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Thème

Modelling Induction Motor Using Recurrent Neural Network

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Dedication

I express my thanks to all those who contributed in many ways to the success of this study and made it an unforgettable experience for me.

To Our God Almighty **ALLAH** who is always there when I am in need. Thank you for guiding me and giving me strength and wisdom in my everyday life. Thank you for always looking out for me and being there for me. Thank you for making all of these happened and ended it with a good outcome.

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Abstract:

In this thesis, a newly developed approach for speed sensorless estimation application of an induction machine using Recurrent Neural Network (RNN) is presented. It only requires the stator voltage and flux of induction motor to obtain an estimation for rotor speed. The theoretical analysis is described, the simulation result using MATLAB software has proven to be successful with very high precision using the proposed method.

Résumé :

Dans cette thèse, une approche nouvellement développée pour l'application d'estimation de vitesse sans capteur d'une machine à induction utilisant un réseau de neurones récurrent (RNN) est présentée. Il ne nécessite que le stator tension et flux du moteur à induction pour obtenir une estimation de la vitesse du rotor. L'analyse théorique est décrite, le résultat de la simulation à l'aide du logiciel MATLAB s'est avéré efficace avec une très grande précision en utilisant la méthode proposée.

الملخص

في هذه الأطروحة، يتم تقديم منهاج تم تطويره حديثًا لتطبيق تقدير السرعة بدون مستشعر للمحركات الكهربائية اللاتزامنية باستخدام الشبكة العصبية المتكررة (الذكاء الاصطناعي) . ويتطلب فقط جهد الجزء الثابت وتدفق الآلة الحثية للحصول على تقدير لسرعة الجزء الدوار. وقد تم وصف التحليل النظري، وأثبتت نتيجة المحاكاة باستعمال برنامج ماتلاب نجاحها بدقة عالية باستخدام الطريقة المقترحة.

Keywords: Induction machine, Induction motor, Stator, Rotor, Artificial neural network (ANN), Recurrent Neural Network (RNN), Speed sensor.

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$\boldsymbol{S}, \boldsymbol{R}$ Index corresponding to the stator and the rotor

$\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{C}$ *In*dex corresponding to the three phases of the stator

$\boldsymbol{a}, \boldsymbol{b}, \boldsymbol{c}$ *I*ndex corresponding to the three phases of the rotor

$\boldsymbol{d}, \boldsymbol{q}$ Axis corresponding to the frame of reference linked to the rotating field

$\boldsymbol{\theta}$ Electric Angle

$\boldsymbol{i_{S\alpha}}, \boldsymbol{i_{S\beta}}$ Stator current in the reference (α, β)

$\boldsymbol{i_{Sd}}, \boldsymbol{i_{Sq}}$ Stator current in the reference(d, q)

$\boldsymbol{i_S}$ Stator current

$\boldsymbol{i_R}$ Rotor current

$\boldsymbol{v_{S\alpha}}, \boldsymbol{v_{S\beta}}$ Stator voltage in the reference(α, β)

$\boldsymbol{v_{Rd}}, \boldsymbol{v_{Rq}}$ Stator voltage in the reference(d, q)

$\boldsymbol{v_S}$ Stator voltage

$\boldsymbol{f_s}$ Stator frequency

$\boldsymbol{\phi_{R\alpha}}, \boldsymbol{\phi_{R\beta}}$ Rotor flow in the reference $(\alpha,)$

$\boldsymbol{\phi_{Rd}}, \boldsymbol{\phi_{Rq}}$ Rotor flow in the reference (d,q)

$\boldsymbol{\phi_R}$ rotor flow

$\boldsymbol{\phi_S}$ stator flow

$\boldsymbol{\omega_S}$ Electric stator speed

$\boldsymbol{\omega_R}$ Electric rotor speed

$\boldsymbol{\omega_{\alpha l}}$ Slip speed

$\boldsymbol{\Omega}$ Mechanical rotor speed

$\boldsymbol{P}$ Number of pole pairs

$\boldsymbol{E_T}$ Electromagnetic Torque

$\boldsymbol{R_T}$ Resistive torque imposed on the machine shaft

$\boldsymbol{J}$ Moment of inertia of the rotating part

$\boldsymbol{M}$ $Stator - rotor\ mutual\ cyclic\ inductance$

L_S, L_R Proper stator and rotor cyclic inductance per phase

R_S, R_R Resistances per phase of stator and rotor

σ Total dispersion coefficient

$[P(\theta_{abs})]$ PARK matrix

$[C]$ CLARK matrix

$w_{i,j}$ Weight of the neural network

General Introduction:

Induction Motors particularly those of the squirrel cage type a brilliant development of the late nineteenth century are the most famous wellsprings of mechanical power in industry practice provided from a three-phase ac line they are simple robust and economical.

Induction motors employ a simple but clever scheme of electromechanical energy conversion. In the squirrel-cage motors, which constitute a vast majority of induction machines, the rotor is inaccessible. No moving contacts, such as the commutator and brushes in dc machines or slip rings and brushes in ac synchronous motors and generators, are needed. This arrangement greatly increases reliability of induction motors and eliminates the danger of sparking, permitting squirrel-cage machines to be safely used in harsh environments, even in an explosive atmosphere. An additional degree of ruggedness is provided by the lack of wiring in the rotor, whose winding consists of uninsulated metal bars forming the "squirrel cage" that gives the name to the motor. Such a robust rotor can run at high speeds and withstand heavy mechanical and electrical overloads. In adjustable-speed drives (ASDs), the low electric time constant speeds up the dynamic response to control commands. Typically, induction motors have a significant torque reserve and a low dependence of speed on the load torque [1] .

Although operating principles of induction motors have remained unchanged, significant technological progress has been made over the years, particularly in the last few decades. In comparison with their ancestors, today's motors are smaller, lighter, more reliable, and more efficient. The so-called

Chapter 01:

The induction machine

I Chapter 01: The induction machine

I.1 Introduction:

The asynchronous motor, or induction motor, is the motor most used in the most electric drives. Its main advantage is the absence of sliding electrical contacts, which leads to a simple, robust mechanical structure and easy to build, their stator is directly connected to the industrial voltage network and constant frequency, it rotates at a speed little different from the synchronism speed; it is he who is used for the realization of almost all the training at constant speed. It also allows the realization of variable speed drives and the place it occupies in this field continues to grow. [2]

Modelling is an essential phase on the approach to simulation and realization, the adopted model should interpret all the phenomena that the designer seeks to highlight in order to predict the behavior in dynamic and steady state of the physical system. Firstly, we will describe the mathematical model of the induction motor (electrical and mechanical equations) in its three-phase frame of reference. Secondly, we will reduce the order of the system by a so-called PARK Transformation this transformation, models the induction motor in a new frame of reference, which consists of transforming the three-phase system into a system with two orthogonal axes (two-phase). Finally, we will present the numerical simulation of the various parameters of the induction motor.

I.2 Classification of rotating electrical machines:

Electric motors are generally classified according to the type of the electrical network in which the motor is connected: direct current motors (DC) and current motors alternative (AC). Motors with AC power supply are subdivided into two synchronous and inductions. The basic difference between an induction machine and a machine synchronous lies in the rotor speed of the induction machine under load does not coincide not (is not equal) the speed of the magnetic field, generated by the voltage feeding

Induction motors are divided into two main categories: single phase and three-phase, the first type of induction motors is not studied in this work. The motors at Three-phase induction are classified according to the type of rotor: cage rotor and wound rotor. [3]

I.3 Constitution of the induction machine:

The induction machine **Figure *I-1*** is made up of a fixed part called the stator and a part rotating called the rotor unlike synchronous and current machines continuous, only the stator windings are coupled to a supply network whose voltages (amplitude and frequency) define the magnetic state of the air gap. The rotor windings are connected to themselves. The induction motor therefore does not have no field windings or permanent magnets. For the rotor flux necessary for the formation of the electromagnetic couple, it is produced from induction represents the induction motor. From a mechanical point of view, the synchronous machine is subdivided into three distinct parts:

The stator: stationary part is the part where the power supply is connected.

The rotor: rotating part, it allows the magnetic charge to rotate.

The bearings: support organs, these constitute the mechanical part. This allowing the rotation of the motor shaft. [4]

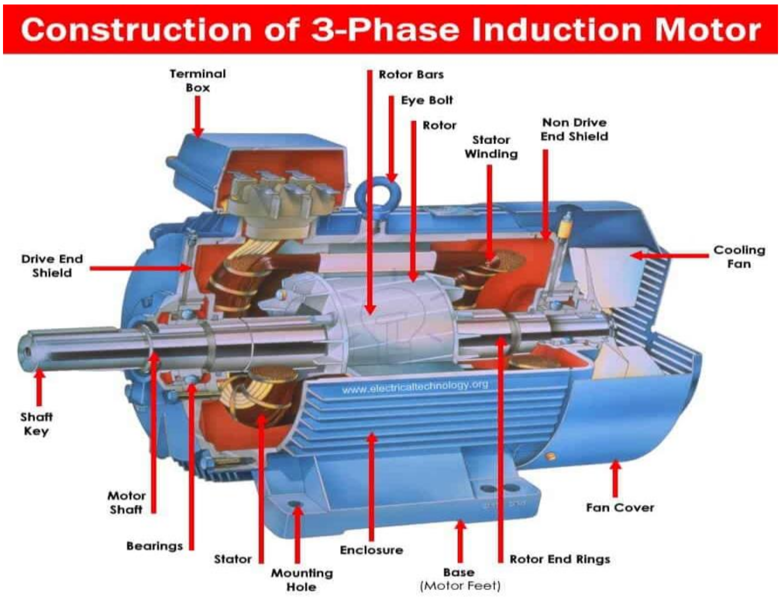


Figure I-1: construction of 3-phase induction motor

I.3.1 The stator:

It is the fixed **Figure *I-2*** part of the motor a casing in cast iron or light alloy encloses a ring of thin sheets (about 0.5 mm thick) in silicon steel. The sheets are isolated from each other by oxidation or by an insulating varnish. The “foliation” of the circuit magnetic reduces hysteresis and eddy current losses. The plates are equipped slots in which the stator windings intended to produce the rotating field (three windings in the case of a three-phase motor). Each winding is consisting of several coils. The mode of coupling of these coils between them defines the number of pole pairs of the motor, therefore the speed of rotation. [5]

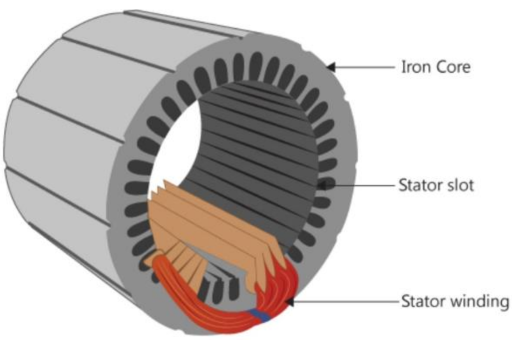


Figure I-2: The stator of induction motor

I.3.2 The rotor:

It is the moving part of the motor **Figure *I-3***. It consists of a stack of thin insulated sheets between them and forming a keyed cylinder on the motor shaft. This element, by its technology, makes it possible to distinguish two families of induction motors: those whose rotor is called "cage", and those whose wound rotor is called "with rings". [5]

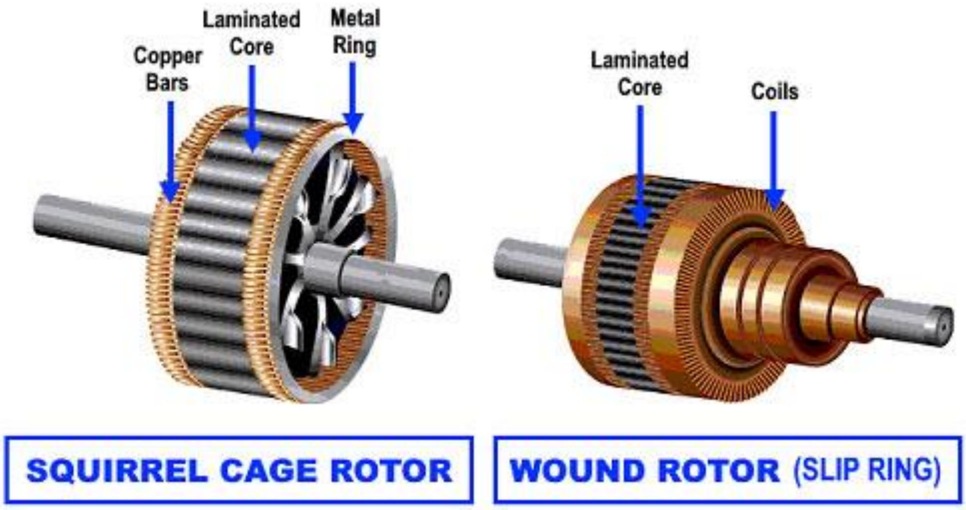


Figure I-3: The rotor of induction motor

I.4 Operating Principle of induction Motor:

The operating principle is entirely based on the laws of induction: the induction machine is a transformer with a rotating magnetic field, the secondary (rotor) of which is short-circuited. The speed of rotation Ns of the rotating field of stator origin, qualified as synchronism, is, as in the case of induction machines, rigidly linked to the frequency fs of the three-phase supply voltages equations (**I-1**):

$$Ns\ (rpm) = 60\ fs\ /\ p \qquad \textbf{I-1}$$

The number of pairs of poles of each of the windings of the stator phases is denoted by p; this in countries, where the frequency of the electrical network is 50 Hz, the synchronism rotation speeds (rpm) are: 3000, 1500, 1000, 750... respectively for motors whose number of poles is 2, 4, 6, 8.... When the rotor rotates at a speed N different from Ns (synchronism), the application of Faraday's law to the rotor windings shows that these become the seat of a system of three-phase electromotive forces themselves generating three rotor currents; according to Lenz's law these deniers are opposed to the cause which gave rise to them, that is to say the relative speed of the stator rotating induction with respect to the rotor. Thus, the effects of the stator induction on the induced rotor currents are manifested by the elaboration of a couple of electromagnetic forces on the rotor such that the speed difference is reduced. Therefore, depending on whether N is lower (hypo-synchronism) or higher (hyper-synchronism) synchronism) at Ns, the machine develops respectively a driving torque tending to increase N or a resisting torque (generating) tending to reduce N; obviously the electro-pneumatic torque is canceled at equal speeds. The network therefore depends on the sign of the gap (Ns — N); this is why induction operation is characterized by the slip g thus defined by the equations (**I-2**);

$$g = (Ns - N) / Ns \qquad \textbf{I-2}$$

Under the nominal operating conditions of the machine as a motor, the slip expressed as a percentage is a few units; an increase in mechanical load causes an increase in slip and Joule losses in the rotor and stator windings. Connected to a constant voltage and constant frequency network, the induction motor therefore has a substantially constant speed in steady state; its controlled variation in fact requires the adjustment of the synchronism speed, that is to say the modification of the power source frequency, which is made possible by the interposition of a static converter frequency changer (Rectifier + Inverter) between the fixed frequency network (50 or 60 Hz) and the induction machine. [6].

I.5 Terminal board:

I.5.1 Star or triangle connection:

There are two possibilities for connecting the motor to the three-phase electrical network. The star connection and delta connection as the figure below **Figure *I-4*** shows [7].

