Addis Ababa University
Addis Ababa Institute of Technology (AAiT)
Department of Electrical and Computer Engineering

Adaptive Control of Multi-layer Switched Reluctance Motor

By
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A thesis

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Advisor

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Approval by Board of Examiners

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Declaration

I, the undersigned declare that this thesis is my original work, and has not been presented for a degree in this or any other university, and all sources of materials used for the thesis have been fully acknowledged.

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List of Acronyms

SRM	Switched reluctance motor
MSRM	Mult-layer switched reluctance motor
MF	Membership function
addmf	Add membership function to FIS
addrule	Add rule to FIS
addvar	Add variable to FIS
defuzz	Defuzzify membership function
evalfis	Perform fuzzy inference calculation
evalmf	Generic membership function evaluation
FIS	Fuzzy Inference System
FLC	Fuzzy logic controller.
ANFIS	Adaptive neuro fuzzy inference system
SRG	Switched reluctance generator
ANN	Artificial neural network
BPN	Backbropagation neural network
mmf	The magneto motive force
I	Current (A).
DC	Direct current
I/O	Input/Output.
L	Inductance (H).
rmmf	Remove membership function from FIS.
Plotfis	Display FIS input-output diagram
Showrule	Display FIS rules.
PM	Permanent magnet

List of Symbols

T	Developed torque (N·m)
I_{comp}	Compensated current
I_{ph}	Phase current
$L(\theta, i)$	The instantaneous inductance
I_{ph}	Phase inductance (H)
T_L	Load torque (N·m)
V_{dc}	DC voltage source
J	Rotor's moment of inertia ($Kg\ m^2$)
B	The flux density (T)
θ	Rotor position
ω	Rotor's angular speed (radians per second)
$\lambda(\theta)$	Flux linkage (weber-turns)
W_c	Co-energy in joule
W_f	Stored field energy
Wm	Work
Φ	The field flux (Wb)
m	No. Of Phases
La	Aligned Inductance
Nr	Rotor pole number.
Ns	Stator pole number.
R_{ph}	Phase resistance (ohm)
L_u	Un-aligned Inductance
β_s	Stator Pole Arc
β_r	Rotor Pole Arc
P_r	No. Of Rotor Pole
ψ	Flux linkage per phase
e	Induced emf
K_b	Emf constant
P_i	Instantaneous power input

T_e	Electromagnetic torque
L_s	Stator inductance
L_r	Rotor inductance
L_m	Mutual inductance
R_s	Stator Resistance
R_r	Rotor inductance
f_1	Switching frequency
ε	Step angle
q	No of phase
N	Number of turns
θ_{on}	Switching on angle
θ_{off}	Switching off angle
θ_{adv}	Advanced angle
θ_{ext}	Extinction angle
D	Coefficient of friction
V	Applied phase voltage
R	Phase resistance
f_i	Activation function
w_{ij}	Weighting factor
b_i	Bias

Abstract

The multi-layer switched reluctance motor (MSRM) are receiving significant attention from industries because of its simple structure, inexpensive manufacturability and reliability. In addition multi-layer switched reluctance motor receiving renewed attention as a viable candidate for various adjustable speed and high torque applications such as in the automotive, traction and aerospace industries. Simple power electronic drive circuit and fault tolerance of converter are specific advantages of multi-layer switched reluctance motor drives, but excessive torque ripple has limited its use to special applications. It is well known that controlling the current adequately can minimize the torque ripple because current is directly proportional to torque.

The magnetization characteristics of the SRM is highly non-linear making the flux linkage and torque as the non-linear functions of both the current and rotor position. Establishing this high precision nonlinear mapping between current and rotor position is used to control the motor accurately for the analysis and control of any switched reluctance motor system. The generating or motoring mode of operation of the motor depends greatly on the value of rising or falling torque and hence it needs to be controlling more accurately the torque ripples for the practical applications.

This thesis investigates the use of fuzzy logic controller and a hybrid intelligent system which is adaptive neuro fuzzy inference system (ANFIS) to reduce the torque ripples of multi-layer switched reluctance motors. Matlab simulink models of multi-layer switched reluctance motors with fuzzy logic controller and adaptive neuro fuzzy inference system (ANFIS) are developed to carry out simulation studies under loaded conditions. A comparison results shows that with fuzzy logic controller, the torque ripple is reduced by twenty two percent (22%) as compared to that without any controller. It is further observed that the adaptive neuro fuzzy inference system (ANFIS) controller reduces the torque ripples by twenty six percent (26%) as compared to that without any controller.

This clearly shows that the torque ripple is reduced by using fuzzy logic controller as well the adaptive neuro fuzzy inference system (ANFIS). Moreover, performance of the adaptive neuro fuzzy inference system is better because it includes learning mechanism to adapt itself to new dynamic conditions.

Key words: Multi-layer switched reluctance motor, fuzzy logic controller, adaptive neuro fuzzy inference system, torque ripples

CHAPTER ONE

Introduction

1.1 Background

Due to the essential of the mechanical loads to our life the switched reluctance motors are widely used. These loads may have rotational, linear, or any other nature of movement according to the load demand. Recently, the great development of electric motors and their electrical drives makes load's characteristics like speed, torque, power and their variations take an important place in the decision of choosing the load driver. In general, dc and induction motors are used to drive a great portion of loads. They have some problems such as poor positioning control, commutation problem in dc motors and the slip ring problems in the wound rotor induction motor [1].

According to the development of power electronics and computer science, researches have been directed towards reluctance motors especially switched reluctance motors (SRM). The switched reluctance motor (SRM) drives for industrial applications are of recent origin. Since 1969, a variable reluctance motor has been proposed for variable speed applications. The origin of this motor can be traced back to 1842, but the “reinvention” has been possible due to the advent of inexpensive, high power switching devices. The switched reluctance motors is similar to the stepper motor expect that it has fewer poles larger stepping angle usually one tooth per pole, higher power output capability and the switched reluctance motor is normally operated with shaft position feed back to synchronize the commutation of the phase currents with precise rotor positions, where as stepper motor is normally run in open loop, i.e without shaft position feedback. Switched reluctance motor is normally designed for efficient conversion of significant amounts of power, stepper motors are more usually designed to maintain step integrity position controls [1] [2].

Switched reluctance motors (SRM) have many advantageous characteristics comparing to those of the conventional AC and DC machines [1]. The mechanical simplicity in construction of the multi-layer switched reluctance motor can be seen through their purely laminated steel structure without permanent magnets, rotor windings and squirrel cage bars. Thus, switched reluctance motors offer high reliability and robustness in operation. Due to their ruggedness, the multi-layer switched reluctance motors are inherently suitable for high speed drives and applications in high temperature and hazardous environments. In addition, the multi-layer switched reluctance motors are efficient and suitable for some applications which required high torque and high dynamics. However, a major disadvantage of SRM is the large torque ripple during lower speeds which produces intensive and undesirable vibration and acoustic noise and limits the application areas of multi-layer switched reluctance motor. Torque ripple reduction in multi-layer switched reluctance motor has become an important and difficult research. Especially, at low speed, the torque ripple is very serious, which will cause undesirable vibration and acoustic noise. To avoid and reduce these disadvantages, many authors have reported methods to minimize the torque ripple which include motor structure design and control strategy.

1.2 Statement of the problem

There has been big interest in switched reluctance motor (SRM) due to the advances on sensors, power electronics and signal processing, has gained a lot of commercial and academic interest. Switched reluctance motor construction simplicity makes it inexpensive, in addition to its reliability, high speed capability, cooling, ruggedness and high torque to inertia ratio makes it a superior choice in different applications. However, excessive torque ripple, and acoustic noise especially at low speeds prevented SRM from widespread use.

This thesis attempts to reduce torque ripples of multi-layered switched reluctance motor using intelligent controllers such as fuzzy logic controller (FLC) and a hybrid intelligent system known as adaptive neuro-fuzzy inference system (ANFIS) based on current compensating technique. It also investigates the performance of the proposed controllers through simulation studies using matlab simulink models.

1.3 Objectives

General objective

The general objective of this thesis is to present a torque ripple control techniques for multi-layer switched reluctance motor for the purpose of better torque regulation of this type of motors in different applications.

Specific Objectives

The specific objectives of this thesis are as follows:

i. To study and analyze principle of operation of multi-layer switched reluctance motors.
ii. To obtain the mathematical model of multi-layer switched reluctance motor and analyze the characteristics of the motor.
iii. To design the fuzzy logic and adaptive neuro fuzzy inference system (ANFIS) controller to reduce the torque ripple of multi-layer switched reluctance motor.
iv. To develop model of the multi-layer switched reluctance motor with proposed controllers using simulink.
v. To carry out simulation studies and to compare the effectiveness of the proposed controllers.
vi. To analyses the simulation results to draw conclusions.

1.4 Methodology

To reduce the torque ripple a compensating current signal is added to the reference current. This signal is dependent of the rotor position and the reference current which in turn depends on the motor speed and the torque load value. The output compensating current signal produced by the controllers I_{comp} is added to the reference current signal, which ideally, should be constant in steady state, but producing significant ripple. The compensating signal should then be adjusted in order to produce a ripple reduced output torque. In fact, it is a function that possesses high mathematical complexity and therefore the production of this signal is quite complicated.

In this thesis, intelligent controllers such as fuzzy logic controller (FLC) and the adaptive neuro-fuzzy inference system (ANFIS) are used to provide compensating current I_{comp} to minimize the torque ripples in multi-layer switched reluctance motor drives. The intelligent controllers has two inputs, reference current(I_{ref}), rotor position (θ) and one output, compensating current I_{comp}.

The torque ripples of the multi-layer switched reluctance motor with the two controllers is studied such as fuzzy logic and adaptive neuro fuzzy inference system (ANFIS) including without any controller. The motor model is designed and membership functions are chosen according to the parameters of the motor model. Fuzzy control is one of the appropriate control schemes for torque control of switched reluctance motor drives. The mamdani fuzzy controller uses the rotor position and reference current as inputs and produces the compensating current as the output. The effectiveness of the proposed adaptive neuro fuzzy inference system controller (ANFIS) compared with the fuzzy logic controller of mult-layer switched reluctance motor. The fuzzy logic and adaptive neuro fuzzy inference system (ANFIS) controllers are designed then applied in simulations. Torque ripple is studied in simulation to find the best under the different controllers.

