VHDL code occupies an area of less than 1% on FPGA, means that the FPGA type Virtex4 XC4VSX35-1011668 supported widely this VHDL code [3].

III.5 Conclusion:

In this chapter, we have studied a neural network that uses simple inputs such as The RMS values for the three stator voltages. Moreover, in order to implement the neural network, we first went through several parametric studies (input selection, output selection, etc.). In this chapter we also implemented a neural network based diagnostic system on FPGA.

In this work, an ANN has been developed and implemented for purpose of diagnosis of induction machine faults. The proposed ANN has one five neurons hidden layer, three binary outputs and three inputs which are the RMS values of the three motor voltages. As the input – targets data for motor diagnosis are available, Levenberg-Marquardt backpropagation algorithm of Neural Network Toolbox has been used to train he ANN. The results have shown through the validation test that the obtained synaptic weights of the ANN are the optimal values by obtaining a very small mean squared error.

One of the most important parameters in the implementation procedure is the modeling of the activation sigmoid function which is very commonly used in ANNs. In this work a method has been applied to approximate the sigmoid function by 2^{nd} order polynomial equation resulting in less computation time and memory requirements.

The system generator has been used to generate the VHDL code corresponding to the ANN model and downloaded into the FPGA Vertex 4 board. Co-Simulation of the induction motor modeled using simulink blocks and the ANN running in the FPGA has been successfully done.

The obtained ANN outputs show the effectiveness of the proposed topology and the approximation of the activation sigmoid function.

The use of high-level design tool such as system generator is very beneficial for the verification and design of any complex diagnosis or control algorithm without using a real system which can be damaged by the algorithm itself.

General conclusion

In this work, we studied the fault diagnosis of inductions motors. We have first studied the different types of machine faults, their causes, then explained how carry out the diagnosis of all kinds. After that, it was found that the neural network technique allows us to control production lines more flexibly. After that we have modeled and simulated the asynchronous motor. Then, we modeled and simulated the diagnostic system which depends on neural network and found effective results in terms of accuracy and speed, and we chose the FPGA circuit in order to implement this system because it is the fastest compared to DSP and Microprocessor.

In fact, the proposed ANN has one five neurons hidden layer, three binary outputs and three inputs which are the RMS values of the three motor voltages. As the input – targets data for motor diagnosis are available, Levenberg-Marquardt backpropagation algorithm of Neural Network Toolbox has been used to train he ANN. The results have shown through the validation test that the obtained synaptic weights of the ANN are the optimal values by obtaining a very small mean squared error.

The system generator has been used to generate the VHDL code corresponding to the ANN model and downloaded into the FPGA Vertex 4 board. Co-Simulation of the induction motor modeled using Simulink blocks and the ANN running in the FPGA has been successfully done. The obtained ANN outputs show the effectiveness of the proposed topology and the approximation of the activation sigmoid function.

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