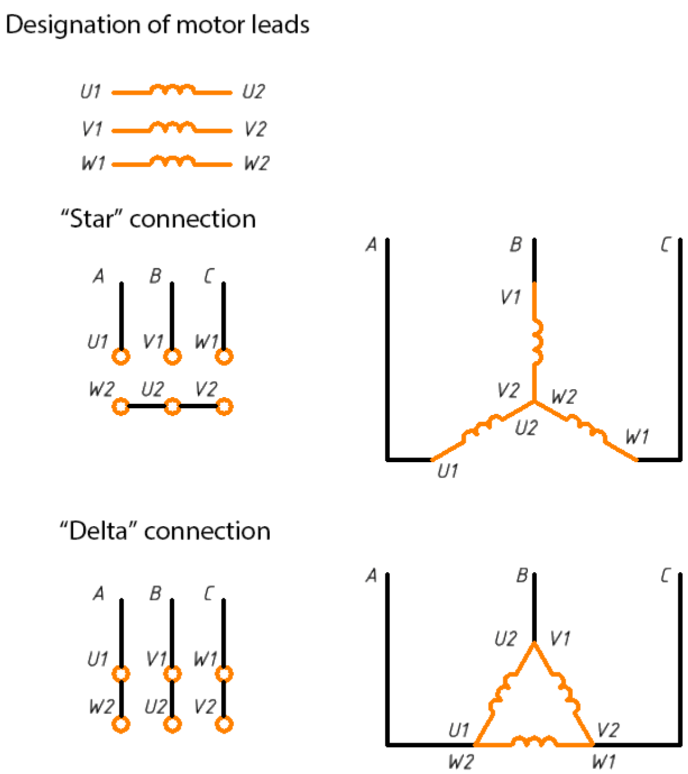


Figure I-4: coupling of induction motors (star and delta)

I.6 Nameplate of induction motor:

Each electrical machine has a nameplate which is a kind of Motor ID card [8]. **Figure *I-5***

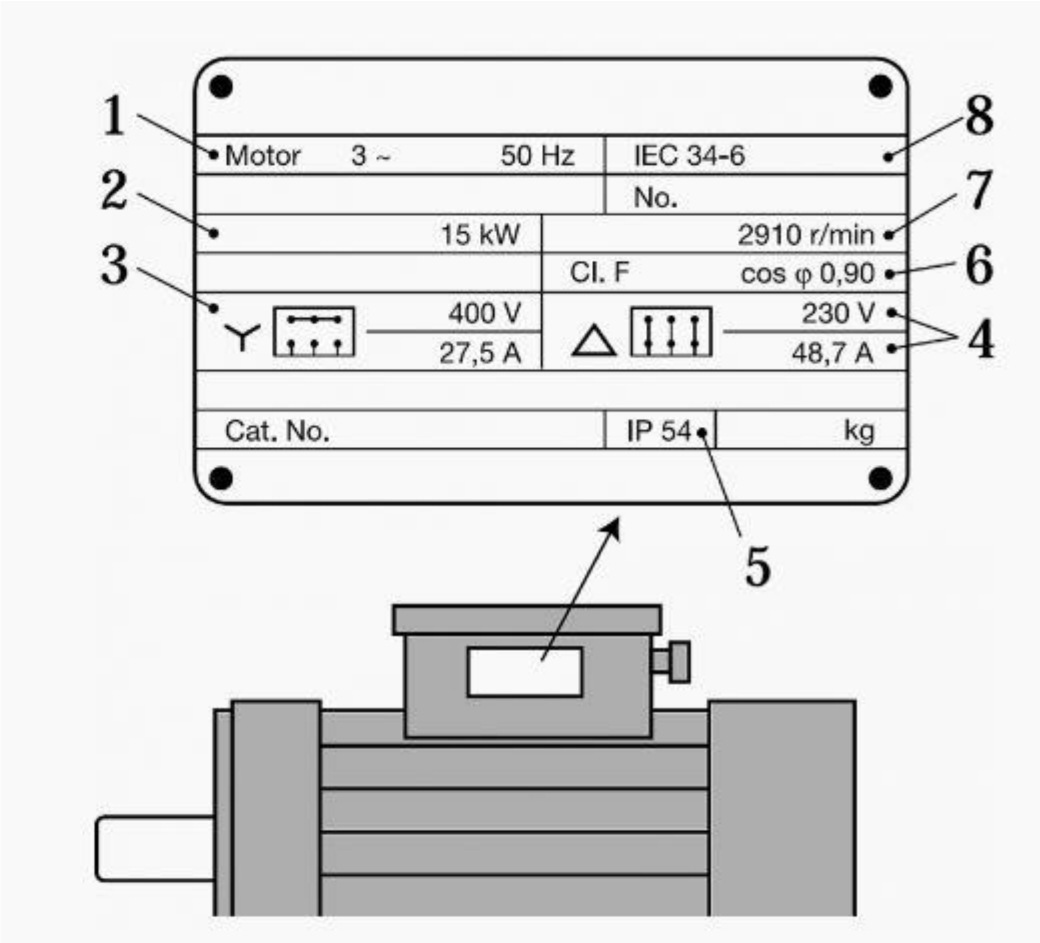


Figure I-5: Example nameplate of induction motor

I.6.1 Example Nameplate:

The nameplate for a Two-pole 15kw motor may have the following important data:

Data 01:

The motor has **three phases** and is for a mains supply with a frequency of **50 Hz**.

Data 02:

The rated output of the motor is 15 **Kw**, i.e. the motor is able to supply a shaft output of **at least 15 Kw** if connected to the mains supply as indicated. The rated output of the induction motor has been written into a standard. This allows the user a free choice of the different motor makes for various applications.

Data 03 and 04:

The stator windings can be connected in a **Star** or **delta formation**. If the mains voltage is **400 v**, the windings must be connected in a “star” formation. The motor current is then **27.5 A per phase**. If the mains voltage is **230 V**, the windings must be connected in a “delta” formation. The motor current is then **48.7 A per phase**.

At start-up, when the current is between 4 and 10 times higher than the rated current, the mains supply may be overloaded.

This has led supply companies to issue regulations ordering the start-up current of large motors to be reduced. This can be achieved by, for example, having the motor start up in a star connection and subsequently switching to a delta connection.

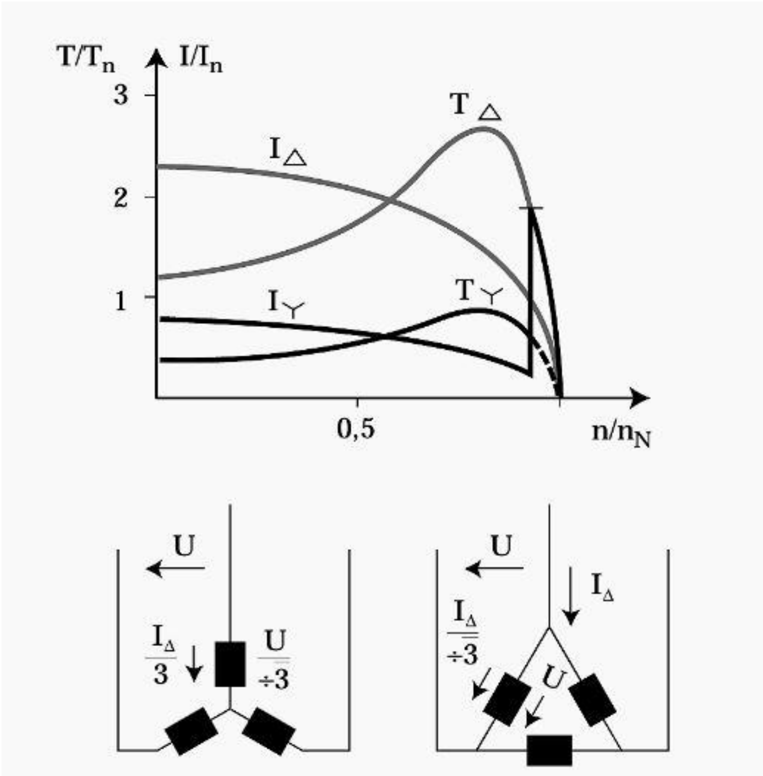


Figure I-6: motor torque and current in star and delta connections

With the star connection power and torque are reduced to 1/3rd, and the motor cannot start at full load. A motor designed for star connection will be overloaded if there is no switch-over to star connection for full-load operation.

Data 05:

The motor protection rating indicates the degree of protection provided by the motor enclosure **against the penetration of liquids and foreign bodies**. Designations used are described in the international standard IEC Publication 34-5.

Protection is indicated by the two letters IP (international Protection) and two digits. These are used to specify the protection level against contact and foreign bodies (first digit), and as liquid (second digit). If required, extra letters can be added.

Data 06:

The rated current Is, which the motor takes up, is called apparent current and can be divided into two: an active current Iw and a reactive current Ib. Cos ϕ indicates the share of the active current as a percentage of the motor current at rated operation. The active current is converted into shaft output, while the reactive current indicates the power required to build up the magnetic field in the motor. Equations (**I-3**):

$$\mathbf{I_S = \sqrt{{I_W}^2 + {I_b}^2}} \qquad \textbf{I-3}$$

The currents can be seen as the sides of a right-angled triangle, where the long side equals the square root of the sum of the short sides squared (following Pythagoras's geometry).

ϕ is the angle between the apparent current and the active current and Cos ϕ is the ratio between the size of the two currents, equations (**I-4**):

$$\mathbf{Cos\ \phi = \frac{I_w}{I_b}} \qquad \textbf{I-4}$$

Data 07:

The rated speed of the motor is the motor speed at rated voltage, rated frequency and rated load.

Data 08:

Electric motors are designed for different types of cooling. Normally the cooling method is stated in accordance with international standard IEC Publication 34-6 [8].

I.7 Electromechanical characteristics:

I.7.1 Nominal power:

The Nominal Power is the mechanical Power available on the motor shaft at its nominal speed is expressed in kilowatts (kW). It is called the useful power the power of an electric motor is linked to its sizing and in particular to its axis height in relationship with speed [9].

I.7.2 Nominal speed

The nominal speed is the speed of the shaft, it is necessary to distinguish the speed of the rotating field of the stator, of the synchronous speed: $n_s = \frac{f}{p}$

$\mathbf{n_s}$: synchronous speed, in [trn/s].

f: network frequency Hz.

p : number of pole pairs.

The rotation speed of the rotor is lower than that of the rotating field [9].

I.7.3 Nominal intensity:

The nominal intensity is the value of the current at nominal power given for the supply voltage depending on the coupling of the windings [9].

I.7.4 Power factor cos φ e and efficiency η

The efficiency and the cos φ evolve according to the motor load the useful power on the shaft of the three-phase motor is given by the equations (**I-5**) [9]:

$$\boldsymbol{P_u = \sqrt{3}.\mathrm{U.I.}\cos\ \varphi.\eta} \qquad \text{I-5}$$

I.7.5 Starting current I_d :

Three-phase induction motors require a high direct starting current $\boldsymbol{I_d}$. Depending on the model used, this current can reach a value of 3 to 15 times greater than that of the rated operational current. As a base value, a value 7 to 8 times higher than that of the rated current of the motor can be used. This has the disadvantage. This means that during motor starting, the supply network must be dimensioned to provide this higher intensity [10].

I.7.6 The torque:

Consider a squirrel-cage motor, powered by a three-phase source whose voltage and frequency are fixed. As the mechanical load increases, the speed gradually decreases. However, when the torque reaches the critical value called the stall point, the speed drops. Suddenly and the motor stops. There is therefore a relationship between the torque developed by the motor and its speed.

I.8 Advantages and disadvantages of the induction machine:

The induction motor is the most widely used electric motor in industry; it is inexpensive, we manufactured in large series, it is robust, reliable and economical.

It operates directly on the AC mains, without prior energy transformations electricity which powers it, it is the industrial motor par excellence which does not have delicate organs like the commutator of the DC motor and which does not use sliding contacts like the synchronous motor (for excitation of the rotor).

The currents circulating in the stator constitute the only external source of the magnetic field. Its speed varies a little when it is loaded, it is said to slip, but this slip is generally not does not exceed a few hundredths of the no-load speed, it is most often negligible. Induction motors do not cause problems for small power units. On the other hand, for the high-power motors, start under reduced voltage to avoid excessive current draw raised.

On the other hand, in the induction motor, the stator currents are both to generate the flux and the torque. The natural decoupling of the DC machine does not exist. On the other hand we cannot know the internal variables of the cage rotor only through the stator.

The inaccessibility of the rotor will lead us to modify the rotor vector equation to express the rotor quantities through their actions on the stator. The structural simplicity therefore hides a great functional complexity due to the characteristics that have just been mentioned but also nonlinearities, difficulty of identification and parameter variations (Rr in particular) [11].

I.9 Conclusion:

In this chapter we have presented some general information about the induction machines, its different constituents as well as its operating principle, which will contribute to start the other chapters and highlights the mathematical model of the induction motor which will be the focus of the second chapter.

Chapter 02: Modelling induction machine

II Chapter 02: Modelling induction machine:

II.1 Introduction:

Modelling is an essential phase on the approach to simulation and realization, the adopted model should interpret all the phenomena that the designer seeks to highlight in order to predict the behavior in dynamic and steady state of the physical system. Firstly, we will describe the mathematical model of the induction motor (electrical and mechanical equations) in its three-phase frame of reference. Secondly, we will reduce the order of the system by a so-called PARK Transformation this transformation, models the induction motor in a new frame of reference, which consists of transforming the three-phase system into a system with two orthogonal axes (two-phase). Finally, we will present the numerical simulation of the various parameters of the induction motor.

II.2 Modelling induction machine:

The modelling of the induction machine is an essential need to observe and analyze the different evolutions of its electromechanical, electrical and on the one hand and on the other hand to provide the necessary control.

We will use a model of the induction machine to describe the behavior dynamics of the different quantities concerned by the control system (torque electromagnetic, magnetic flux, currents, voltages……), to do this we must hold taking into account some simplifying assumptions [12].

II.2.1 Simplifying assumptions:

The modelling of the induction machine is based on a number of simplifying assumptions, which are:

• The magnetic circuits are symmetrical.

• The induction distribution in the air gap is sinusoidal.

• The air gap is constant.

• Saturation phenomena are neglected, which makes it possible to consider the magnetic flux as a linear function of the currents.

• The effect of notching is negligible.

• The influence of skin effect and heating on the characteristics is not taken into account.

Thus, among the important consequences of these assumptions, we can cite:

- The additivity of the flow.
- The constancy of the self-inductors.
- The law of sinusoidal variation of the mutual inductances between the stator and rotor windings as a function of the electrical angle between their magnetic axes.

II.2.2 Modelling Induction Machine in the abc three-phase plane:

Consider a three-phase induction machine with a stator and a rotor represented schematically by **Figure *II-1*** and whose phases are identified respectively by SA, SB, SC. The electrical angle θ variable as a function of time defines the instantaneous relative position between the magnetic axes of the SA and Ra phases chosen as reference axes [13].

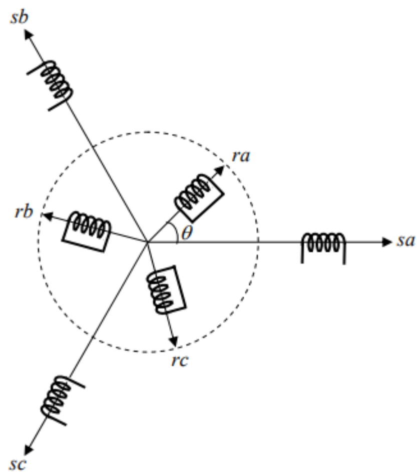


Figure II-1: Schematic representation of a three-phase induction machine.

II.2.2.1 General equations of the three-phase induction machine:

Under these conditions, if it is considered that the induction motor is three-phase at the stator and at the rotor. The three types of equations reflecting the behavior of the motor are [14].

Electrical equations:

The voltage equations of the three stator phases are, equations (**II-1**):

$$\begin{cases} V_{sa} = R_s i_{sa} + \frac{d}{dt}\Phi_{sa} \\ V_{sb} = R_s i_{sb} + \frac{d}{dt}\Phi_{sb} \\ V_{sc} = R_s i_{sc} + \frac{d}{dt}\Phi_{sc} \end{cases} \qquad \textbf{II-1}$$

The voltage equations of the three rotor phases are, equations (**II-2**):

$$\begin{cases} V_{ra} = R_r i_{ra} + \frac{d}{dt}\Phi_{ra} \\ V_{rb} = R_r i_{rb} + \frac{d}{dt}\Phi_{rb} \\ V_{rc} = R_r i_{rc} + \frac{d}{dt}\Phi_{rc} \end{cases} \qquad \textbf{II-2}$$

With $\Phi = \mathbf{L} * \mathbf{i}$

V_{sa}, V_{sb}, V_{sc} : Voltages applied to the three stator phases.

i_{sa}, i_{sb}, i_{sc} : Currents which cross the three stator phases.

$\Phi_{sa}, \Phi_{sb,}, \Phi_{sc}$: Total fluxes through these windings.

V_{ra}, V_{rb}, V_{rc} : Rotor voltages.

i_{ra}, i_{rb}, i_{rc} : Rotor currents.

$\Phi_{ra}, \Phi_{rb,}, \Phi_{rc}$: Rotor fluxes.

R_S : Resistance of a stator phase.

R_r : Resistance of a rotor phase.