1.5 Thesis organization

This thesis contains five chapters and that are given below:

Chapter 1 represents a general introduction to the work proposed in this thesis. It presents an overview of the switched reluctance motors. It contains introduction, advantage, disadvantage, application, problem of the statement and objectives.

The second chapter explains about construction and principle of operation of SRM, elementary operation of SRM, Converter topology for SRM drive, magnetization curve, derivation of the relationship between induction and rotor position nonlinear analysis, static torque curve and characteristics of SRM. This chapter also studies mathematical modeling and control of multi-layer switched reluctance motor, its torque control strategies with different control parameters, and the overall closed block diagram representation of MSRM. In addition torque ripple minimization using the advanced control strategy, simulation model of multi-layer switched reluctance motor and simulation results are discussed.

Chapter 3 introduction to fuzzy logic controller, torque control model of multi-layer switched reluctance motor and implementation using fuzzy logic controller technique are presented in chapter 3. Simulation result and analysis of multi-layer switched reluctance motor drive using the proposed controller was elaborated.

Chapter 4 presents introduction to artificial neural network, biological neuron, learning sachems of (ANFIS) adaptive neuro fuzzy inference system controller of multi-layer switched reluctance motor concepts are elaborated. Lastly forming, implementing and simulation results of multi layer switched reluctance motor using (ANFIS) will be analyzed.

The last chapter gives the overall conclusion and scope for future work of the thesis.

CHAPTER TWO

Mathematical modeling and control of switched reluctance motor

2.1 History of switched reluctance machine

The principles of switched reluctance machines (SRMs) have been around since the mid-1800s the machine was invented by Davidson and was used to propel a locomotive on the Glasgow-Edinburgh railway. Although the concept was novel, the full potential of the motor could not be utilized with the mechanical switches available in those days. The interest in switched reluctance motors revived with the advent of fast-acting power semiconductor switches in the 1970s. Professor Lawrenson‟s group established the fundamental design and operating principles of the machine with their extensive research during the 1970s and 1980s. SRM technology is now slowly penetrating into the marketplace with the advantage of providing an efficient drive system at a lower cost [1].

2.2 Advantages, disadvantages and application of switched reluctance motor

In this section, the advantages, disadvantages and application of switched reluctance motors are presented as follows.

Advantages of switched reluctance motor

In a switched reluctance motor, only stator consists of phase windings while rotor is made of steel laminations without any conductors or permanent magnet. So, the switched reluctance motor has several advantages over conventional motors [1] [3].

(a) Switched reluctance motor drive maintain high efficiency over wide speed and load range because as there is no winding present on rotor. So, copper loss, heat loss reduces in this case. So, efficiency of switched reluctance motor drive increases.

(b) As there is no windings or permanent magnets on its rotor, and there are no brushes on its stator, along with its salient rotor poles make the switched reluctance motor's rotor inertia less than that of its conventional motor. So, switched reluctance motor can accelerate more quickly.

(c) As it does not have a brush commutator mechanical speed limit, no winding or permanent magnet present on rotor. So, it can run up to high speeds. It can also operate at low speeds providing full rated torque.

(d) As there are no windings or permanent magnet present on rotor so, the cost of the switched reluctance motor drive reduces.

(e) It follows four quadrant operations; it can run forward or backward direction. We can call it as motoring or generating mode of operation.

(f) Rugged construction suitable for high temperature and vibrating zone.

(g) Most losses that will occur in switched reluctance motor that must be in stator which can easily be cooled.

(h) Torque produced by switched reluctance motor is independent of the polarity of the phase current, allowing the use of simplified power converters with a reduced number of semi converter switches.

Disadvantages of switched reluctance motor

The switched reluctance motor also comes with a few disadvantages among which torque ripple and acoustic noise are the most critical. The higher torque ripple also causes the ripple current in the DC supply to be quite large, necessitating a large filter capacitor [1]. The doubly salient structure of the switched reluctance motor also causes higher acoustic noise compared with other machines. The absence of permanent magnets imposes the burden of excitation on the stator windings and converter, which increases the converter KVA requirement. Compared with PM brushless machines, the per unit stator copper losses will be higher, reducing the efficiency and torque per ampere. However, the maximum speed at constant power is not limited by the fixed magnet flux as in the PM machine, and, hence an extended constant power region of operation is possible in switched reluctance motors. As the inductance of the winding is very high and it is required to remove the stored energy after excitation so, a large energy removal period is usually required limiting the maximum current to relatively low range and switched reluctance motor drive cannot operate directly from ac or dc supply and require current pulse signal for torque production. The requirement of rotor position sensor, higher torque pulsation and acoustic noise are the major drawbacks of SRM drive and that may limit the SRM in some application [3] [4].

Application of switched reluctance motor derives

Switched reluctance motor drive has greater potential in motion control because it will give high performance in harsh condition like high temperature and dusty environment. The simple motor structure and inexpensive power electronic requirement have made the switched reluctance motor an attractive alternative to both AC and DC machines in adjustable-speed drives. Few of such applications are electric vehicles application; general purpose industrial drives, servo drives and most of them are listed below [5-6].

- Application-specific drives: compressors, fans, pumps, centrifuges.
- Aircraft applications.
- Aerospace [7].
- Household appliances like washing machine and vacuum cleaners.
- Variable speed and servo type application.

2.3 Switched reluctance motor configuration

The SRM is a single-excited machine with phase coils wound around diametrically opposite stator poles. Therefore, the phase excitation makes the rotor poles to be aligned with the produced flux-lines along that phase in order to minimize the reluctance of the magnetic path and generate the reluctance torque. Continuous rotor position information is needed to control phase excitation in a suitable way to achieve smooth, continuous torque and high efficiency. The machine operation and salient feature can be deduced from the torque expression. The torque expression is nothing but the relationship between machine flux linkages or inductance and rotor position. The torque v/s speed characteristics of the machine operation in all of its four quadrants can be derived from the inductance v/s rotor position characteristics of the machine. Switched Reluctance Machine can be designed of any phases. For single phase machine it has low performance but high volume application [7].

A reluctance machine is one in which torque is produced by the tendency of its moveable part to move to a position where the inductance of the excited winding is maximized. To produce a torque the stator winding inductance varies with the position of rotor, because torque in this machine is directly proportion to variation of winding inductance with angular position and square of motor phase current. [7], [8]

$$Torque \; \alpha \; i^2 \; \frac{dl}{d\theta} \;\; , \; T = i^2 \, \frac{l_{max} - l_{min}}{\Delta\theta} \qquad (2.1)$$

Where l_{max} : occurs when a pair of rotor is exactly aligned with excited stator pole.

l_{min} : occurs when rotor pole is moving away from the aligned position.

i : Motor phase current.

θ : Angular position. and T : Torque

The variation of the phase inductance of SRM with rotor angle relative to the motor poles is shown in figure 2.1, where l_{max} is the maximum inductance of the aligned positions, which occur when any pair of rotor poles is exactly aligned with the excited stator poles of a certain phase, and l_{min} is the minimum inductance of the unaligned positions, which occur when the interpolar axis of the rotor is aligned with the excited stator poles. The phase inductance is increased as the rotor pole enters under the stator pole until the aligned position where the inductance has its maximum value, and when the rotor pole is moving far from the aligned position, the phase inductance will decrease until reaching its minimum value at the unaligned position [8], [9]. The produced torque in SRM is proportional to the square of the phase current which means that it depends on the magnitude of the phase current not on its direction [9].

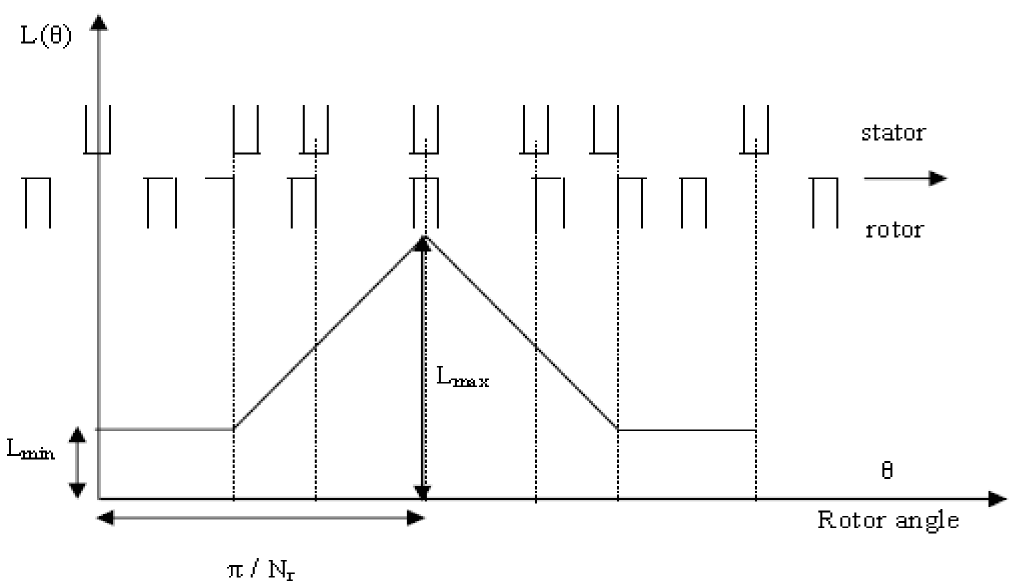


Figure 2.1 The phase inductance related to the motor poles

No torque is produced at the aligned and unaligned position, since

$$\frac{dl}{d\theta} = 0 \tag{2.2}$$

SRM is usually supplied from DC power supply which is switched on and off while transferring among phases using electronic switches. (Transistors, Thyristors). According to the relationship between the speed and the fundamental frequency if the poles are wound oppositely in pairs to form the phases, therefore each phase produces a pulse of torque on each passing rotor pole.

$$f_1 = nN_r = \frac{rpm}{60}\ N_r\ [Hz] \qquad (2.3)$$

Where f_1 = Switching frequency

N_r = No of rotor poles

n = Speed (rev/sec)

The step angle (ε) is defined as the angle between two successive torque pulses, and is computed by:

$$\varepsilon = \frac{2\pi}{qN_r}[rad] \qquad (2.4)$$

Where q = no of phases

qN_r = Steps per revolution

Switched Reluctance Motor can be made up of laminated stator and rotor cores with Ns =2mq poles on the stator and Nr poles on rotor. Where m is number of phases and each phase made up of concentrated windings placed on 2q stator poles. Switched reluctance motor is having salient pole stator with concentrated winding and salient pole rotor with no winding or permanent magnet. As both stator and rotor have salient pole structure, hence we can say that switched reluctance motor is having doubly salient structure which is single excited with different number of stator and rotor poles [1] [8]. It is constructed in such a manner that in no way the rotor poles in a position where the torque due to current in any phase is zero. There are two distinct configurations of the linear switched reluctance motor, Longitudinal flux linear switched reluctance motor and transverse flux linear switched reluctance motor both configurations can be obtained by unrolling the stator and rotor of the rotary switched reluctance motor with the radial magnetic flux path and the axial magnetic flux path respectively [10]. The flux path in the longitudinal machine is in the direction of the translator motion. This machine is simpler to manufacture, mechanically robust and has lower eddy current losses, as the flux is in the same direction as the translator movement. The transverse flux design has the flux path perpendicular to the direction of the translator motion. It allows a simple track consisting of individually mounted transverse bars. As the flux is perpendicular to the direction of motion, an electro motive force (EMF) is induced in the core resulting in high eddy current losses [11].

The common stator/rotor pole configuration is 6/4, 8/6, 10/8. In stator the coils on two diametrically opposite poles are connected in series in order to form single phase. So, 6/4 stator/rotor pole configuration means that represent the three phase configuration of switched reluctance motor drive. Similarly 8/6 and 10/8 stator/rotor pole configuration represents the four and five phase configuration of switched reluctance motor drive. Similarly for 8/6 SRM configuration it have eight stator and six rotor poles and in 10/8 SRM configuration it have ten stator pole and eight rotor poles are present. Figure 2.2 and 2.3 shows the stator and rotor pole configuration of three and four phases respectively [10-12].

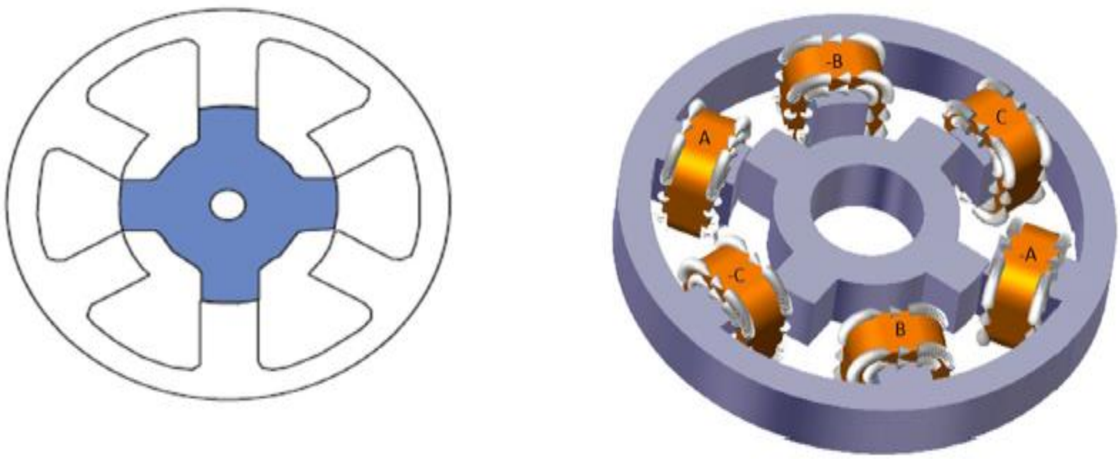


Figure 2.2 6/4 Switched reluctance motor configuration

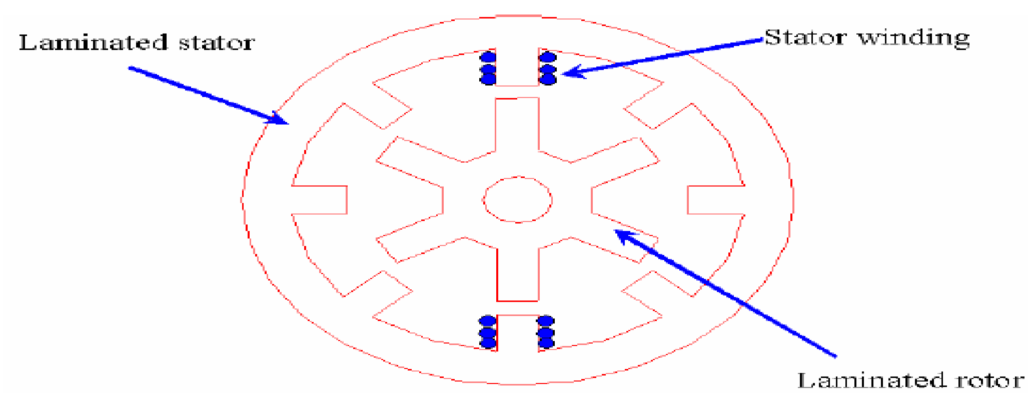


Figure 2.3 A cross section of a four phase, 8/6 SRM

2.4 Principle of operation of the multi-layer switched reluctance motor

Consider that the rotor poles $r_1$and $r_1{}'$ and stator poles c and c' are aligned. Apply a current to phase a with the current direction as shown in Figure 2.4a. A flux is established through stator poles a and a' and rotor poles r_2 and $r_2{}'$ which tends to pull the rotor poles r_2 and $r_2{}'$ toward the stator poles a and a' respectively. When they are aligned, the stator current of phase a is turned off and the corresponding situation is shown in Figure 2.4b. Now the stator winding b is excited, pulling r_1 and r_1' toward b and b' in a clockwise direction. Likewise energization of the c phase winding results in the alignment of r_2 and $r_2{}'$ with c and c' respectively. Hence, it takes three phase energizations in sequence to move the rotor by 90^0 and one revolution of rotor movement is affected by switching currents in each phase as many times as there are number of rotor poles. The switching of currents in the sequence abc results in the reversal of rotor rotation is seen with the aid of figures 2.4a and b [13] [14].

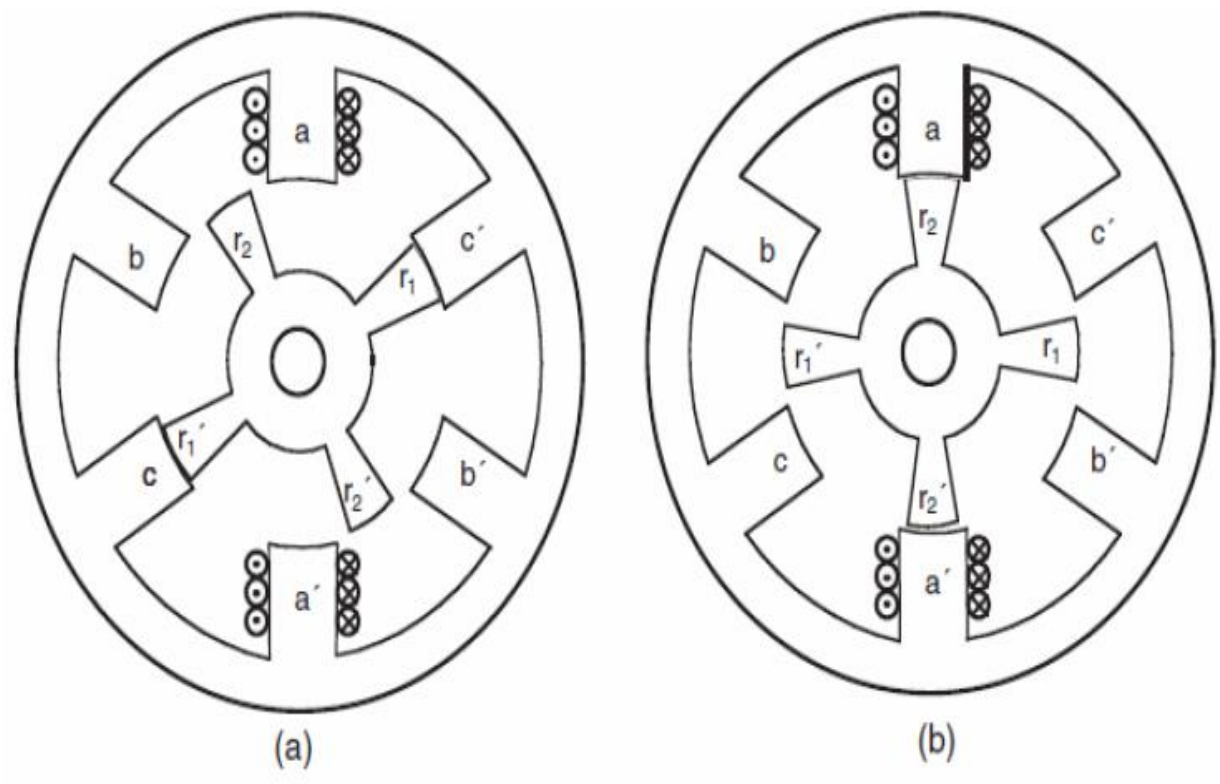


Figure 2.4 Operation of switched reluctance motor. (a) Phase c aligned. (b) Phase a aligned

An electromagnetic system in order to form stable equilibrium position gives rise to minimum magnetic reluctance is the main principle of operation of switched reluctance motor. When the two diametrically opposite poles are excited, the nearest rotor poles are attracted towards each other, in order to produce torque. When the two rotor poles get aligned with the stator pole then it gets deenergize and the adjacent stator pole gets energizes to attract another pair of rotor poles. According to this principle switched reluctance motor is operated. When both the stator and rotor poles gets aligned with each other then that position is known as aligned position. The phase inductance during the aligned position reaches its maximum value known as L_a as the reluctance reaches its minimum value. The phase inductance decreases gradually as the rotor poles move away from its aligned position. When the rotor poles get completely unaligned or misaligned from stator poles then the phase inductance at that moment reaches its minimum value known as L_u. Reluctance in this case reaches its maximum value [14].