Equations (**II-1**) and **II-2**) can be written in the following matrix form:

For the stator, equations II-3):

$$\begin{bmatrix} V_{sa} \\ V_{sb} \\ V_{sc} \end{bmatrix} = \begin{bmatrix} R_s & 0 & 0 \\ 0 & R_s & 0 \\ 0 & 0 & R_s \end{bmatrix} \begin{bmatrix} i_{sa} \\ i_{sb} \\ i_{sc} \end{bmatrix} + \frac{d}{dt} \begin{bmatrix} \Phi_{sa} \\ \Phi_{sb} \\ \Phi_{sc} \end{bmatrix} \qquad \textbf{II-3}$$

Or in condensed form as follows, equations **II-4**) :

$$\left[V_{s(abc)}\right] = [R_s]\left[i_{s(abc)}\right] + \frac{d}{dt}\left[\Phi_{s(abc)}\right] \qquad \textbf{II-4}$$

For the rotor, equations (II-5):

$$\begin{bmatrix} V_{ra} \\ V_{rb} \\ V_{rc} \end{bmatrix} = \begin{bmatrix} R_r & 0 & 0 \\ 0 & R_r & 0 \\ 0 & 0 & R \end{bmatrix} \begin{bmatrix} i_{ra} \\ i_{rb} \\ i_{rc} \end{bmatrix} + \frac{d}{dt} \begin{bmatrix} \Phi_{\mathrm{ra}} \\ \Phi_{\mathrm{rb}} \\ \Phi_{\mathrm{rc}} \end{bmatrix} \qquad \textbf{II-5}$$

Or in condensed form as follows, equations **II-6**):

$$\left[V_{r(abc)}\right] = [R_r]\left[i_{r(abc)}\right] + \frac{d}{dt}\left[\Phi_{r(abc)}\right] \qquad \textbf{II-6}$$

Magnetic equations:

The simplifying hypotheses cited earlier lead to linear relationships between flows and currents of the induction machine, these relationships are written matrix as follows: [15].

For the stator, equations (II-7):

$$\begin{bmatrix} \Phi_{sa} \\ \Phi_{sb} \\ \Phi_{sc} \end{bmatrix} = [L_s] \begin{bmatrix} i_{sa} \\ i_{sb} \\ i_{sc} \end{bmatrix} + [M_{sr}] \begin{bmatrix} i_{ra} \\ i_{rb} \\ i_{rc} \end{bmatrix} \qquad \textbf{II-7}$$

For the rotor, equations (II-8) :

$$\begin{bmatrix}\Phi_{ra}\\ \Phi_{rb}\\ \Phi_{rc}\end{bmatrix} = [L_r]\begin{bmatrix}i_{ra}\\ i_{rb}\\ i_{rc}\end{bmatrix} + [M_{rs}]\begin{bmatrix}i_{sa}\\ i_{sb}\\ i_{sc}\end{bmatrix} \qquad \textbf{II-8}$$

Such as:

$[M_{sr}] = [M_{rs}]^T$

We denote by:

$[\boldsymbol{L_s}]$: Matrix of stator inductors.

$[\boldsymbol{L_r}]$: Matrix of rotor inductors.

$[\boldsymbol{M_{sr}}]$: Matrix of stator mutual inductances.

$[\boldsymbol{M_{rs}}]$: Matrix of rotor mutual inductances.

Where, equations **II-9**) and (**II-10**):

$$[L_S] = \begin{bmatrix} l_S M_S M_S \\ M_S l_S M_S \\ M_S M_S l_s \end{bmatrix} \qquad \textbf{II-9}$$

$$[L_r] = \begin{bmatrix} l_r M_r M_r \\ M_r l_r M_r \\ M_r M_r l_r \end{bmatrix} \qquad \textbf{II-10}$$

And, equations (**II-11**):

$$[M_{sr}] = [M_{rs}]^T = M_0 \begin{bmatrix} \cos(\theta) \cos\left(\theta - \frac{2\pi}{3}\right) \cos\left(\theta + \frac{2\pi}{3}\right) \\ \cos\left(\theta + \frac{2\pi}{3}\right) \cos(\theta) \cos\left(\theta - \frac{2\pi}{3}\right) \\ \cos\left(\theta - \frac{2\pi}{3}\right) \cos\left(\theta + \frac{2\pi}{3}\right) \cos(\theta) \end{bmatrix} \qquad \textbf{II-11}$$

With:

l_s : inductance of a stator phase.

l_r : Inductance of a rotor phase.

$\mathrm{M_s}$: Mutual inductance between stator phases.

$\mathrm{M_r}$: Mutual inductance between rotor phases.

θ : Electrical angle defines the instantaneous relative position between the stator axes and the rotor axes which are chosen as reference axes.

M : Maximum mutual inductance between phase of stator and corresponding phase of rotor.

Mechanical equations:

The study of the characteristics of the induction machine introduces the variation not only of electrical parameters (voltage, current, flow) but also of mechanical parameters (torque, speed), equations (**II-12**) [16].

$$\boldsymbol{E_T} = P\left[i_{s(abc)}\right]^T \frac{d}{dt}[\mathrm{M}_{sr}]\left[i_{r(abc)}\right] \qquad \textbf{II-12}$$

To have a complete model of the machine it is necessary to introduce the equation of the movement of the machine is expressed as follows, equations (**II-13**):

$$J\frac{d}{dt}\Omega_r = \mathrm{E_T} - \mathrm{R_T} - f\Omega_r \qquad \textbf{II-13}$$

With:

J : Moment of inertia of the rotating masses.

$\mathrm{R_T}$: Resistant torque imposed on the machine shaft.

Ω_r : Rotor speed.

$\mathrm{E_T}$: Electromagnetic torque.

f : Viscous coefficient of friction.

The equations (I.4) thus obtained are with variable coefficients resulting in the resolution complexity of the model defined by (I.3). This will lead to the use of Park's transformation to make these parameters constant.

II.2.3 Park Transformation:

The purpose of Park's transformation is to treat a wide range of machines in a unified way by reducing it to a single model. This conversion is often called axis transformation, a fact corresponding to the two windings of the original machine followed by a rotation, the electrically and magnetically equivalent windings. This transformation thus, for the purpose of making the mutual inductances of the model independent of the angle of rotation [17].

II.2.3.1 Different landmarks:

The isotropy of the induction motor allows a great flexibility in the composition of the equations of the machine according to two axes using the components of Park that requires the use of a reference which makes it possible to simplify the analytical expressions as much as possible. There are different possibilities for the choice of the axis reference, which is practically reduced to three orthogonal reference frames (two-phase systems) [18].

1- Stationary referential relative to stator: $(\alpha - \beta) \rightarrow \omega_{\text{obs}} = 0$.
2- Stationary referential relative to rotor: $(x - y) \rightarrow \omega_{obs} = \omega_R$.
3- Stationary referential relative to the rotating field: $(\text{d} - \text{q}) \rightarrow \omega_{\text{obs}} = \omega_{\text{S}}$.

Where:

ω_{obs} : Angular speed of rotation of the two-phase axis system relative to the three-phase axis system.

II.2.4 Modelling induction motor in the two-phase plan dq:

Due to the existence of continuous trigonometric terms in the matrix of mutual inductances [Msr], the coefficients of the differential equations are variable and the analytical resolution of the system comes up against practically insurmountable difficulties to obtain a system of equations with constant coefficients, the stator and rotor windings are transformed into two orthogonal two-phase windings dq according to the PARK transformation. The conversion involves the transformation of electrically and magnetically equivalent windings. **Figure *II-2*** represents the transformation of real windings abc into orthogonal windings d-q [14].

- Direct along the axis (d).
- Quadrature (transverse) along the axis (q).
- homopolar (o).

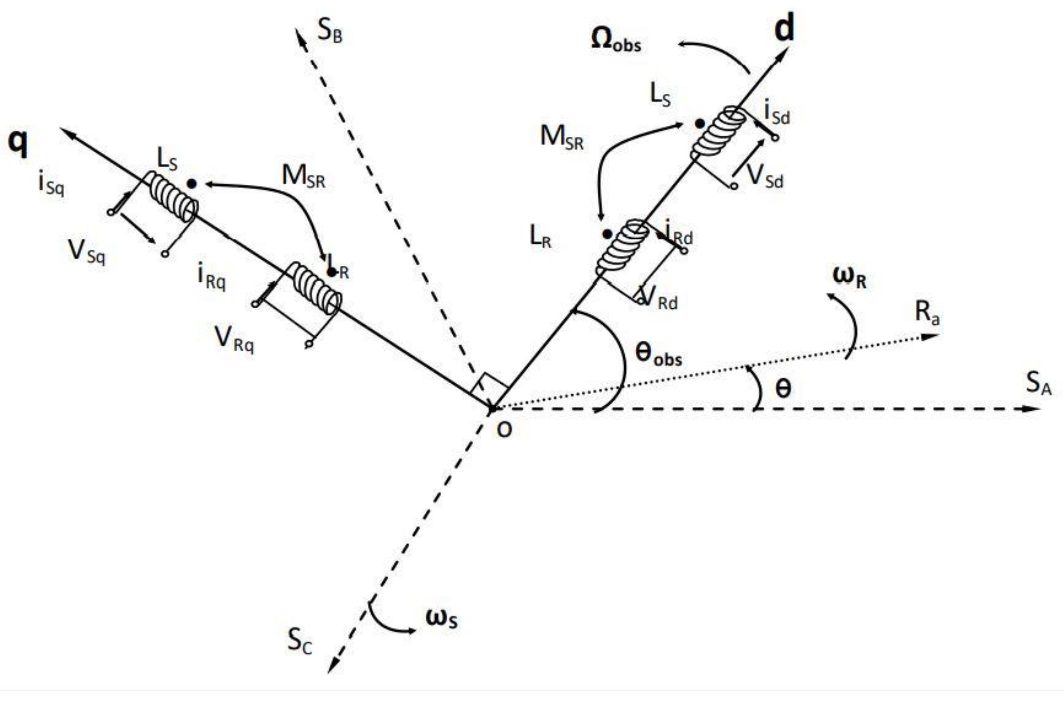


Figure II-2: Rotating frame of axes (d– q)

Where:

$\theta_{obs} = \int \omega_{obs} dt$: is any observation position between the two-phase axis systems with relative to the three-phase axis system.

The application of the Park transformation to the induction machine corresponds to a transformation of the three coils (statoric and rotoric) to two equivalent coils taking up the same consideration or aspects in terms of flow, torque, current or month an image which will be perfectly proportional to them [19].

For the transition from the three-phase system to the two-phase system, we have the following equivalents equations (**II-14**) [20].

$$\begin{aligned} &\text{The voltage equivalent: } [\boldsymbol{V}_{dq0}] = [P(\theta_{obs})][\boldsymbol{V}_{\boldsymbol{abc}}] \\ &\text{The current equivalent: } [\boldsymbol{i}_{dq0}] = [P(\theta_{obs})][\boldsymbol{i}_{abc}] \\ &\text{The flow equivalent: } [\Phi_{dq0}] = [P(\theta_{obs})][\Phi_{abc}] \end{aligned} \qquad \textbf{II-14}$$

Where:

$[P(\theta_{obs})]$ is Park's matrix

In the case of a reverse passage, we have, equations **II-15**):

$$\begin{cases} [\boldsymbol{V}_{abc}] & = [P(\theta_{obs})]^{-\mathbf{1}}[\boldsymbol{V}_{dq\mathbf{0}}] \\ [\boldsymbol{i}_{abc}] & = [P(\theta_{obs})]^{-\mathbf{1}}[\boldsymbol{i}_{dq\mathbf{0}}] \\ [\Phi_{abc}] & = [P(\theta_{obs})]^{\mathbf{1}}[\Phi_{dq0}] \end{cases} \qquad \textbf{II-15}$$

The matrix of transformation of Park modified direct and inverse is then written, equations (**II-16**)

$$[P(\theta_{obs})] = \sqrt{\frac{2}{3}} \begin{bmatrix} \cos(\theta_{obs}) \cos\left(\theta_{obs} - \frac{2\pi}{3}\right) \cos\left(\theta_{obs} - \frac{2\pi}{3}\right) \\ -\sin(\theta_{obs}) - \sin\left(\theta_{obs} - \frac{2\pi}{3}\right) - \sin\left(\theta_{obs} + \frac{2\pi}{3}\right) \\ \frac{1}{\sqrt{2}} \frac{1}{\sqrt{2}} \frac{1}{\sqrt{2}} \end{bmatrix} \qquad \textbf{II-16}$$

The factor $\left(\sqrt{\frac{2}{3}}\right)$: is there to retain instant electrical power [15].

$$[P(\theta_{obs})]^T = \sqrt{\frac{2}{3}}\begin{bmatrix} \cos(\theta_{obs}) & -\sin\left(\theta_{obs}-\frac{2\pi}{3}\right) & \frac{1}{\sqrt{2}} \\ \cos\left(\theta_{obs}-\frac{2\pi}{3}\right) & -\sin\left(\theta_{obs}-\frac{2\pi}{3}\right) & \frac{1}{\sqrt{2}} \\ \cos\left(\theta_{obs}+\frac{2\pi}{3}\right) & -\sin\left(\theta_{obs}+\frac{2\pi}{3}\right) & \frac{1}{\sqrt{2}} \end{bmatrix} \qquad \textbf{II-17}$$

When the angle θ_{obs} assigned to the zero value, the Park transformation is called Clarke transformation and the passage matrix is written as follows, equations (**II-18**):

$$[C] = \frac{\sqrt{3}}{2}\begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{bmatrix} \qquad \textbf{II-18}$$

II.2.4.1 Application of Clark Transformation to the System (induction motor):

We have found that:

$$\left[V_{s(abc)}\right] = [R_s]\left[i_{s(abc)}\right] + \frac{d}{dt}\left[[L_s]\left[i_{s(abc)}\right] + [M_{sr}]\left[i_{r(abc)}\right]\right]$$

$$\left[V_{r(abc)}\right] = [R_r]\left[i_{r(abc)}\right] + \frac{d}{dt}\left[[L_r]\left[i_{r(abc)}\right] + [M_{rs}]\left[i_{s(abc)}\right]\right]$$

And

$$[C] = \frac{\sqrt{3}}{2}\begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} \qquad \text{And} \qquad [C]^{-1} = \frac{\sqrt{3}}{2}\begin{bmatrix} 1 & 0 & \frac{1}{\sqrt{2}} \\ -\frac{1}{2} & \frac{\sqrt{3}}{2} & \frac{1}{\sqrt{2}} \\ -\frac{1}{2} & -\frac{\sqrt{3}}{2} & \frac{1}{\sqrt{2}} \end{bmatrix}$$

So

$$\begin{bmatrix} x_\alpha \\ x_\beta \\ x_0 \end{bmatrix} = [C]\begin{bmatrix} x_a \\ x_b \\ x_c \end{bmatrix} \qquad \text{And} \qquad \begin{bmatrix} x_a \\ x_b \\ x_c \end{bmatrix} = [C]^{-1}\begin{bmatrix} x_\alpha \\ x_\beta \\ x_0 \end{bmatrix}$$

So, we have:

The electrical equations:

- **For the stator:**

$$\left[V_{s(abc)}\right] = [R_s]\left[i_{s(abc)}\right] + \frac{d}{dt}\left[\Phi_{s(abc)}\right]$$

$$[C]^{-1}\left[V_{s(\alpha\beta 0)}\right]=[R_s]\left[[C]^{-1}\left[i_{s(\alpha\beta 0)}\right]\right]+\frac{d}{dt}\left[[C]^{-1}\left[\Phi_{s(\alpha\beta 0)}\right]\right]$$

Donc

$$\left[V_{s(\alpha\beta 0)}\right]=[R_s]\left[i_{s(\alpha\beta 0)}\right]+\frac{d}{dt}\left[\Phi_{s(\alpha\beta 0)}\right]$$

$$\left[V_{s(\alpha\beta)}\right]=[R_s]\left[i_{s(\alpha\beta)}\right]+\frac{d}{dt}\left[\Phi_{s(\alpha\beta)}\right]$$

So

The general electrical equation is, equations (II-19):

$$\begin{cases} V_{s\alpha} = R_s i_{s\alpha} + \dfrac{d}{dt}\Phi_{s\alpha} \\ V_{s\beta} = R_s i_{s\beta} + \dfrac{d}{dt}\Phi_{s\beta} \\ V_{r\alpha} = R_r i_{r\alpha} + \dfrac{d}{dt}\Phi_{r\alpha} = 0 \\ V_{r\beta} = R_r i_{r\beta} + \dfrac{d}{dt}\Phi_{r\beta} = 0 \end{cases} \qquad \textbf{II-19}$$

The magnetic equations is, equations (II-20):

$$\begin{bmatrix} \psi_{s\alpha} \\ \psi_{s\beta} \\ \psi_{r\alpha} \\ \psi_{r\beta} \end{bmatrix} = \begin{bmatrix} L_s & 0 & M\cos(\theta) & -M\sin(\theta) \\ 0 & L_s & M\sin(\theta) & M\cos(\theta) \\ M\cos(\theta) & -M\sin(\theta) & L_r & 0 \\ M\sin(\theta) & M\cos(\theta) & 0 & L_r \end{bmatrix} \begin{bmatrix} I_{s\alpha} \\ I_{s\beta} \\ I_{r\alpha} \\ I_{r\beta} \end{bmatrix} \qquad \textbf{II-20}$$

We have that **Figure *II-3***:

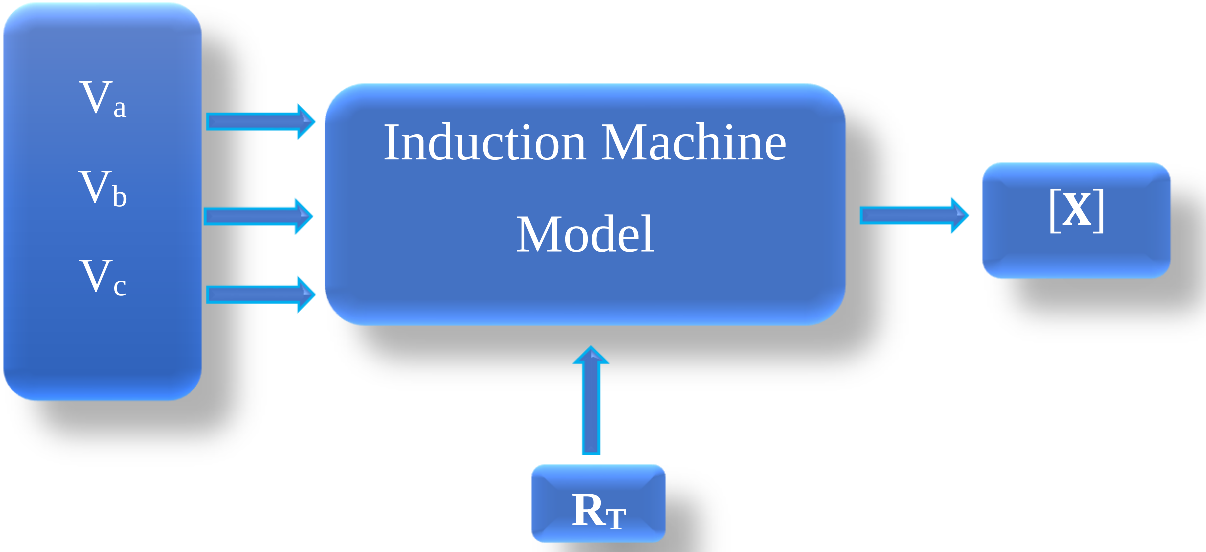


Figure II-3: Block diagram of the induction machine supplied with voltage

The output vector[X], can have one of these forms

$$[\boldsymbol{X}] = \begin{bmatrix} i_{sd} \\ i_{sq} \\ i_{rd} \\ i_{rq} \end{bmatrix} \textbf{ Or } [\boldsymbol{X}] = \begin{bmatrix} \Phi_{sd} \\ \Phi_{sq} \\ \Phi_{rd} \\ \Phi_{rq} \end{bmatrix} \textbf{ or } [\boldsymbol{X}] = \begin{bmatrix} \Phi_{sd} \\ \Phi_{sq} \\ i_{rd} \\ i_{rq} \end{bmatrix} \text{ or } [\boldsymbol{X}] = \begin{bmatrix} i_{sd} \\ i_{sq} \\ \Phi_{rd} \\ \Phi_{rq} \end{bmatrix}$$

So, if we have chosen that the state vector is: $[\boldsymbol{X}] = \begin{bmatrix} i_{sd} \\ i_{sq} \\ \Phi_{rd} \\ \Phi_{rq} \end{bmatrix}$

We will find that, equations (II-21) :

$[\dot{X}] = [A][X] + [B][V]$

$$\begin{cases} \dfrac{di_{s\alpha}}{dt} = a_1 i_{s\alpha} + a_2 \psi_{s\alpha} + a_3 \omega_r \psi_{r\beta} + \dfrac{1}{\sigma L_s} V_{s\alpha} \\ \dfrac{di_{s\beta}}{dt} = a_1 i_{s\beta} - a_3 \omega_r \psi_{s\alpha} + a_2 \psi_{r\beta} + \dfrac{1}{\sigma L_s} V_{s\beta} \\ \dfrac{d\psi_{r\alpha}}{dt} = a_4 i_{s\alpha} + a_5 \psi_{r\alpha} - \omega_r \psi_{r\beta} \\ \dfrac{d\psi_{r\beta}}{dt} = a_4 i_{s\beta} + a_5 \psi_{r\beta} + \omega_r \psi_{r\alpha} \end{cases} \quad \textbf{II-21}$$

With:

$$a_1 = -\left(\frac{1}{T_r\sigma} + \frac{1-\sigma}{T_r\sigma}\right), a_2 = \frac{M}{\sigma L_s L_r T_r}, a_3 = \frac{M}{\sigma L_s L_r}, a_4 = \frac{M}{T_r}, a_5 = -\frac{1}{T_r}$$

$$\sigma = 1 - \frac{M^2}{L_s L_r},\ T_s = \frac{L_s}{R_s},\ T_r = \frac{L_r}{R_r}$$

Mechanical equation, equations (II-22):

$$\begin{gathered} E_T - \mathrm{R_T} = J\frac{d\Omega_m}{dt} + f\Omega_m \\ \Omega_m = p\omega_r \end{gathered} \qquad \textbf{II-22}$$

Expression of the torque, equations (II-23):

$$\mathrm{E_T} = \frac{3}{2}p\frac{M}{L_r}\left(\psi_{r\alpha}i_{s\beta} - \psi_{r\beta}i_{s\alpha}\right) \qquad \textbf{II-23}$$

II.3 Conclusion:

In this chapter, we made the modelling of the induction machine this modelling based on Park's theory, the primary interest of this transformation is to simplify the problem in the three-phase model.

Chapter 03: Artificial neural network

III Chapter 03: Artificial neural network

III.1 Introduction

Neural network is the most generic form of AI for emulation of human thinking compared to expert systems and fuzzy logic. In 1943, McCulloch and Pitts first proposed a network composed of binary-valued artificial neurons that were capable of performing simple threshold logic computations. The modern era of neural network with rejuvenated research practically started in 1982 when Hopfield presented his invention. Since then, many network models and learning rules have been introduced. The neural network is famous for its learning ability and arbitrary approximation to any continuous function. [21]

Recently, neural networks have been used for the parameter identification and state estimation of induction motor drive systems, object recognition, and speech recognition. Furthermore, many recent works showed that neural networks can be successfully used in a number of tasks in natural language processing such as language modelling, paraphrase detection and word embedding extraction.

III.2 Biological Neural Network (BNN)

Table III-1: Fuels of Functional Organization in the Brain

Global	conscious awareness, behavior, truth, beauty, conscience, and so on
Systemic	autonomic, sensorimotor, sensory, motor, instinctive, affective, representational, volitional, cognitive, and so on
Neuroelectric networks	local, composite, neurons, ions, membranes
Chemical	neurotransmitters/synaptic transmission; monoamine transmitter systems; chemical neuroregulator systems, and so on
Molecular	molecular neurobiology

A central quality of the operational organization of the brain is its hierarchical array of multiple levels of functioning. A representation of this is shown in **Table *III-1*** This feature of hierarchical levels of ordered functioning can be seen in cosmological structures, is most pronounced in biological systems, and is probably more developed in the brain than in any other known system. The essential ingredient is that each individual level (say, conscious awareness, appetitive behavior, neural network activity patterns, neural transmitter or neurohormonal systems, certain genetic predispositions) seems to have its own principles of operation, logic, and cohesion, but at the same time seems to stand in some significant influential way(s) (either dependent or supportive) with the levels below and above it. One of the most fundamental and difficult questions one can ask about the functional organization of the brain is about the degrees of relative upward and downward influences and autonomies between and within these levels. [22]

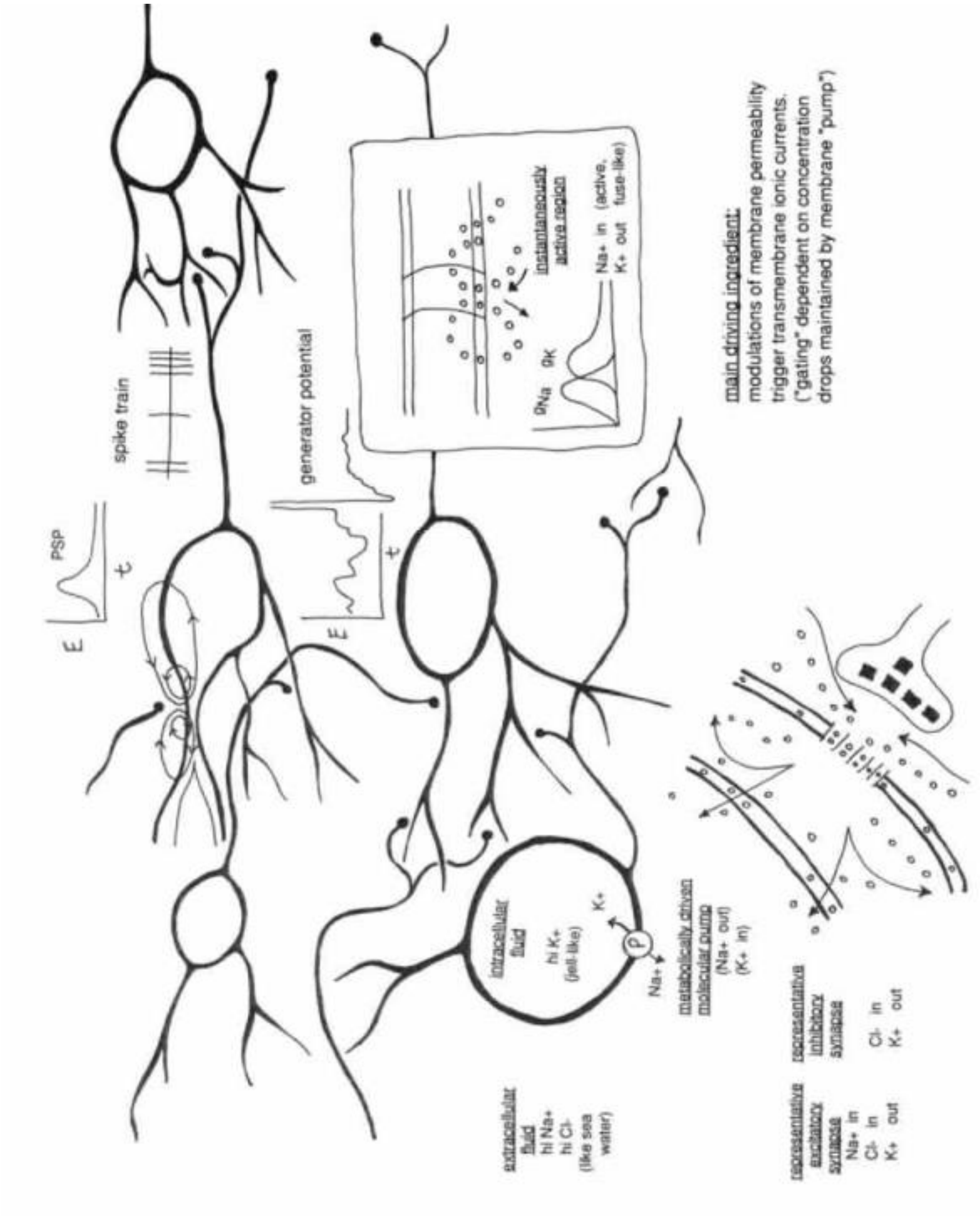


Figure III-1: Primary Neuroelectric Signals.

Figure *III-1* illustrates the primary Neuroelectric signals used by neurons and neural networks in representing information. One may succinctly characterize the main characteristics of this signaling at a surface level as follows. The typical neuron consists functionally of dendritic tree, a cell body or soma, and an axon with its terminal projections. The dendritic tree and soma serve as input regions of the neuron, where characteristic input signals are manifested; the soma serves further as a triggering section, where input signals are converted to output signals; and the axonal regions serve as output regions, where characteristic output signals are manifested. [22]

The characteristic output signal of individual neurons consists of individual action or spike potentials and their collection into temporally variable sequences called spike trains. To a first approximation, one thinks of action potentials as discrete, unitary events that have essentially the same time courses and amplitudes whenever they occur. That is, the significant fact about action potentials is that they occur and when they occur. The view is analogous to the firing of a bullet from a gun: the event projected following the pulling of the trigger is sensibly identical from one event to another. Action potentials are sudden excursions wherein the transmembrane potential rises some 100 mV or so above its resting level, inside relative to outside. [22]

The characteristic potentials at the input ends of neurons are PSPs (standing for postsynaptic potentials). PSPs are much smaller than action potentials and are continuous, graded, analog signals as illustrated in **Figure *III-1***. They have a short rise time (usually about 2 msec or less) and a longer gradual decay period (usually approximately exponential with time constant about 5 to 15 msec in vertebrate neurons). Individual PSPs are the unitary input responses in neurons; each PSP is the response originating under a synapse in a neuron to a single action potential in the presynaptic terminal. The rise time of PSPs corresponds to the period when the synapse is active; the decay period corresponds to the natural relaxation of the membrane potential to its resting level after the synapse is closed, and sometimes to a decay period of this synaptic conductance modulation. The rise time of the PSP directly under and close to a synapse usually corresponds closely in time to the duration of the input action potential. [22]

Spread out in time and decay in magnitude as they are conducted passively along the membrane away from the synapse. PSPs initiated on passive dendrites a hundred or more microns from the soma and observed at the soma can exhibit very slow rise times, perhaps as long as 5 to 10 msec. PSPs can be either excitatory (EPSPs) or inhibitory (IPSPs) depending on whether they are positive or negative fluctuations in transmembrane potential (inside relative to outside). Unitary PSPs initiated in dendrites as observed at the soma are usually very small, of the order of 0.1 to 1 mV. Their peak values in dendritic trees may be considerably larger, perhaps approaching 50 or even more mV. [22]

The potential recorded with an intracellular electrode in the soma regions of neurons is typically a graded continuous analog signal, one such manifestation of which is illustrated in **Figure *III-1***. Such a signal represents the confluent resultant of the interactions of all the input PSPs continually bombarding the neuron, and it may be referred to as the generator potential. To a first approximation one may picture this interaction as a simple algebraic summation of the positive and negative excitatory and inhibitory PSPs, although, the interactions are in fact, nonlinear. The magnitude of the generator potential varies between about 10 mV negative and some 10 to 25 mV positive. This composite signal can be called the neuron generator potential, because it generates the ongoing sequence of action potentials that constitute the output spike train of the neuron. The triggering of a single action potential by a generator potential is illustrated in **Figure *III-1***. [22]

Individual action potentials are triggered when the generator potential exceeds a critical value, known as the threshold. The threshold may be an approximately constant value in a given neuron or may vary depending on the time history of the generator potential. This last factor, known as accommodation, represents the desensitizing of neurons by maintained input activation. It results in transient responses to steady inputs known as on and off responses. When a neuron fires a single action potential, the neuron is thrown into a rather short period of absolute and then relative refractoriness, wherein it is impossible, then difficult to fire subsequent action potentials. Absolute refractoriness typically lasts less than a millisecond or so, and relative refractoriness may last of the order of 10 to 30 msec. Typical upper limits of neuronal firing in normal function are about 30 to 50 per second, determined in large part by these refractory mechanisms. Threshold values for vertebrate neurons are typically about 10 to 25 mV; they set the upper limits for somatic generator potentials. Output action potentials are typically triggered at the place where the axon emerges from the cell body, the axon hillock. When action potentials are generated at the axon hillock, they .are propagated essentially without change to all the synaptic terminals of the neuron. [22]

In summary, a surface-level view of the rudiments of neuroelectric signaling is quite simple: primary neuroelectric signals consist of PSPs and generator potentials at the input regions of neurons and action potentials and spike trains at the output regions. Action potentials are converted to PSPs at the synaptic junctions between neurons; generator potentials are converted to action potentials by means of threshold rules at the somas of neurons. Neural networks operate by feeding ongoing spike trains in large numbers of neurons to each other and to distal target neurons by virtue of vast numbers of synaptic interconnections determined by the particular anatomical structure of the system under consideration. [22]

Information is represented in the nervous system by coordinated patterns of activity involving large or vast numbers of interconnected neurons. There are some 100 billion or more neurons in the brain, with approximately 10 billion in the human cerebral cortex, and perhaps as many as 100 billion cerebellar Purkinje cells alone. Typical central neurons receive from a few thousand (spinal cord) input synapses to tens or even a hundred thousand (cerebral cortex) input synapses. The degree of interconnectivity and the corresponding amount of neuronal material attributed to thin, filigreed instruments of interconnection dendrites and axons is astounding. The axons from a single human brain, for example, if laid out end to end would stretch to the moon and back. [22]