The torque production in the switched reluctance motor is explained using the elementary principle of electromechanical energy conversion in a solenoid, as shown in figure 2.5a. The solenoid has N turns, and when it is excited with a current i the coil sets up a flux φ. Increasing the excitation current will make the armature move towards the yoke, which is fixed. The flux vs magnetomotive force (mmf) is plotted for two values of air gap, x_1 and x_2, where $x_1 > x_2$ and is shown in figure 2.5b. The flux vs. mmf characteristics for x_1 are linear because the reluctance of the air gap is dominant, making the flux smaller in the magnetic circuit. The electrical input energy is written as [15]:

$$W_e = \int ei\, dt = \int i\, dt \frac{dN\varphi}{dt} = \int Ni\, d\varphi = \int F d\varphi \qquad (2.5)$$

Where e is the induced emf and F is the mmf. This input electrical energy, W_e is equal to the sum of energy stored in the coil, W_f, and energy converted into mechanical work, W_m . It is written as:

$$W_e = W_f + W_m \qquad (2.6)$$

When no mechanical work is done, as in the case of the armature starting from position x_1, the stored field energy is equal to the input electrical energy given by equation (2.6). This corresponds to area OBEO in figure 2.6b. The complement of the field energy, termed co-energy, is given by area OBAO in figure 2.6b and mathematically expressed as $\int \varphi dF$. Similarly, for the position x_2 of the armature, the field energy corresponds to area OCDO and the co energy is given by area OCAO. For incremental changes, equation (2.6) is written as:

$$\delta W_e = \delta W_f + \delta W_m \qquad (2.7)$$

For a constant excitation of F_1 given by the operating point A in figure 2.6b, the various energies are derived as:

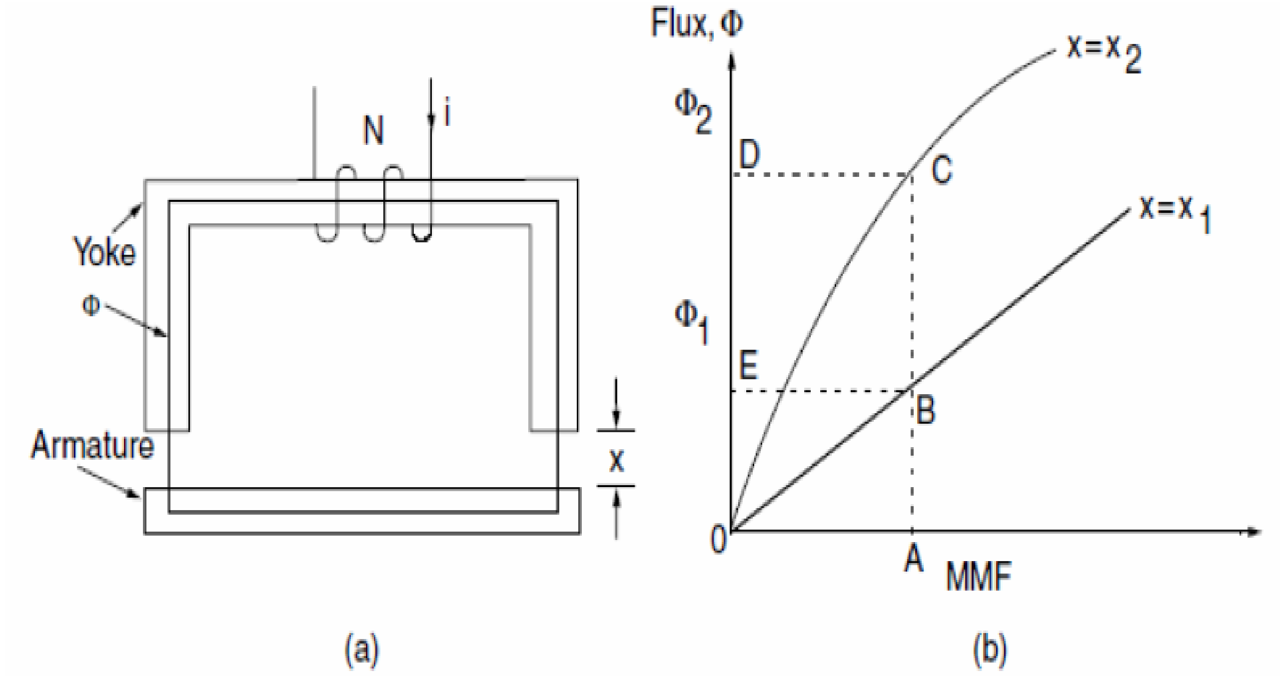


Figure 2.5 Electromagnetic energy convertion in a solenoid and its characteristics. (a) A solenoid. (b) Flux v. mmf characteristics.

For a constant excitation of F_1 given by the operating point A in figure 2.6b, the various energies are derived as:

$$\delta W_e = \int_{\varphi_1}^{\varphi_2} F_1 d\varphi = F_1(\varphi_2 - \varphi_1) = area(BCDEB) \quad (2.8)$$

$$\delta W_f = \delta W_{f at\, x=x_2} - \delta w_{f\ at\ x=x_2} = area(OCDO) - area(OBEO) \quad (2.9)$$

Using Eqs. (2.7) to (2.9), the incremental mechanical energy is derived as:

$$\delta W_m = \delta W_e - \delta W_f = area(OBCO) \quad (2.10)$$

and that is the area between the two curves for a given magneto motive force. In the case of a rotating machine, the incremental mechanical energy in terms of the electromagnetic torque and change in rotor position is written as:

$$\delta W_m = T_e \delta\theta \quad (2.11)$$

Where T_e is the electromagnetic torque and $\delta\theta$ is the incremental rotor angle. Hence, the electromagnetic torque is given by:

$$T_e = \frac{\delta W_m}{\delta\theta} \quad (2.12)$$

For the case of constant excitation (i.e., when the mmf is constant), the incremental mechanical work done is equal to the rate of change of co energy, W_f which is nothing but the complement of the field energy. Hence, the incremental mechanical work done is written as:

$$\delta W_m = \delta W_f' \tag{2.13}$$

Where

$$W_f' = \int \varphi dF = \int \varphi d\,(Ni) = \int (N\varphi) di = \int \lambda(\theta, i)\, di = \int L(\theta, i) i di \tag{2.14}$$

Where the inductance L and flux linkages λ are functions of the rotor position and current. This change in co-energy occurs between two rotor positions, θ_2 and θ_1. Hence, the air gap torque in terms of the co-energy represented as a function of rotor position and current is:-

$$T_e = \frac{\delta W_m}{\delta \theta} = \frac{\delta W_f{}'}{\delta \theta} = \frac{\delta W_f'\,(i, \theta)}{\delta \theta}\ where\ i = constant \tag{2.15}$$

If the inductance is linearly varying with rotor position for a given current, which in general is not the case in practice, then the torque can be derived as:

$$T_e = \frac{dL(\theta,i)}{d\theta} \cdot \frac{i^2}{2} \tag{2.16}$$

Where

$$\frac{dL(\theta, i)}{d\theta} = \frac{L(\theta_2, i) - L(\theta_1, i)}{\theta_2 - \theta_1}\ where\ i = constant \tag{2.17}$$

and this differential inductance can be considered to be the torque constant expressed in $N.M/A^2$. It is important to emphasize at this juncture that this is not a constant and that it varies continuously. This has the implication that the switched reluctance motor will not have a steady-state equivalent circuit in the sense that the dc and ac motors have. The following are the implications of equation (2.15) [17] [18].

The torque is proportional to the square of the current; hence the current can be unipolar to produce unidirectional torque. Note that this is quite contrary to the case for ac machines. This unipolar current requirement has a distinct advantage in that only one power switch is required for control of current in a phase winding. Such a feature greatly reduces the number of power switches in the converter and thereby makes the drive economical. The torque constant is given by the slope of the inductance vs rotor position characteristic. It is understood that the inductance of a stator winding is a function of both the rotor position and current, thus making it nonlinear.

Because of its nonlinear nature, a simple equivalent circuit development for this motor is not possible [18].

Since the torque is proportional to the square of the current, this machine resembles a dc series motor. Hence, it has a good starting torque. A generating action is made possible with unipolar current due to its operation on the negative slope of the inductance profile. The direction of rotation can be reversed by changing the sequence of stator excitation, which is a simple operation.

2.5 Derivation of the relationship between inductance and rotor position non linear analysis

Since the torque characteristics are dependent on the relationship between flux linkages and rotor position as a function of current, it is worthwhile to conceptualize the control possibilities and limitations of this motor drive. For example, a typical phase inductance vs rotor position is shown in figure 2.6. for a fixed phase current. The inductance corresponds to that of a stator-phase coil of the switched reluctance motor neglecting the fringe effect and saturation. The significant inductance profile changes are determined in terms of the stator and rotor pole arcs and number of rotor poles. The rotor pole arc is assumed to be greater than the stator pole arc for this illustration, which is usually the case. From figures 2.6a and b, the various angles are derived as [16-17]:

$$\theta_1 = \frac{1}{2}\left[\frac{2\pi}{P_r} - (\beta_s + \beta_r)\right] \qquad (2.18a)$$

$$\theta_2 = \theta_1 + \beta_s \qquad (2.18b)$$

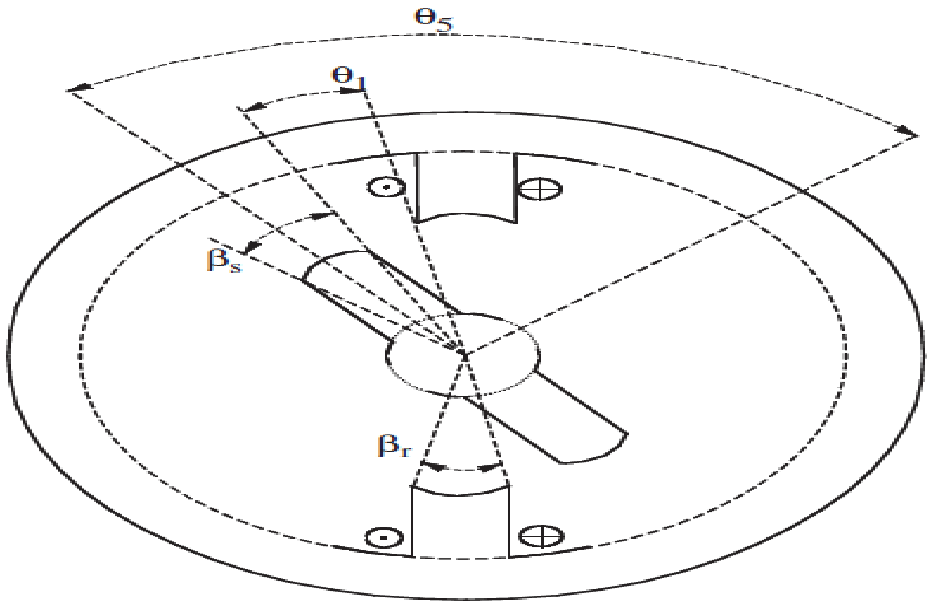
$$\theta_3 = \theta_2 + (\beta_r - \beta_s) \qquad (2.18C)$$

$$\theta_4 = \theta_3 + \beta_s \qquad (2.18d)$$

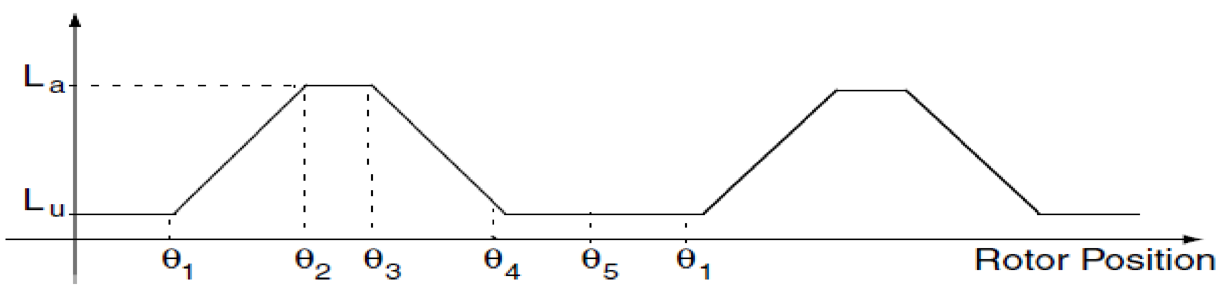
$$\theta_5 = \theta_4 + \theta_1 = \frac{2\pi}{P_r} \qquad (2.18e)$$

Where β_s and β_r are stator and rotor pole arcs, respectively, and P_r is the number of rotor poles. Four distinct inductance regions emerge:

From 0 to θ_1 and θ_4 to θ_5: The stator and rotor poles are not overlapping in this region and the flux is predominantly determined by the air path, thus making the inductance minimum and almost a constant. Hence, these regions do not contribute to torque production. The inductance in this region is known as unaligned inductance, L_u[16] [18].



(a)



(b)

Figure 2.6 Derivation of inductance vs rotor position from rotor and stator pole arcs for an unsaturated switched reluctance machine

From θ_1 to θ_2: Poles overlap, so the flux path is mainly through stator and rotor laminations. This increases the inductance with the rotor position, giving it a positive slope. A current impressed in the winding during this region produces a positive (i.e., motoring) torque. This region comes to an end when the overlap of poles is complete.

From θ_2 to θ_3: During this period, movement of rotor pole does not alter the complete overlap of the stator pole and does not change the dominant flux path. This has the effect of keeping the inductance maximum and constant, and this inductance is known as aligned inductance, L_a. As there is no change in the inductance in this region, torque generation is zero even when a current is present in this interval. In spite of this fact, it serves a useful function by providing time for the stator current to come to zero or lower levels when it is commutated, thus preventing negative torque generation for part of the time if the current has been decaying in the negative slope region of the inductance.

From $\theta_3 to\ \theta_4$: The rotor pole is moving away from overlapping the stator pole in this region. This is very much similar to the $\theta_1\ to \theta_2$ region, but it has decreasing inductance and increasing rotor position contributing to a negative slope of the inductance region. The operation of the machine in this region results in negative torque (i.e., generation of electrical energy from mechanical input to the switched reluctance machine). It is not possible to achieve the ideal inductance profiles shown in figure 2.6 in an actual motor due to saturation. Saturation causes the inductance profile to curve near the top and thus reduces the torque constant. Hence, saturating the machine beyond a point produces a diminishing return on torque and power output.

2.6 Magnetization curve

It represents the relationship between the flux-linkage and current of a certain phase at different rotor positions. The most two important points in these curves are the unaligned and the aligned positions. Figure 2.6 shows the magnetization curves of a SRM where each curve belongs to a certain value of rotor angle that vary between the unaligned (the lowest curve) to the aligned position (the highest curve) [18]. Due to saturation and varying reluctance with rotor position, there is no simple analytical solution to express the field which is produced by phase winding. Energy conversion approach that is presented in is used to analyze energy conversion. Flux linkage is a function of both rotor position and excitation current and also, it is nonlinear function. One of the most important parameter which affects on flux linkage is air gap.

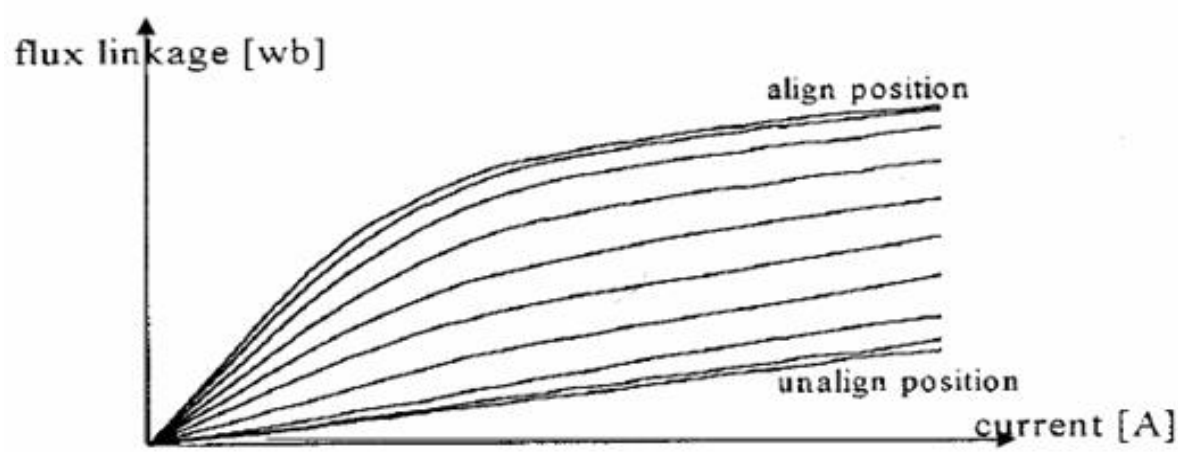


Figure 2.7 The magnetization curves of switched reluctance motor

Figure 2.7 shows the region of increasing inductance is marked by motoring where a positive torque is produced through this region and the region of decreasing inductance is marked by generating or braking where a negative torque is produced through this period.
In practical curves the corners are smoother than those shown in the figure due to the fringing effect which cannot be neglected as in the idealized curves [18], [19].

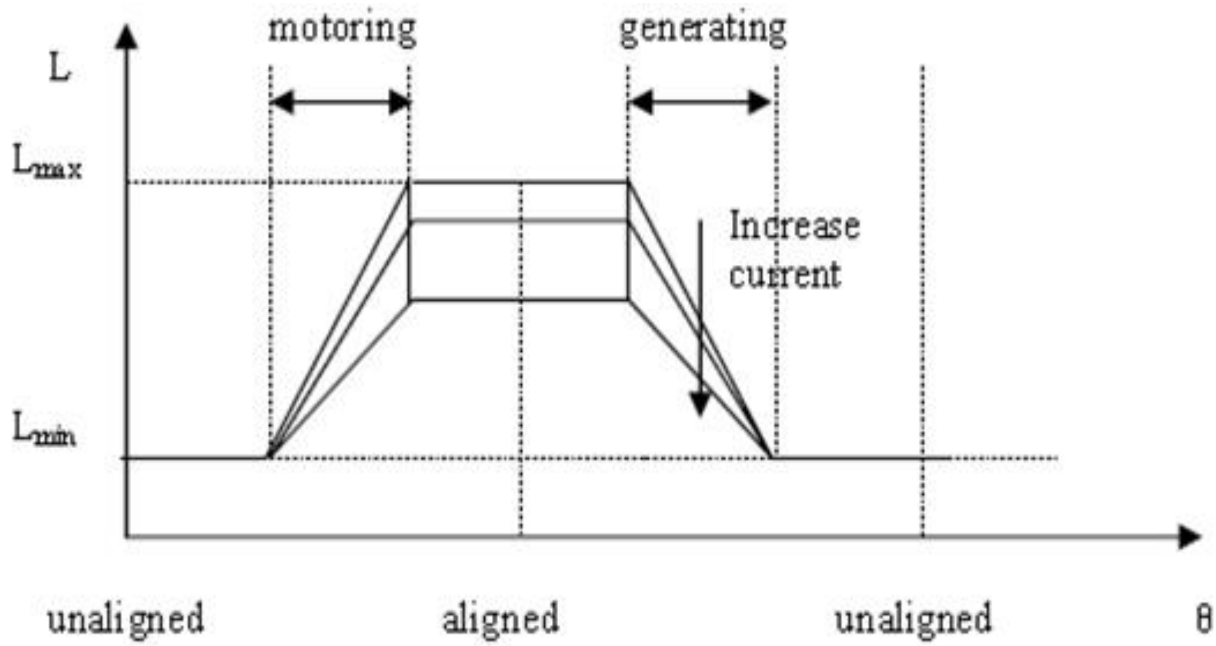


Figure 2.8 The motoring and generating curves of switched reluctance motor

The conduction period under idealized conditions (which is the difference between the on-angle and the off-angle of the phase) may exceed the step angle, this leads to an overlapping between phases (its length equal to the difference between the conduction angle and the step angle) which is desirable in small amount because it results in minimizing the torque ripple, but in large amount it imposes transient or vibratory stresses.