The operations of neural networks must be interpreted in terms of vastly numerous divergent-convergent synaptic junctions between vastly numerous populations. These junctions are divergent in the sense that any one projecting neuron activates typically thousands of receiving cells, and convergent in the sense that any one receiving neuron receives from typically thousands of sender cells. Typical central neurons must receive several hundred active PSPs instantaneously, or alternatively PSPs numbering into the low thousands spread over a time constant or two, to be driven across threshold to spike production. Then the firing of this particular cell will be significant only if its firings are correlated in time with firings of hundreds or thousands of other neurons projecting to common receiving cells. To properly grasp the operative dynamics of these systems one needs to develop visual images that represent this extensive parallel as well as serial integration of signals. [22]

Synapses are centrally significant in this contemporary view that coordinated patterns of activity over vast numbers of interconnected neurons are the Neuroelectric manifestations of meaning and representation that neural networks, and not neurons, are the fundamental functional units of Neuroelectric signaling in the brain. Specific individual patterns of this sort are seen to be served and maintained by corresponding specific sets of synapses whose strengths are appropriately adjusted to maintain the pattern and resist the incursions of alien patterns. The enormous numbers of synapses in the brain (about 10^{14}) are appropriate and perhaps necessary to allow for the embedding of very large numbers of distinct patterns of this sort. [22]

In this context, long-term synaptic plasticity is thought to be the primary anatomical substrate of learning, memory, and representation in the mammalian and human nervous system. Individual synapses are thought to be selectively increased or perhaps decreased in strength to enhance or diminish their participation as desired in the formation of various multineuronal dynamic firing patterns, which in turn constitute the Neuroelectric representation of particular psychological elements. The Neuroelectric firing patterns can be considered the realizations of such representations, and the synaptic specializations underlying them can be considered their anatomical beds. [22]

A specific salient embodiment of this theory that changing synaptic effectiveness is the substrate of learning, memory, and representation is the suggestion that the stalks of synaptic spines under synapses on pyramidal cells in the cerebral cortex and hippocampus increase in size to allow larger responses to the same level of presynaptic activation by deceasing longitudinal resistance to synaptic currents. [22]

That neural networks rather than neurons are the functional units of organization of the nervous system is underscored by recent principles found in the field of development. The nervous system overbuilds: considerably more neurons and more synaptic connections are originally laid down than are ultimately retained. The specific connectivities of mammalian and human neural nets are constructed under the general guidance of an individual's unique genetic inheritance, but the development is winnowed and carefully fine-tuned according to one's unique life experience, primarily during the very critical prenatal and early postnatal learning periods. Large numbers of neurons and synaptic connections that are not actively used die and are weeded away during these periods. It seems likely that only those cells and networks involved in mediating useful systemic operations and interactions with the environment are maintained. [22]

This process may reach some sort of climax in adolescence. It has been suggested that a particularly critical stage in adolescence occurs wherein as many as 80% of cortical synapses fall away. The picture is that early in adolescence local and regional cortical connections are close to all-to-all, whereas in late to post adolescence only some one in six or seven of these survive. If this is so, it would seem likely that such an event would reflect the end of long trial period in which one's basic representation of many features of the external world were being established. After this event, one's representations of many basic features of this world would be relatively fixed. [22].

III.3 Artificial Neural Network (ANN)

III.3.1 What is artificial neural network?

The artificial neural network (ANN) abstracts the neural network of human brain on information processing, thus different networks forms in according to different connection modes [1]. ANN works as an operational model including numerous nodes (or neurons) connected to each other. There are extension neural network such as back propagation (BP) network (BPN), wavelet neural network (WNN), and genetic neural network (GNN) [23].

BP network (BPN) is in essence a feedback network. Similar to other typed of neural network, there are at least one hidden layer and a linear output layer in the BPN. The hidden layer could use functions such as sigmoid function as the transfer function, and the output layer uses transfer function such as linear function. The BPN learning process composes of the signal forward propagation and the error backward propagation. The signal forward propagation process means that the inputs are transmitted from input layer to output layer, going through the hidden layer. With the output deviation from desired value, the error is transferred back. The neurons are transferred backward layer by layer, which is sharing the output error. Thus, all the weights are adjusted corresponding to the error signal variation. These two processes are periodic until the error meets the accuracy requirements or reaching learning number limit [24].

III.3.2 Mathematical models and structures of artificial neural network

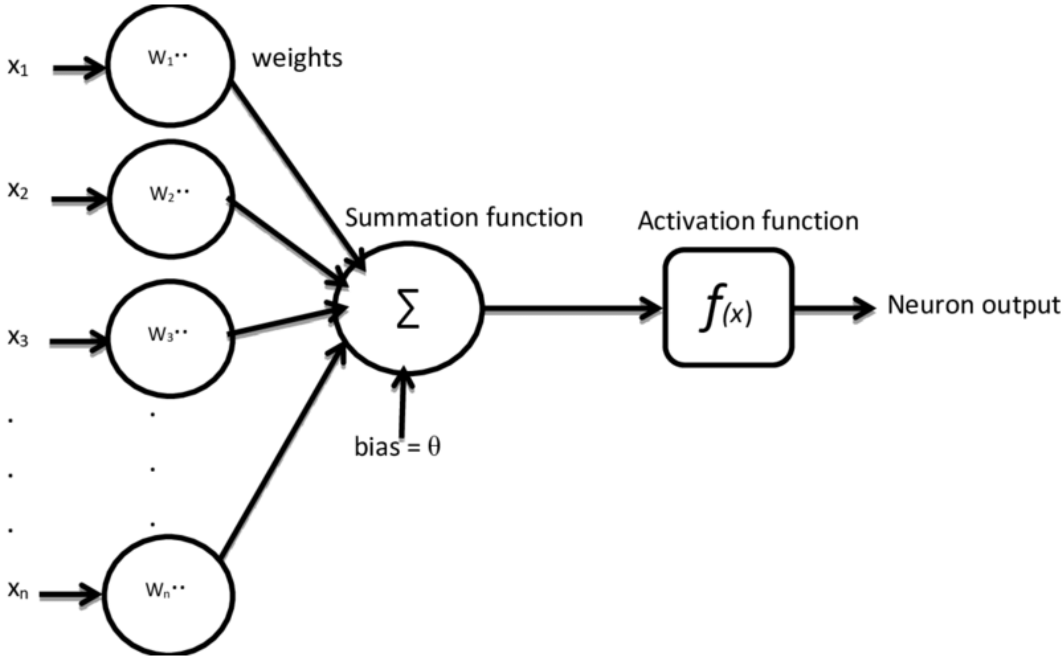


Figure III-2: The Structure of The Artificial Neuron.

The table below **Table *III-2*** shows the mapping between a biological neuron and an artificial neuron:

Table III-2 : biological neuron and an artificial neuron

biological neuron	artificial neuron
Synapses	Weight of connections
Axons	Output signal
Dendrites	Input signal
Core or Suma	Activation function

A classic calculation of the output y of a neuron is given by the equations (**III-1**):

$$\text{Output} = f(\Sigma(\mathrm{W} * \mathrm{X}) + \mathrm{b}) \qquad \textbf{III-1}$$

Where f (·) is a nonlinear function that is called the activation function, and W and b are the weight and bias associated with the neuron. The purpose of the activation function is to introduce nonlinearity which enables neural networks to tackle very complex nonlinear problems. Common activation functions include Sigmoid, hyperbolic tangent function (Tanh), rectified linear unit (ReLU), and leaky ReLU (LReLU). The respective formulas and curves are presented in **Figure *III-3***. In general, the parameter W and b are randomly initialized and then iteratively updated according to back-propagated loss (error) using the gradient descent method. [25]

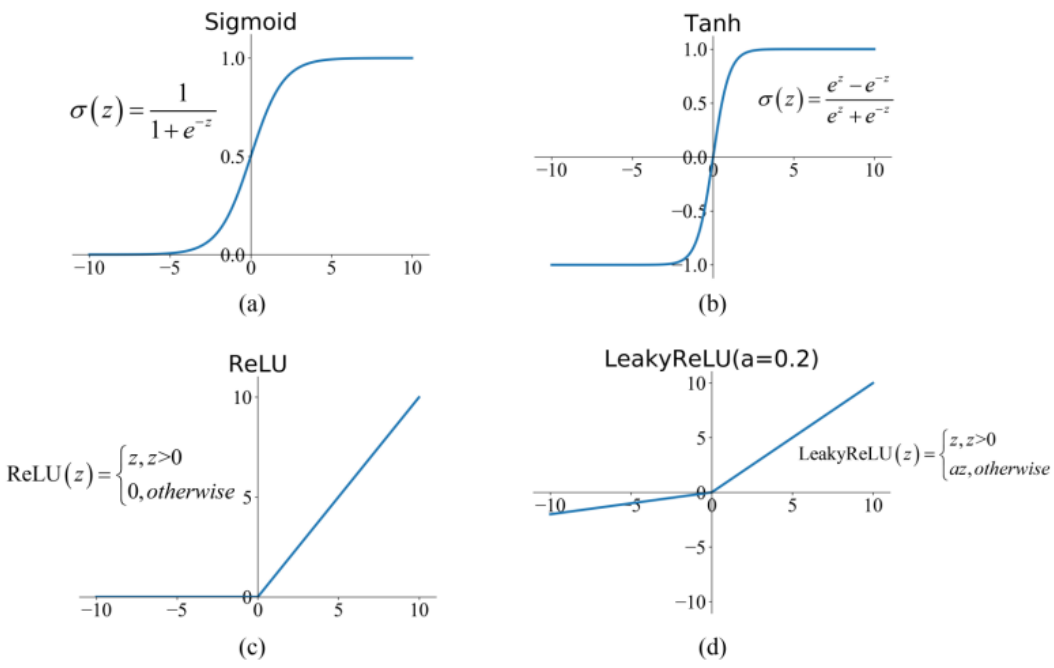


Figure III-3 : Commonly used Activation Functions.

III.3.3 Different models of neural network

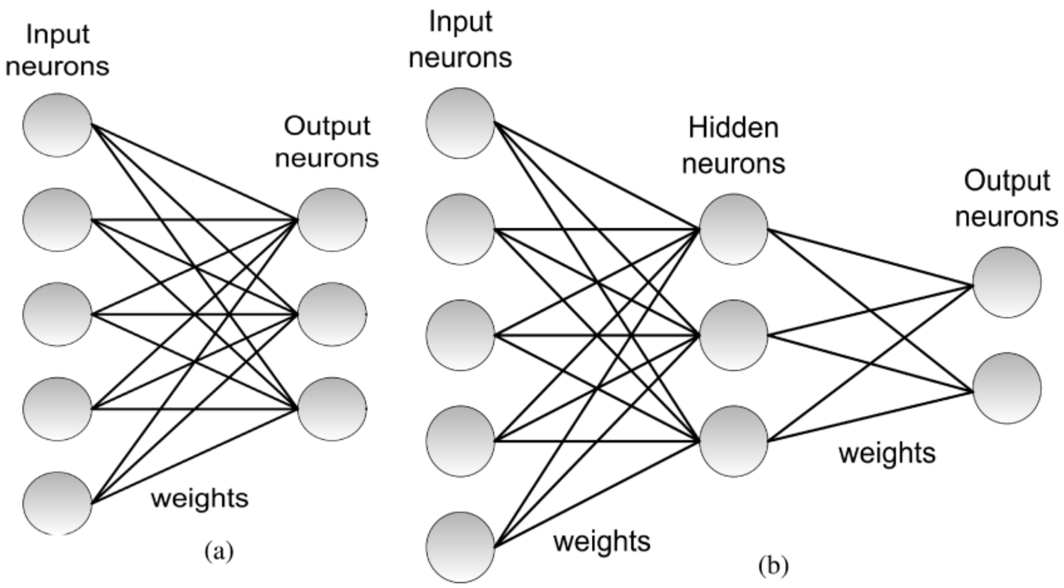
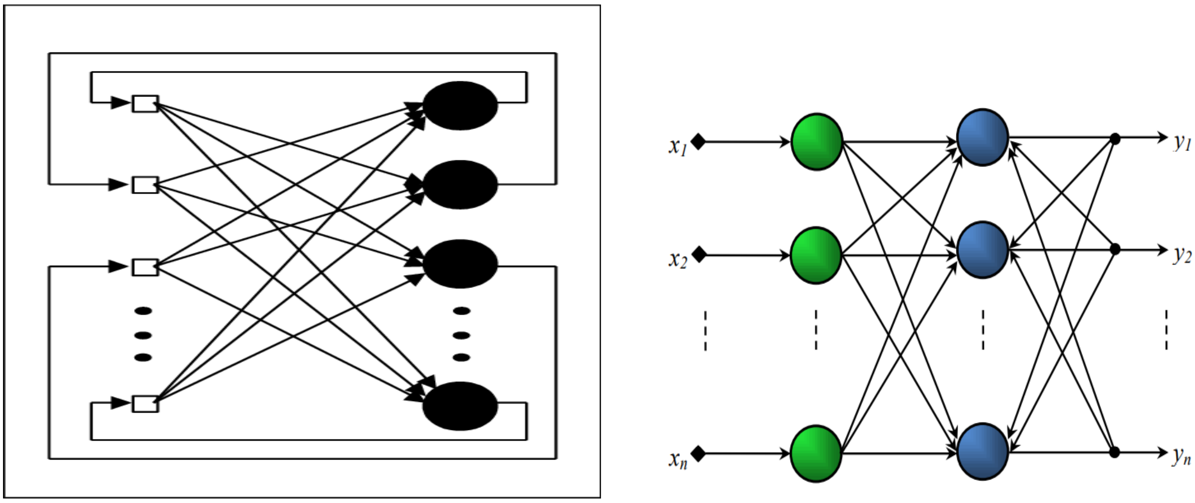


Figure III-4: Different Models of Neural Networks.

In **Figure *III-4*** (a) Architecture of a single layer **perceptron**. The architecture consists of a layer on input neurons fully connected to a single layer of output neurons. (b) Extension to a multi-layer perceptron including more than one layer of trainable weights. In this example, the network includes 3 layers: input, hidden and output layer. Each connection between two neurons is given by a certain weight.

Simple single-layer or multi-layer structure has no connections to previous layers.



(A): The Hopfield Network Model **(B): Kohonen Model**

Figure III-5: the Hopfield network and Kohonen Model

The Hopfield Network is typical recurrent fully interconnected to all other units, and it is a simple assembly of perceptrons that is able to overcome the XOR problem **Figure *III-5*** (A).

Complex Hopfield and Kohonen structure include connections to previous layers.

III.4 Recurrent Neural Network (RNN)

III.4.1 What is recurrent neural network?

Recurrent neural networks have been an important focus of research and development during the 1990's. They are designed to learn sequential or time-varying patterns. A recurrent net is a neural network with feedback (closed loop) connections. Examples include BAM, Hopfield, Boltzmann machine, and recurrent backpropagation networks. Recurrent neural network techniques have been applied to a wide variety of problems. Simple partially recurrent neural networks were introduced in the late 1980's by several researchers including Rumelhart, Hinton, and Williams to learn strings of characters. Many other applications have addressed problems involving dynamical systems with time sequences of events. [26]

This is some interesting examples to give the idea of the breadth of recent applications of recurrent neural networks. For example, the dynamics of tracking the human head for virtual reality systems is being investigated. The forecasting of financial data and of electric power demand are the objects of other studies. Recurrent neural networks are being used to track water quality and minimize the additives needed for filtering water. And, the time sequences of musical notes have been studied with recurrent neural networks. Some focus on systems for language processing. Others look at real-time systems, trajectory problems, and robotic behavior. [26]

Another definition for a recurrent neural network (RNN) is a neural network that simulates a discrete-time dynamical system that has an input x_t, an output y_t and a hidden state h_t. In our notation the subscript t represents time. The dynamical system is defined by

$$\mathbf{h}_t = f_h(\mathbf{x}_t, \mathbf{h}_{t-1})$$

$$\mathbf{y}_t = f_o(\mathbf{h}_t)$$

Where f_h and f_o are a state transition function and an output function, respectively. Each function is parameterized by a set of parameters; θ_h and θ_o. [27]

Given a set of N training sequences $D = \left\{\left(\left(\mathbf{x}_1^{(n)}, \mathbf{y}_1^{(n)}\right), \ldots, \left(\mathbf{x}_{T_n}^{(n)}, \mathbf{y}_{T_n}^{(n)}\right)\right)\right\}_{n=1}^{N}$, the parameters of an RNN can be estimated by minimizing the following cost function, equations (**III-2**)

$$J(\boldsymbol{\theta}) = \frac{1}{N}\sum_{n=1}^{N}\sum_{t=1}^{T_n} d\left(\mathbf{y}_t^{(n)}, f_o\left(\mathbf{h}_t^{(n)}\right)\right) \qquad \textbf{III-2}$$

Where $\mathbf{h}_t^{(n)} = f_h\left(\mathbf{x}_t^{(n)}, \mathbf{h}_{t-1}^{(n)}\right)$ and $\mathbf{h}_0^{(n)} = \mathbf{0}$ **.** d(a, b) is a predefined divergence measure between a and b, such as Euclidean distance or cross-entropy. [27]

III.4.2 Conventional Recurrent Neural Network

A conventional RNN is constructed by defining the transition function and the output function as, equations (**III-3**) and (**III-4**):

$$\mathbf{h}_t = f_h(\mathbf{x}_t, \mathbf{h}_{t-1}) = \phi_h(\mathbf{W}^\top \mathbf{h}_{t-1} + \mathbf{U}^\top \mathbf{x}_t) \qquad \textbf{III-3}$$

$$\mathbf{y}_t = f_o(\mathbf{h}_t, \mathbf{x}_t) = \phi_o(\mathbf{V}^\top \mathbf{h}_t) \qquad \textbf{III-4}$$

Where W, U and V are respectively the transition, input and output matrices, and ϕ_h and ϕ_o are element-wise nonlinear functions. It is usual to use a saturating nonlinear function such as a logistic sigmoid function or a hyperbolic tangent function for ϕ_h. An illustration of this RNN is in **Figure *III-6*** (a).

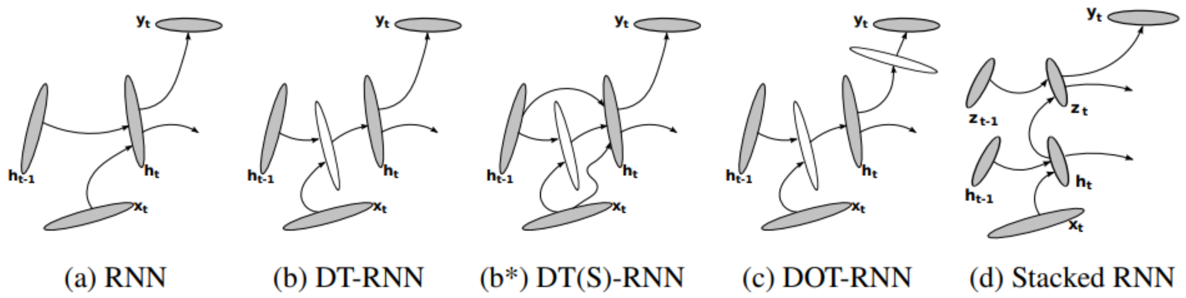


Figure III-6: Illustrations of different recurrent neural networks (RNN).

Figure *III-6* represents an illustrations of different recurrent neural networks (RNN).

(a) A conventional RNN.

(b) Deep Transition recurrent neural network (DT-RNN).

(b*) Deep Transition recurrent neural network with shortcut connections (DTS-RNN).

(c) Deep Transition, Deep Output recurrent neural network (DOT-RNN).

(d) Stacked RNN.

III.4.3 Recurrent Neural Network Architectures

The architectures range from fully interconnected **Figure *III-7*** (A) to partially connected networks **Figure *III-7*** (B), including multilayer feedforward networks with distinct input and output layers. Fully connected networks do not have distinct input layers of nodes, and each node has input from all other nodes. Feedback to the node itself is possible. [26]

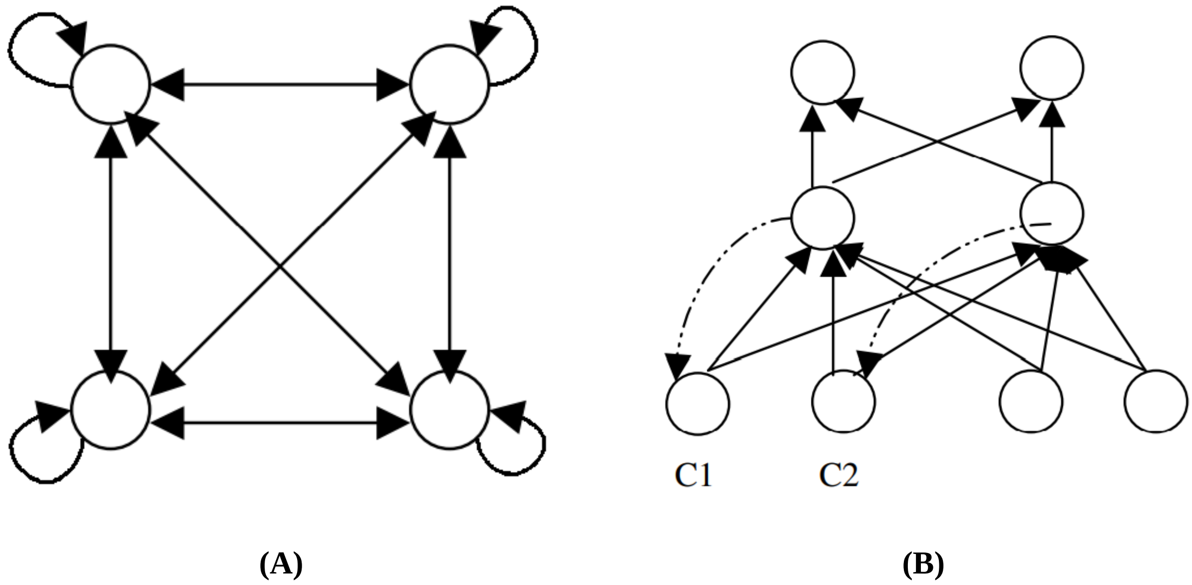


Figure III-7: examples of a fully connected RNN

Simple partially recurrent neural networks **Figure *III-7*** have been used to learn strings of characters. Although some nodes are part of a feedforward structure, other nodes provide the sequential context and receive feedback from other nodes. Weights from the context units (C1 and C2) are processed like those for the input units, for example, using backpropagation. The context units receive time-delayed feedback from, in the case of **Figure *III-7*** the second layer units. Training data consists of inputs and their desired successor outputs. The net can be trained to predict the next letter in a string of characters and to validate a string of characters. [26]

Two fundamental ways can be used to add feedback into feedforward multilayer neural networks. Elman introduced feedback from the hidden layer to the context portion of the input layer. This approach pays more attention to the sequence of input values. Jordan recurrent neural networks use feedback from the output layer to the context nodes of the input layer and give more emphasis to the sequence of output values.

III.4.4 Learning in Recurrent Neural Network

Learning is a fundamental aspect of neural networks and a major feature that makes the neural approach so attractive for applications that have from the beginning been an elusive goal for artificial intelligence. Learning algorithms have long been a focus of research. [26]

Hebbian learning and gradient descent learning are key concepts upon which neural network techniques have been based. A popular manifestation of gradient descent is back-error propagation introduced by Rumelhart in 1986 and Werbos in1993. While backpropagation is relatively simple to implement, several problems can occur in its use in practical applications, including the difficulty of avoiding entrapment in local minima. The added complexity of the dynamical processing in recurrent neural networks from the time-delayed updating of the input data requires more complex algorithms for representing the learning. [26]

To realize the advantage of the dynamical processing of recurrent neural networks, one approach is to build on the effectiveness of feedforward networks that process stationary patterns. Researchers have developed a variety of schemes by which gradient methods, and in particular backpropagation learning, can be extended to recurrent neural networks. Werbos introduced the backpropagation through time approach in 1990, approximating the time evolution of a recurrent neural network as a sequence of static networks using gradient methods. Another approach from Lapedes and Farber in 1986 deploys a second, master, neural network to perform the required computations in programming the attractors of the original dynamical slave network. [26]

III.4.5 Learning process

Among the desirable properties for a neural network, the most fundamental is surely the ability to learn from its environment, to improve its performance through a learning process. But what is learning? Unfortunately, there is no general definition, universally accepted, because this concept affects too many distinct notions that depend on the point of view that one adopts. In the context of artificial neural networks, we will adopt a pragmatic point of view by proposing the following definition: Learning is a dynamic and iterative process allowing the parameters of a network to be modified in response to the stimuli it receives from its environment. The type of learning is determined by the way in which parameter changes occur. This definition implies that a network must be stimulated by an environment, that it undergoes changes in response to this stimulation, and that these provoke in the future a new response to the environment. Thus, the network can improve over time. [28]

In most architectures, learning results in a modification of synaptic efficiency, meaning a change in the value of the weights that connect the neurons from one layer to another. Let the weight $w_{i,j}$ connect the neuron i to its input j. At time t, a change $\Delta w_{i,j}(t)$ in weight can be expressed simply as follows, equations (**III-5**):

$$\Delta w_{i,j}(t) = w_{i,j}(t+1) - w_{i,j}(t) \qquad \textbf{III-5}$$

And therefore, $w_{i,j}(t+1) = w_{i,j}(t) + \Delta w_{i,j}(t)$ with $w_{i,j}(t+1)$ and $w_{i,j}(t)$ representing respectively the new and old values of the weight $w_{i,j}$. [28]

A set of well-defined rules allowing to carry out such a process of adaptation of the weights constitutes what is called the learning algorithm of the network. One of different types of rules as well as different principles that can guide the learning of a neural network is by error correction. [28]

III.4.5.1 By error correction

The first rule that can be used is based on the correction of the error observed at the output. Let $a_i(t)$ be the output obtained for neuron i at time t. This output results from a stimulus p(t) that is applied to the inputs of the network, one of the neurons of which corresponds to neuron i. Let $d_i(t)$ be the output that we want to obtain for this same neuron i at time t. Then, $a_i(t)$ and $d_i(t)$ will generally be different and it is natural to calculate the error $e_i(t)$ between what we obtain and what we would like to obtain, equations (**III-6**):

$$e_i(t) = d_i(t) - a_i(t) \qquad \textbf{III-6}$$

And look for a way to reduce this error as much as possible. In vector form, we get, equations (***III-7***):

$$e(t) = \mathrm{d}(t) - \mathrm{a}(t) \qquad \textbf{III-7}$$

With $\mathbf{e}(t) = [e_1(t)e_2(t) \cdots e_i(t) \cdots e_S(t)]$ which designates the vector of errors observed on the S output neurons of the network. Error correction learning consists of minimizing a performance index F based on the error signals $e_i(t)$, in order to make the outputs of the network converge with what we would like them to be. A very popular criterion is the sum of squared errors, equations (**III-8**):

$$F(\mathbf{e}(t)) = \sum_{i=1}^{S} e_i^2(t) = \mathbf{e}(t)^T \mathbf{e}(t) \qquad \textbf{III-8}$$

Now, it is important to notice that the free parameters of a network are its weights. Let's take all of these weights and put them together in the form of a vector $\mathrm{w}(t)$ at time t. To minimize $\big(\mathrm{e}(t)\big) = F\big(\mathrm{w}(t)\big) = F(t)$, we will start by choosing initial weights (t = 0) at random, then we will modify these weights in the following way, equations (**III-9**):

$$\mathbf{w}(t+1) = \mathbf{w}(t) + \eta \mathbf{x}(t) \qquad \textbf{III-9}$$

Where the vector $\mathrm{x}(t)$ designates the direction in which we will look for the minimum and η is a positive constant determining the amplitude of the step in this direction (the learning speed). The objective is to ensure that $\mathrm{F}(t+1) < \mathrm{F}(t)$. But how can we choose the direction x so that the previous condition is respected? Consider the 1st order Taylor series around $\mathrm{w}(t)$, equations (**III-10**):

$$F(t+1) = F(t) + \nabla F(t)^T \Delta \mathbf{w}(t) \qquad \textbf{III-10}$$

Where $\nabla F(t)$ designates the gradient of F with respect to its free parameters (the weights w) at time t, and $\Delta \mathrm{w}(t) = \mathrm{w}(\mathrm{t}+1) - w(t)$. But, so that $\mathrm{F}(t+1) < \mathrm{F}(t)$, the following condition must be satisfied, equations (**III-11**):

$$\nabla F(t)^T \Delta \mathbf{w}(t) = \eta \nabla F(t)^T \mathbf{x}(t) < 0 \qquad \textbf{III-11}$$

Any vector $\mathrm{x}(t)$ which respects the inequality of the equation **III-11** therefore points in a direction that decreases F. This is then referred to as a “descent” direction. [28]

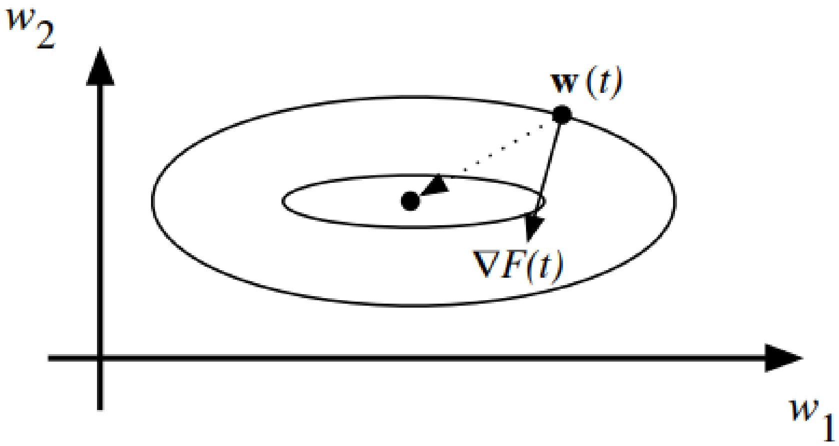


Figure III-8: Gradient descent trajectory.

To obtain maximum descent, given $\eta > 0$, the vector $\mathrm{x}(t)$ must points in the opposite direction to the gradient because it is in this case that the scalar product will be minimum, equations (**III-12**):

$$\mathrm{x}(t) = -\nabla F(t) \qquad \textbf{III-12}$$

This generates the so-called “gradient descent” rule, equations (**III-13**) :

$$\Delta \mathrm{w}(t) = -\eta \nabla F(t) \qquad \textbf{III-13}$$

Illustrated in **Figure *III-8***. In the space of weights, this **Figure *III-8*** shows the level curves of F represented by hypothetical ellipses. The dotted arrow shows the optimal direction to reach the minimum of F. The full arrow shows the direction of the gradient which is perpendicular to the curve line in $\mathrm{w}(t)$. The exact expression of the gradient depends on the activation function used for the neurons. [28]

III.5 Conclusion

The next years we should see major advances in theory and design, as well as an increase in the number of applications for the creative solution of major practical challenges. The growing use of recurrent neural networks should spark interest in research and development while also raising new theoretical and design challenges. The continued development in hybrid systems should evolve in new and better applications for recurrent neural networks.

Chapter 4:

Simulation Results

IV Chapter 04: simulation results:

IV.1 Introduction:

After we found the mathematic model of the induction motor in the last chapter. In the first part of this chapter, we will simulate the motor model in MATLAB program, and then we will analyze and interpret the results obtained from different experiments.

In the second part of this chapter, we will use the results obtained from the simulation of the induction motor in order to create an artificial neural network that calculates the speed of the motor based on the measurement of the following quantities. The stator current Alpha $i_{s\alpha}$, the stator current Beta $i_{s\beta}$, the rotor flow Alpha $\psi_{r\alpha}$,the rotor flow Beta $\psi_{r\beta}$ .Then we analyze all the results obtained.

IV.2 Simulation of the induction machine model:

The induction machine is normally supplied directly from the industrial network by a system of balanced three-phase voltages.

In some applications for which speed variation is necessary, the motor will be powered by a system of three-phase voltages or by a system of three-phase currents (injected) into the stator windings, through an electronic power converter placed between the motor and the electrical industrial network [29].

Figure *IV-1* represents the induction machine model simulated using the SIMULINK software under MATLAB. The parameters of the induction machine used in this work are given in the Appendix. The simulation will be done in the (α, β) frame of reference for a nominal load test after a no-load start.

The supply voltages assumed to be perfectly sinusoidal with equal and constant amplitudes, they can be presented as follows, equations (**IV-1**):

$$\begin{cases} V_{sa} = \sqrt{2}V_S\sin\left(\omega_s t\right) \\ V_{sb} = \sqrt{2}V_S\sin\left(\omega_s t - \frac{2\pi}{2}\right)(\mathbf{I}-31) \\ V_{sc} = \sqrt{2}V_S\sin\left(\omega_s t + \frac{2\pi}{2}\right) \end{cases} \qquad \textbf{IV-1}$$

With:

V_S : RMS voltage value.

ω_s : Power pulse.