The overlapping between the phases is not the same for all motor constructions. For example, with 6/4 three phase SRM the step angle is 30 deg, the maximum conduction angle is 45 deg, and equal 1.5 times the step angle while the step angle with 8/6 four phase SRM is 15 deg , the maximum conduction angle is 30 deg which is 2.0 times the step angle.

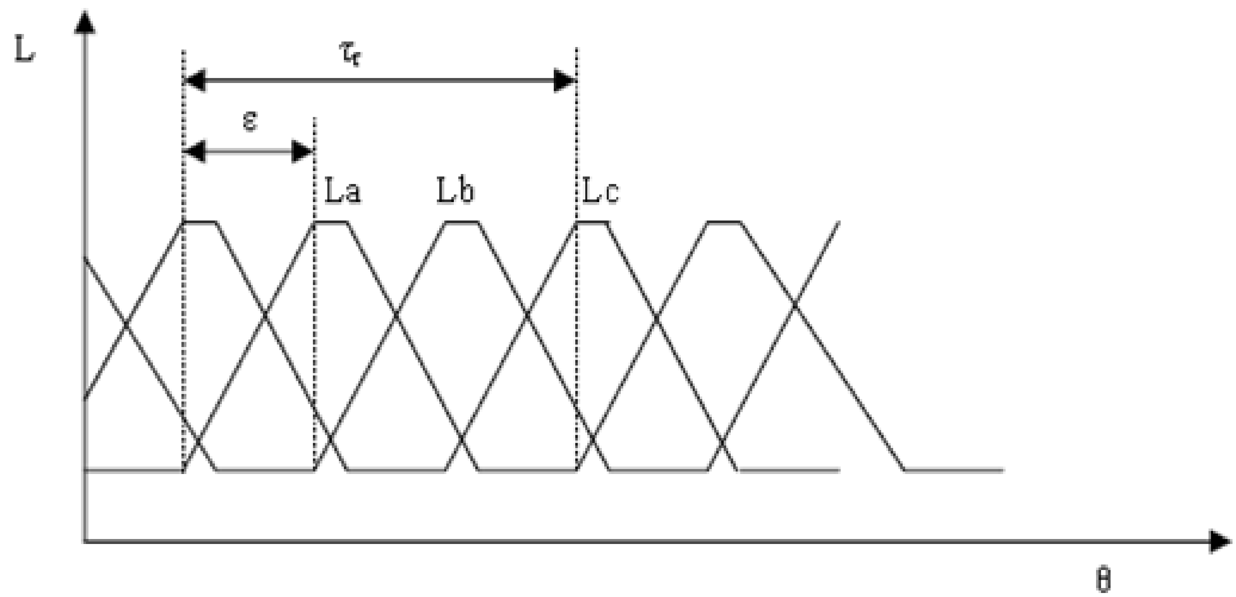


Figure 2.9 The inductance of three phases 6/4 Switched reluctance motor

Figure 2.8 shows the inductance of a three phase SRM. It can be noted from this figure that it is required for producing torque at all positions that the entire 360 degrees must be covered by segments of rising inductance for different phases and the phase currents must be commutated and sequenced to coincide with the appropriate segments [20] [21].

2.7 Static torque curves

These curves represent the phase torque values as a function of rotor angle at different values of current. It computed by integrating the magnetization curves to obtain the co-energy curves as a function of rotor angle at different values of current [20].

$$W = \int_0^i \Psi di \tag{2.19}$$

These curves are differentiated relative to the rotor angle at fixed values of current to get finally the static torque curves which have the form shown in figure 2.9 and also to determine the rating of machine power.Where T is the torque produced by one phase.

$$T(\theta, i) = \left(\frac{\partial W}{\partial \theta}\right) \; where \; i = constant \tag{2.20}$$

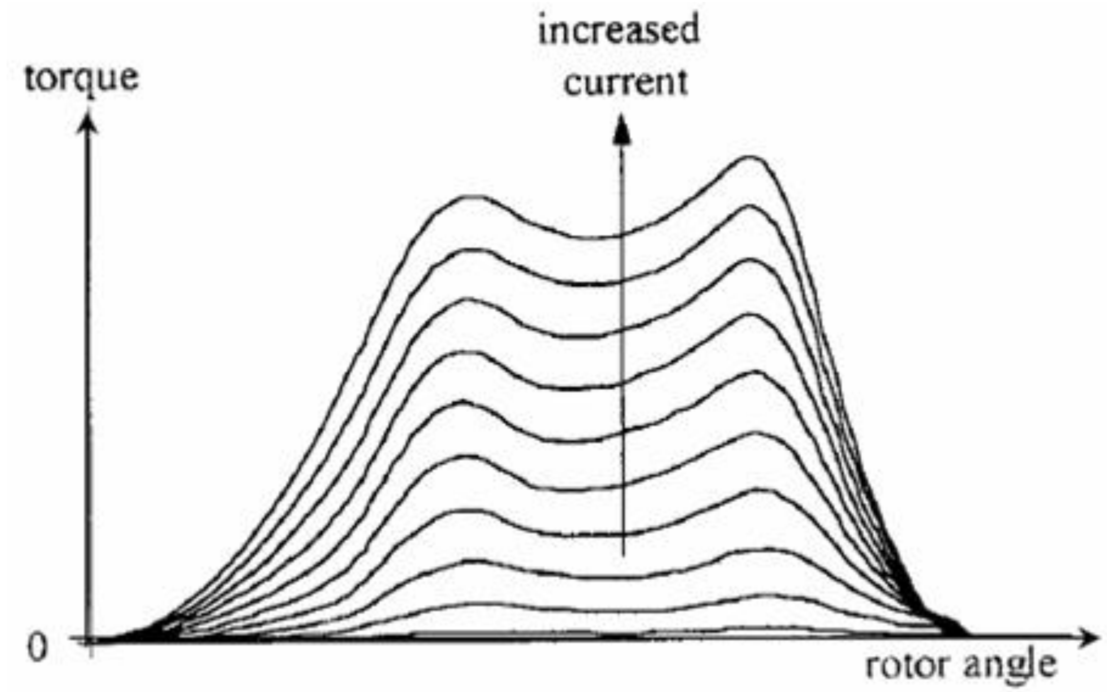


Figure 2.10 The static torque curves of switched reluctance motor

The importance of these curves comes from that they imply all the possible capabilities of torque/phase produced on the motor shaft at any value of rotor angle and current [21].

2.8 Multi-layer switched reluctance motor drive system

The SRM is fed from DC supply, which transverse the motor phases via the converter; so the delivered energy given to each motor phase has a nature of pulse. For ideal operation of switched reluctance drives, where the produced torque is constant with no torque ripple or speed vibration, the current pulses should have a rectangular waveform [22].

It must coincide with the rising inductance part of the inductance waveform for motoring operation, but for generation or braking operation it must coincide with the falling inductance part of this waveform. For these two cases of operation the current must be switched on and off in synchronism with the rotor position corresponding to rising and falling inductance. The supply should be distributed equally among phases taking in account that each current pulse has a period length equal to the step angle. This idealized case is not a practical form of operation, because the phase current is affected by the position of the on and off points, the circuit time constants, the operating speed and its effect on the switched reluctance drive behavior. Figure 2.10 shows the variations of the phase inductance and current profile.

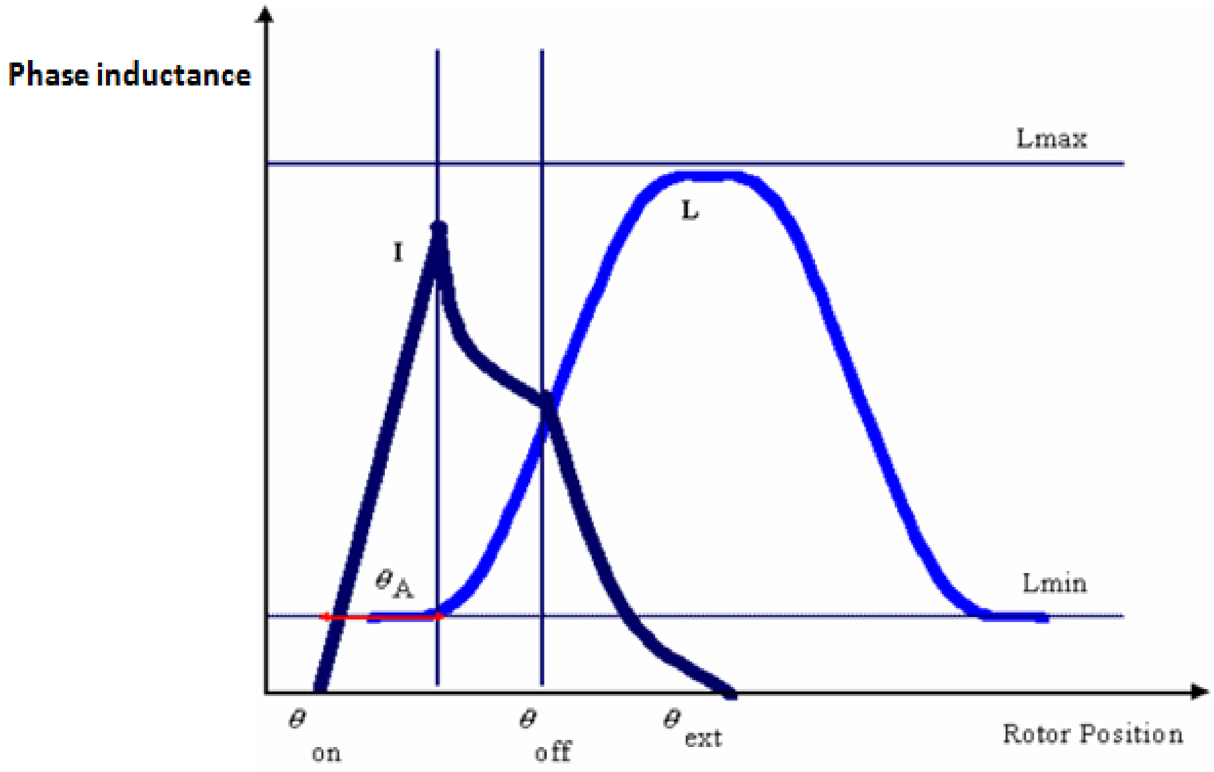


Figure 2.11 The variation of phase inductance and current profile

θ_{on} = Switching on angle (its values starts from 30 degrees)

θ_{adv} = Advanced angle (its values starts from 45 degrees)

θ_{off} = Switching off angle (its values starts from 90 degrees)

θ_{ext} = Extinction angle (its values 120 degrees)

The terminal voltage equation for one phase could be written in the form:

$$V = iR + \frac{d\Psi}{dt} \tag{2.21}$$

Where $$\Psi = N\phi = LI \ and \ \ \Psi = L(\theta) \tag{2.22}$$

Since the flux Ψ is a function of both current i and rotor angle θ

$$\Psi = \Psi(i, \theta)$$

$$V = iR + \frac{d\Psi}{d\theta}\frac{d\theta}{dt} + \frac{d\Psi}{di}\frac{di}{dt} \tag{2.23}$$

$$V = iR + \omega i\frac{dL}{d\theta} + L\frac{di}{dt} \tag{2.24}$$

$$V = iR + e + L\frac{di}{dt} \tag{2.25}$$

Where L is the incremental inductance (the slope of the magnetization curve), and e is the back emf. (it depends on the angular rotor speed ω). At high speed the back emf value is high, and in turn it limits the phase current from reaching undesirable values. At low speeds the back emf is low and the current may exceed the maximum allowed values.

A typical SRM drive system is shown in figure 2.11. It is made up of four basic components: power converter, control logic circuit, position sensor and the switched reluctance motor [23].

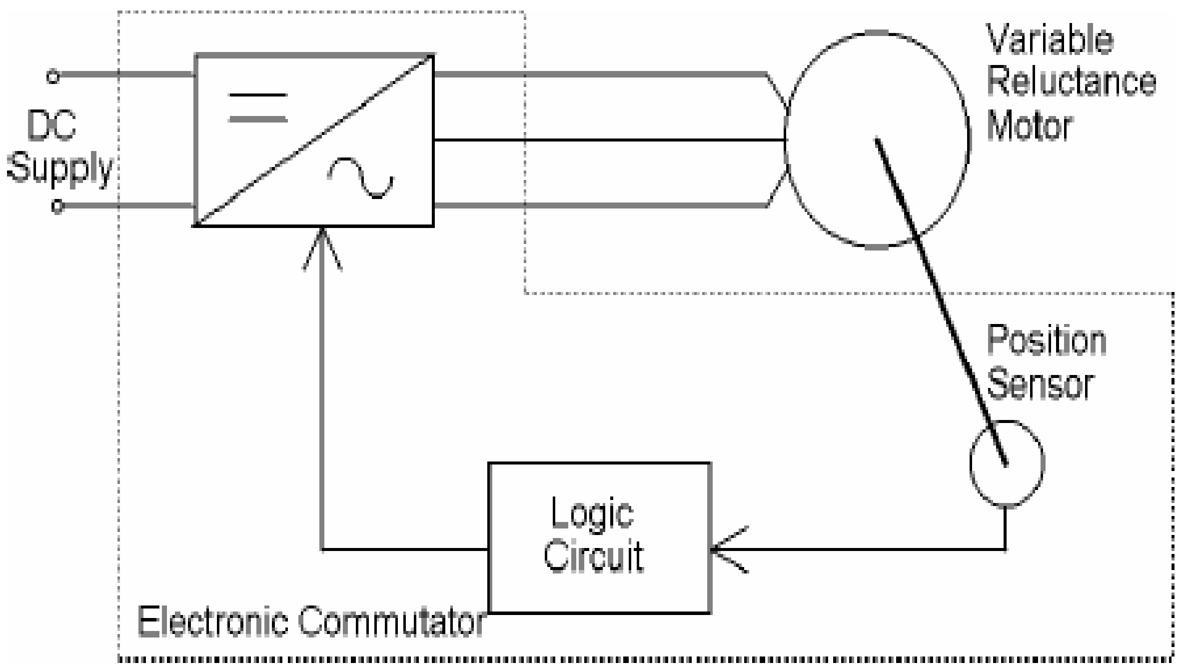


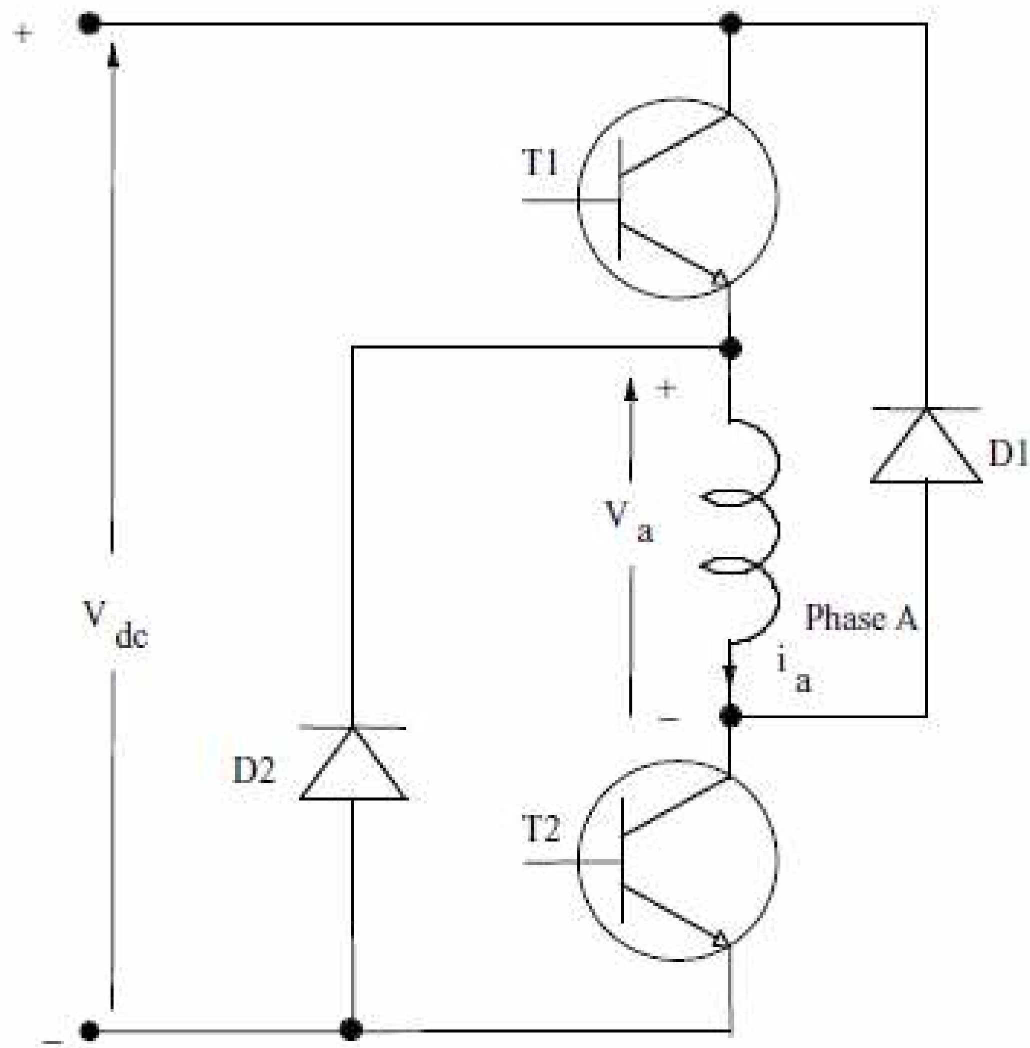
Figure 2.12 Typical switched reluctance drive system

2.9 Power converters for multi-layer switched reluctance motor drives

In order to achieve the smooth rotation and optimal torque output the phase to phase switching in the switched reluctance motor drive is required with respect to rotor position. The phase to phase switching logic can only be realized by using the semi converter device. We can also say that the power semi converter device topology put a great impact on switched reluctance motor's performance. As the torque produced in the switched reluctance motor drive is independent of the excitation current polarity. So, it requires only one switch per phase winding. Where as for other ac machine it requires two switches per phase in order to control the current. For ac motor the winding is also not present in series with the switches, which gives rise to irreparable damage in shoot through fault. But in case of switched reluctance motor as the winding is present in series with the switch, so, during shoot-through fault the rate of rise in current can be limited or reduced by using winding inductance and provides time to protective relay in order to isolate the faults. Switched reluctance motor drive is more reliable because in this case all the phases are independent of each other. Even though if some problem will occur to switched reluctance motor and one winding gets damaged then also switched reluctance motor can provide the uninterrupted operation with reduced power output [21] [23].

2.9.1 Asymmetric bridge converter

Figure 3.5a shows the asymmetric bridge converter considering only one phase of the SRM. The rest of the phases are similarly connected. Turning on transistors T1 and T2 will circulate a current in phase A of the SRM. If the current rises above the commanded value, T1 and T2 are turned off. The energy stored in the motor winding of phase A will keep the current in the same direction until it is depleted. Hence, diodes D1 and D2 will become forward biased leading to recharging of the source. That will decrease the current, rapidly bringing it below the commanded value. This operation is explained with the waveforms of figure 2.13b. Assuming that a current of magnitude I_p is desired during the positive inductance slope for motoring action, the A phase current command is generated with a linear inductance profile. Here, phase advancing both at the beginning and during commutation are neglected. The current command $i_a{}'$ is enforced with a current feedback loop where it is compared with the phase current, i_a. The current error is presumed to be processed through a hysteresis controller with a current window of Δi. When the current error exceeds $-\Delta i$, the switchesT1 and T2 are turned off simultaneously.
Hysteresis current controller is considered here due to its simplicity in concept and implementation. At that time, diodes, D1 and D2 take over the current and complete the path through the dc source [1] [4].



(a)

Note that the voltage of phase A is then negative and will equal the source voltage, V_{dc}. During this interval, the energy stored in the machine inductance is sent to the source, thus exchanging energy between the load and source repeatedly in one cycle of a phase current. After the initial startup, during turn-on and turn-off of T1 and T2, the machine phase winding experiences twice the rate of change of dc link voltage, resulting in a higher deterioration of the insulation. This control strategy (strategy I) hence puts more ripples into the dc link capacitor, thus reducing its life and also increasing the switching losses of the power switches due to frequent switching necessitated by energy exchange. These can be ameliorated with an alternate switching strategy.