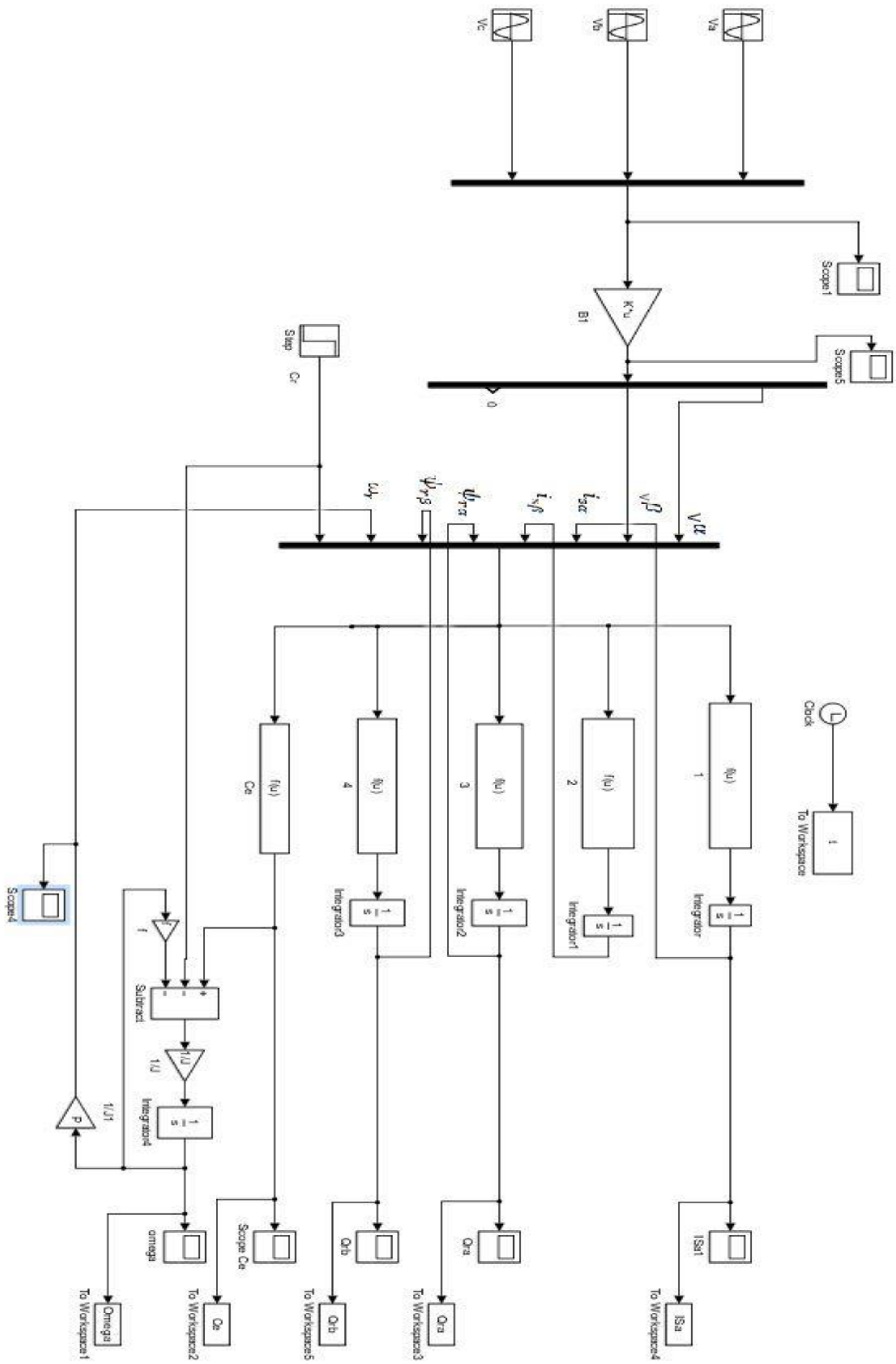


Figure IV-1: The induction machine model

IV.2.1 Simulation results:

IV.2.1.1 No-load :

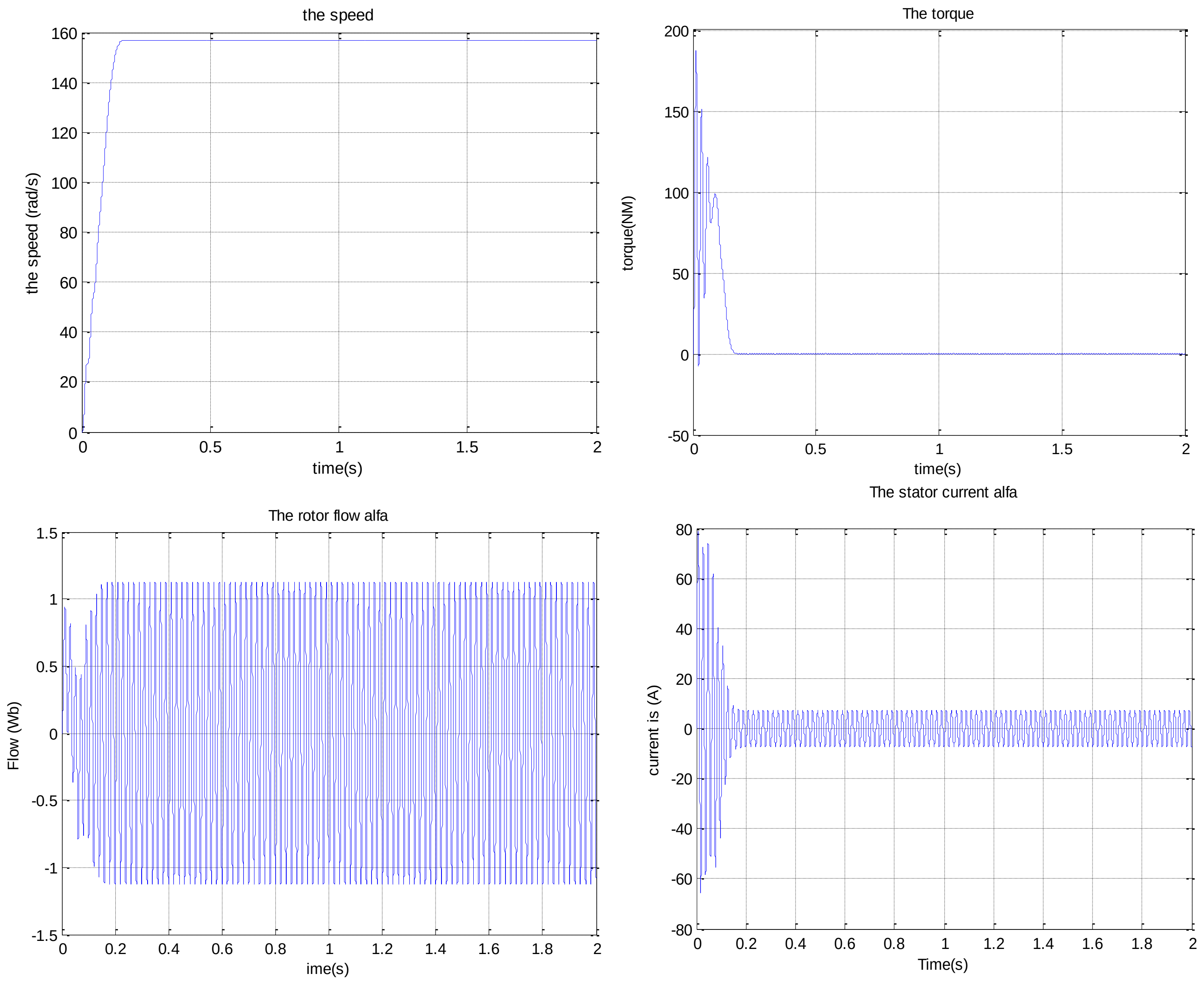


Figure IV-2: Simulation results of the induction machine model during no load start

IV.2.1.2 Under load:

(**R_T=60** N.m) in **t=1s**:

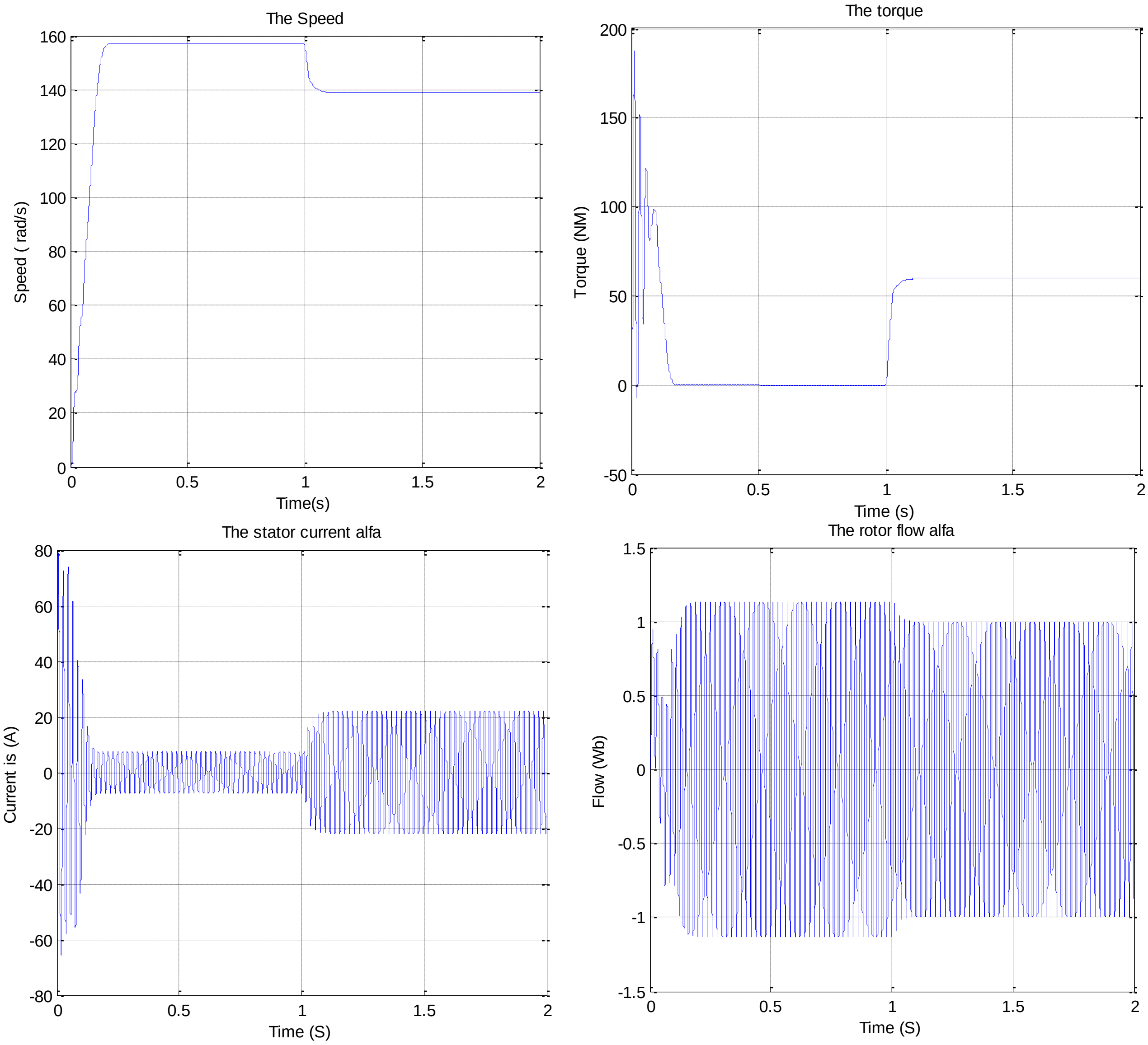


Figure IV-3: Simulation results of the induction machine model under load

IV.2.2 Interpretation of simulation results:

Note that the parameters of the machine are given in **appendix.** In the first step, we will digitally simulate the operation of the induction machine powered directly by the standard 220/380V, 50HZ network and without the disturbance application (R_T= 0).

Examination of the curves in **Figure *IV-2*** shows that no-load starting with a nominal voltage makes it possible to have:

At the first moments, the stator currents present successive oscillations around zero, but which quickly disappear after a few vibrations, the steady state is reached, these oscillations can cause the destruction of the machine by overheating in the event of excessive repetitions.

During the transient state, the torque is strongly pulsating, present at the first moments of starting of the important beats followed by a number of oscillations before stabilizing at zero.

In the second step, a torque disturbance (**R_T=60N.m**) is applied to the motor shaft at instants (**t=1 s**) and the simulation results are grouped in the **Figure *IV-3***.

When the load is applied, the electromagnetic torque reaches its reference value to compensate for this stress with an almost instantaneous response.

Before stabilizing at the resistive torque value, there is a decrease in rotor speed which results in very high slip. The stator currents changing according to the load applied to the motor shaft.

IV.3 Simulation of the artificial neural network:

In this part, we will create an artificial neural network **Figure *IV-4*** in **MATLAB Simulink** based on the results obtained in the first part of the simulations.

Our network has

4 inputs:

- The stator current Alpha $i_{s\alpha}$
- The stator current Beta $i_{s\beta}$
- The rotor flow Alpha $\psi_{r\alpha}$
- The rotor flow Beta $\psi_{r\beta}$

Hidden layers

1 output:

- The speed of the motor (Omega)

Where the goal of this experiment is to create an artificial neural network that performs the same work as the **speed sensor** of the induction motor.

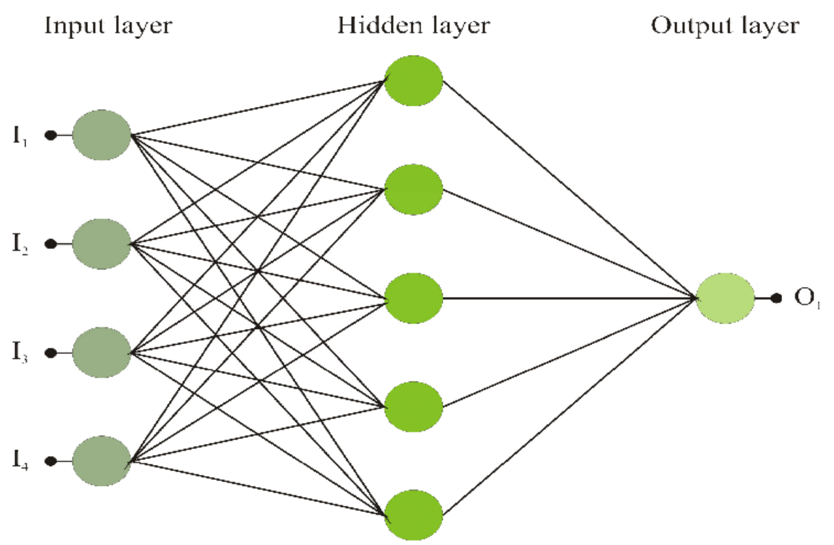


Figure IV-4: Artificial neural network

IV.3.1 Simulation settings are:

IV.3.1.1 Artificial neural network type: Recurrent Neural Network (RNN)

Example:

The **Figure *IV-5*** represents an artificial neural network of type RNN containing:

4 Inputs

1 Hidden Layer (5 neural)

1 Output

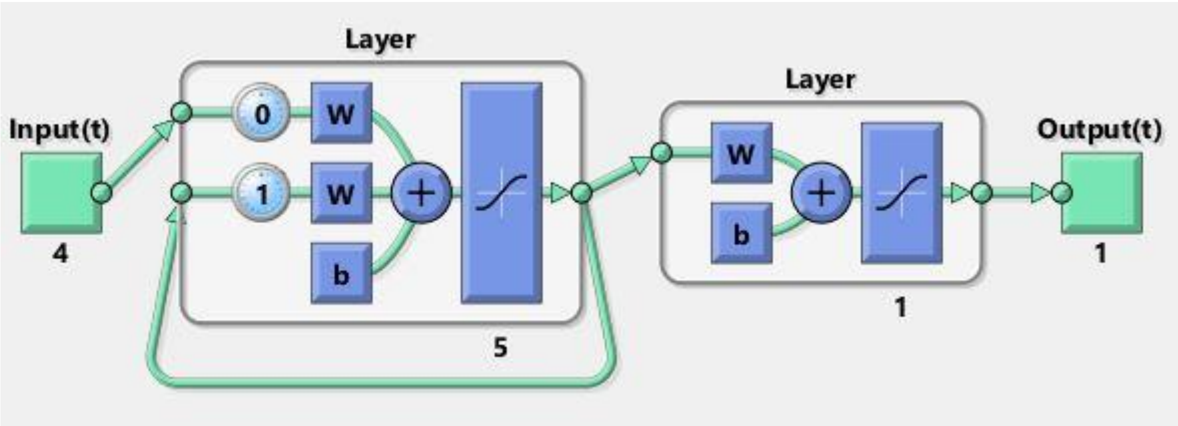


Figure IV-5: Recurrent Neural Network (RNN)

IV.3.1.2 The database:

In essence, an AI database is a database created solely for the aim of speeding up the training of Machine Learning (ML) models. As vendors roll out more AI-based features that need significant compute power, a number of tech companies are already building dedicated AI chips to alleviate the hefty processing burden in new hardware products. In this sense, artificial intelligence is defined as a set of strategies that allow a computer to solve tasks that would require intelligence if completed by humans. [30].

In an in-memory database, an AI database integrates data warehousing, sophisticated analytics, and visualizations. Within milliseconds, AI databases should be able to absorb, examine, evaluate, and visualize fast-moving, complicated data. The goal is for businesses to make more efficient, data-driven decisions by lowering costs, generating new revenue, and integrating machine learning models. [30].

So, in our simulation. The database of inputs and outputs was extracted by the simulation of the motor rotation for **5 seconds** with changes in the Torque of the motor $\mathbf{R_T}$.

Where:

- When applying the following Torques:

R_T1 = 10 in T= 1s

R_T2 = 40 in T= 3s

R_T3 = -50 in T= 4s

The motor speed changes as follows **Figure *IV-6***:

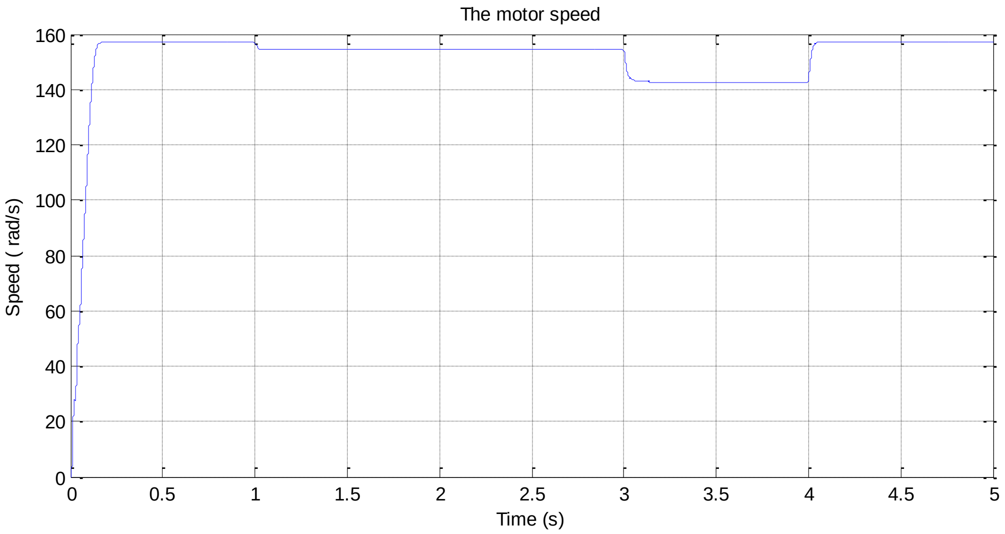


Figure IV-6: The motor speed

We notice from this **Figure *IV-6*** that the motor speed changes with the change in the value of the Torque. Where when a positive torque is applied to the motor at the moment **1** and **3 seconds**, we notice a decrease in the motor speed, but when we apply a negative torque at the moment **4 seconds**, we notice an increase in the motor speed.

So, we will train **the output** of our artificial neural network based on these results.

The database extracted from simulation of the motor rotation for **5** second is a matrix of **(50014x6)** **Table *IV-1*.**

Where the first column in this matrix represents the time starting from **0 seconds** in the first line and ending in **5 seconds** in the last line where it takes **50014 values.**

The columns **2, 3,4** and **5** represent the values of: the stator current Alpha $i_{s\alpha}$, the stator current Beta $i_{s\beta}$, the rotor flow Alpha $\psi_{r\alpha}$, the rotor flow Beta $\psi_{r\beta}$ that are measured during the simulation for **5 seconds** with difference value of torque as mentioned before, and **these** columns represent **the inputs** of the neural network.

The last column in this matrix represents the motor speed values during the simulations where it takes **50014 values.** And these values represent **the output** of the neural network.

Table IV-1: the Database of 4 inputs and 1 output

	4 Inputs				1 Output
Time (s)	The stator current Alpha (A)	The stator current Beta (A)	The rotor flow Alpha (Wb)	The rotor flow Beta (Wb)	The speed of the motor (Rad/s)
0	0	-367,648489	0	0	0
…… …. …..	……. …….. …….	……… ……… ……..	………. …….. ……….	………. …….. ………	…….. …….. ………
5	-262,470345	-257,110191	-5,406733	5,192375	156,997760

IV.3.2 The training result of the recurrent neural network (RNN):

In order to train the neural network, we simulate the six experiments shown in the **Table *IV-2***

Where in experiment **01** and **02** the number of hidden layers in the neural network (RNN) was **1** and the number of neurons in the hidden layer was **5** and then **10.**

In experiment **03** and **04** the number of hidden layers in the neural network (RNN) was **2** and the number of neurons in the hidden layers was **(10, 10)** and then **(10, 20).**

In experiment **05** and **06** the number of hidden layers in the neural network (RNN) was **3** and the number of neurons in the hidden layers was **(5, 10, 10)** and then **(20, 10, 10).**

Table IV-2: The training result of the recurrent neural network (RNN):

simulation	number of hidden layers	number of neurons	time of training	error value
01	1	5	20 s	24.0
02	1	10	02 min,17 s	6.65
03	2	(10.10)	24 min,57 s	0.656
04	2	(10.20)	2 h,15 min,15 s	0.1254
05	3	(5.10.10)	27 min,26 s	0.514
06	3	(20.10.10)	24 h,47 m,06 s	0.00452

The arrangement having given the smallest error is arrangement number **06** with **3** hidden layers **(20.10.10)** after **1000 iterations,** Function used is **logsig.**

So, the recurrent neural network final is **Figure *IV-7*:**

It is a recurrent neural network (RNN) contains: 4 inputs, 1 output and 3 hidden layers (20.10.10)

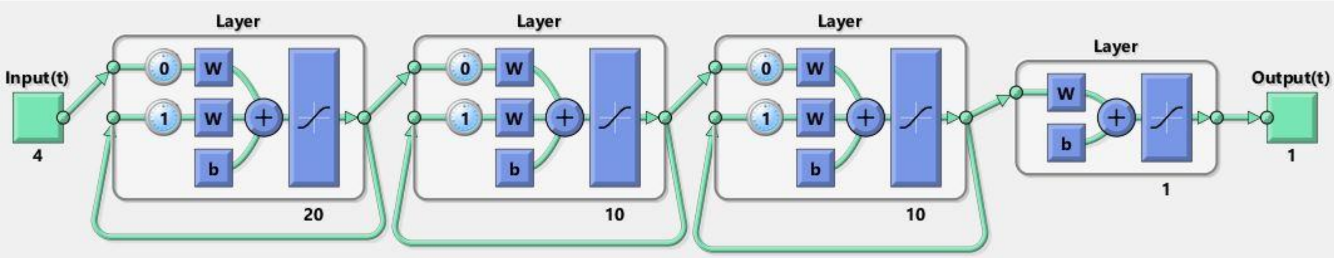


Figure IV-7: The recurrent neural network of the arrangement number 06

The **Figure *IV-8*** represents the results obtained by training this recurrent neural network (RNN): Where the graph represents the change in the mean squared Error (MSE) value of the network in terms of the Epochs, where it reached a value of **0.0046672** at epoch number **1000**.

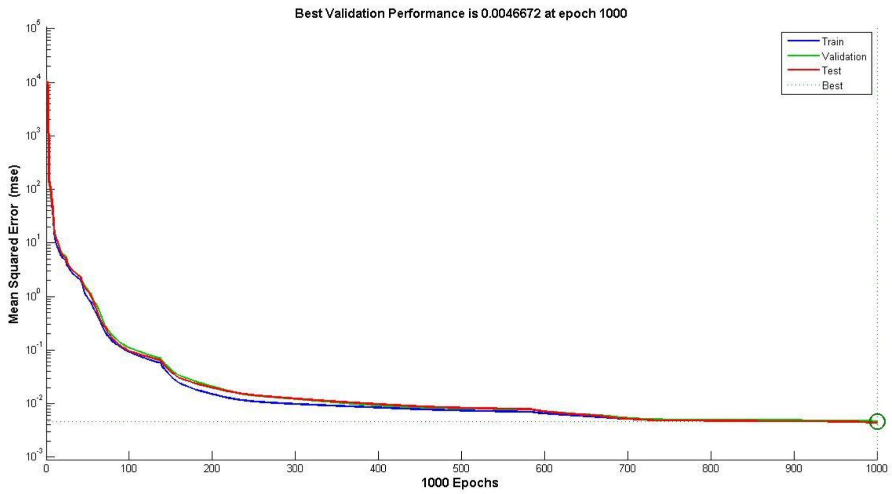


Figure IV-8 : *The represents the results obtained by training of the RNN*

IV.3.3 Test of the recurrent neural network:

In the experiment the database of inputs and outputs was extracted by the simulation of the motor rotation for **7** seconds with changes in the Torque of the motor R_T.

Where:

When applying the following Torques:

$\mathbf{R_T1}$ = 50 in **T**= 1s

$\mathbf{R_T2}$ = -45 in **T**= 5 s

The motor speed changes as follows **Figure *IV-9***:

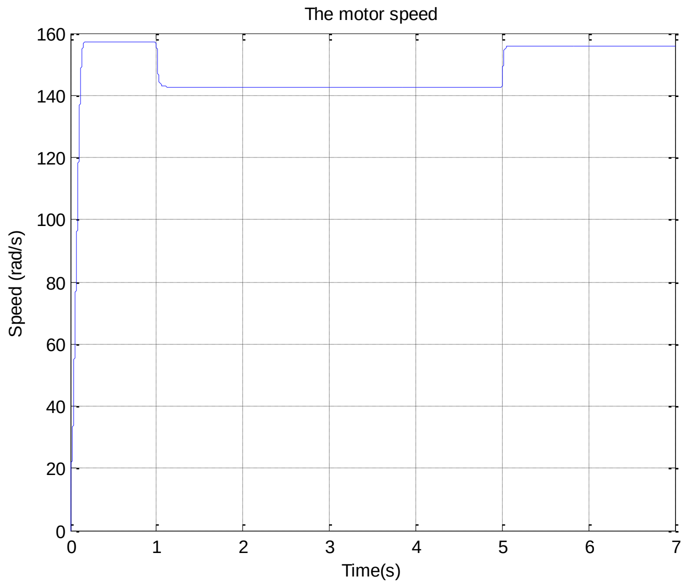


Figure IV-9: The motor speed

We notice from this **figure** that the motor speed changes with the change in the value of the Torque. Where when a positive torque is applied to the motor at the moment **1 seconds**, we notice a decrease in the motor speed, but when we apply a negative torque at the moment **5 seconds**, we notice an increase in the motor speed.

So, we are going to use the values of:

- The stator current Alpha $i_{s\alpha}$
- The stator current Beta $i_{s\beta}$
- The rotor flow Alpha $\psi_{r\alpha}$
- The rotor flow Beta $\psi_{r\beta}$

That extracted by the simulation of the motor rotation in this experiment **(7 s)** as inputs of the recurrent neural network.

The output of the recurrent neural network is **Figure *IV-10***:

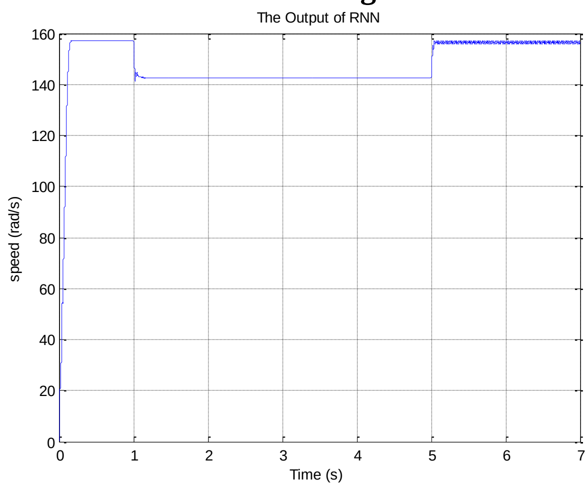


Figure IV-10: The output of the recurrent neural network

IV.3.4 Interpretation of simulation results

IV.3.4.1 The Comparison of the results:

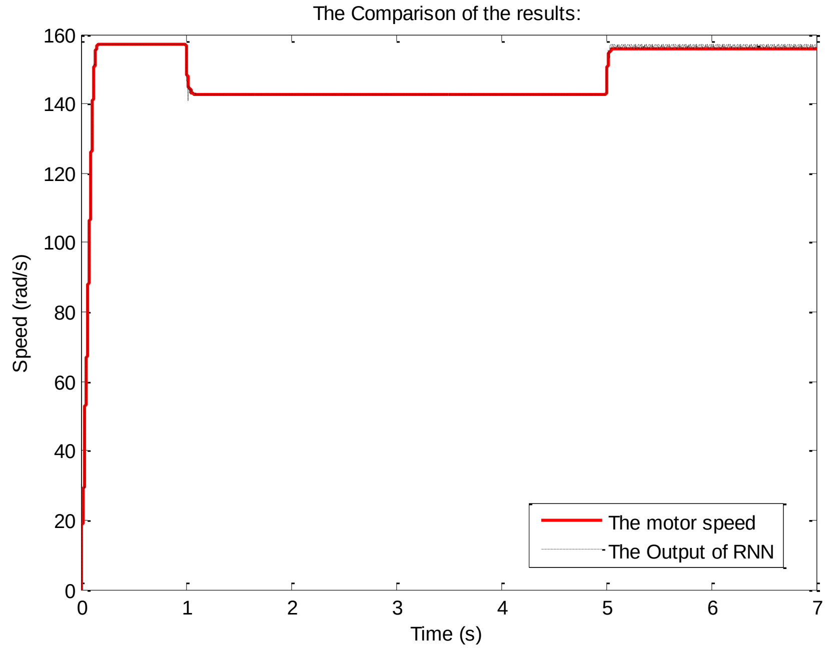


Figure IV-11: The Comparison of the results

From the ***Figure IV-11*** we note that when comparing the results obtained from the neural network (Output of the RNN) with the real motor speed graph, there is an almost perfect match for the results. This indicates that the neural network (RNN) is well trained and the error rate is very small.

IV.3.4.2 The final result:

We can use this neural network as a sensor for the motor speed.

Where it calculates the rotational speed of the motor based on the measurement of the following quantities:

- The stator current Alpha $i_{s\alpha}$
- The stator current Beta $i_{s\beta}$
- The rotor flow Alpha $\psi_{r\alpha}$
- The rotor flow Beta $\psi_{r\beta}$

IV.4 Conclusion:

In this chapter, we analyzed the results obtained after simulating of the induction motor in both cases (No-load and Under load) , Then we used the obtained results to create a neural network that calculates the motor speed based on the measurement of the following quantities. The stator current Alpha i_sα, the stator current Beta i_sβ, the rotor flow Alpha ψ_rα,the rotor flow Beta ψ_rβ.

And in the end, we noticed the success of the experiment, as we could consider that this neural network is worked as the **speed motor sensor.**

General Conclusion:

Monitoring the rotor speed of induction machine is necessary in order to improve the control performance and fault diagnosis. Due to the specific structure of induction machine and its tough operating environment, it is difficult and expensive to install sensors to monitor the speed traditionally.

In this thesis, we have proposed a mathematical model for induction machine, then a new speed sensorless estimation method based upon the Recurrent Neural Network (RNN). The recurrent neural network have been trained using Neural Network Toolbox (nntool) for MATLAB-SIMULINK program from Math Works corporation, so the RNN can estimate the speed, following the speed from induction machine model, and it requires only the stator current and the rotor flow of induction machine for the input signals.

Simulation results show that the RNN can produce very high precision and robust speed estimation performance.

Appendix

The machine used is a standard squirrel cage induction machine. Its main characteristic feels the following:

Nominal power	**4KW**
nominal voltage	**220/380 V**
Nominal current	**15 A**
Number of pole	**2**
Cos φ	**0.8**
rotational speed	**1500 tr/min**

Electrical Parameters:

Stator resistance	**1.2 Ω**
Rotor resistance	**1.8 Ω**
Stator cyclic inductance	**0.1554 H**
Rotor cyclic inductance	**0.1568 H**
mutual inductance	**0.15 H**

Mechanical Parameters:

Rotor moment of inertia	**0.07 Kg.m2**
Physical coefficient of friction	**0.00 SI**

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