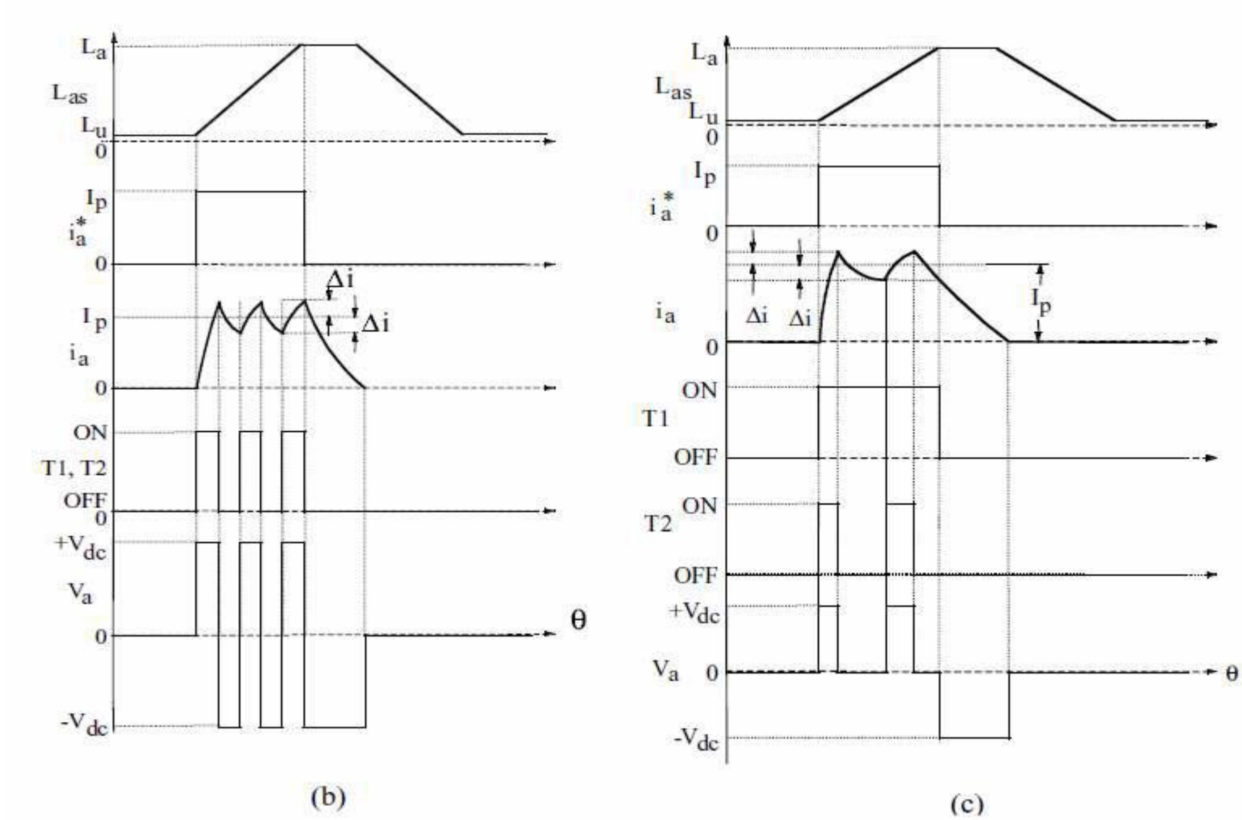


Figure 2.13 (a) Asymmetric converter for switched reluctance motor with freewheeling and regeneration capability (b) Operational waveforms of the asymmetric bridge converter using strategy I (c) Operational waveforms of the asymmetric bridge converter using strategy II

The energy stored in the phase A can be effectively circulated in itself by turning off, say, T2 only (strategy II). In that case, the current will continue to flow through T1, phase A, and D1, the latter having forward biased soon after T2 is turned off. The voltage across the winding becomes zero if the diode and transistor voltage drops are neglected. That will take the phase current from $I_P + \Delta I$ to $I_P - \Delta i$ in a time greater than had it been forced against the source voltage using the previous strategy. This particular fact reduces the switching frequency and hence the switching losses. When the current command goes to zero, both T1 and T2 are turned off simultaneously. During this interval, the voltage across the winding is −Vdc as long as D1 and D2 conduct (i.e., until i_a goes to zero) and thereafter the winding voltage is zero. The voltage across T2 during its off time and when T1 is on is equal to the source voltage, Vdc. Hence, the power switches and diodes have to be rated to a minimum of source voltage at least. The current ratings of the switches are equal to or less than $I_p/\sqrt{q}$ by interchanging the off times between T1 and T2 in one cycle of phase conduction. Similarly, the current rating of the diodes can be evaluated. While such a self circulation will keep the current going for a longer time compared to recharging the source voltage, it has the advantage of converting the stored energy to useful mechanical work. While this form of control can be used for current control, the recharging of the source is advantageous when the current has to be turned off rapidly. Such an instance arises when the inductance profile becomes flat or is starting to have a negative slope. Any further conduction of current in such regions entails a loss of energy or production of negative torque, thus reducing the average motoring torque. Note that this converter requires two transistors and two diodes for each phase, resembling the conventional ac motor drives [16] [19].

2.10 Characteristic of switched reluctance motor

The SRM is an electric machine that converts the reluctance torque into mechanical power. In the SRM, both the stator and rotor have a structure of salient-pole, which contributes to produce a high output torque. The torque is produced by the alignment tendency of poles. The rotor will shift to a position where reluctance is to be minimized and thus the inductance of the excited winding is maximized [17]. The SRM has a doubly salient structure, but there are no windings or permanent magnets on the rotor [19]. The rotor is basically a piece of steel (and laminations) shaped to form salient poles. So it is the only motor type with salient poles in both the rotor and stator. As a result of its inherent simplicity, the SRM promises a reliable and a low-cost variable-speed drive and will undoubtedly take the place of many drives now using the cage induction, PM and DC machines in the short future. The number of poles on the SRM’s stator is usually unequal to the number of the rotor to avoid the possibility of the rotor being in a state where it cannot produce initial torque, which occurs when all the rotor poles are aligned with the stator poles. Figure 2.14 shows a 8/6 SRM with one phase asymmetric inverter. This four phase SRM has 8 stator and 6 rotor poles, each phase comprises two coils wound on opposite poles and connected in series or parallel consisting of a number of electrically separated circuit or phases. These phase windings can be excited separately or together depending on the control scheme or converter. Due to the simple motor construction, an SRM requires a simple converter and it is simple to control [19] [20].

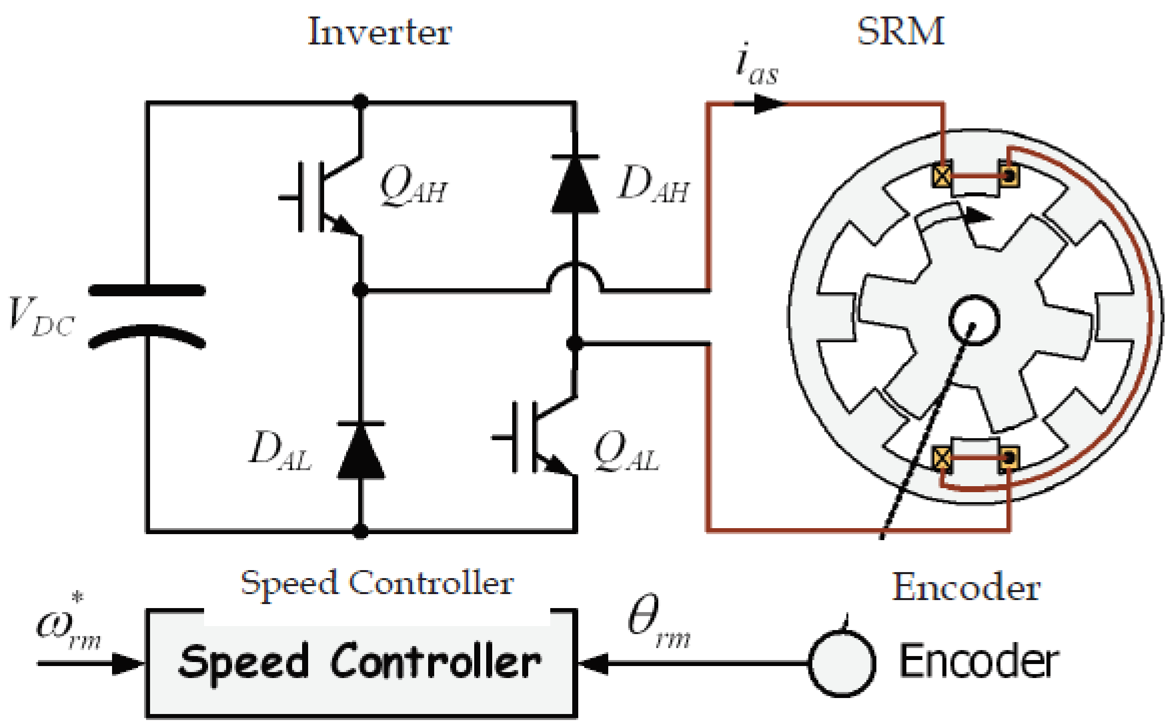


Figure 2.14 Switched reluctance motor with one phase asymmetric inverter

The aligned position of a phase is defined to be the situation when the stator and rotor poles of the phase are perfectly aligned with each other $(\theta_1 - \theta_2)$, attaining the minimum reluctance position and at this position phase inductance is maximum (L_a).

The phase inductance decreases gradually as the rotor poles move away from the aligned position in either direction. When the rotor poles are symmetrically misaligned with the stator poles of a phase $(\theta_3 - \theta_s)$, the position is said to be the unaligned position and at this position the phase has minimum inductance (L_u). Although the concept of inductance is not valid for a highly saturated machine like SR motor, the unsaturated aligned and unaligned incremental inductances are the two key reference positions for the controller.

The relationship between inductance and torque production according to rotor position is shown in figure 2.14. There are some advantages of an SRM compared with the other motor type. The SRM has a low rotor inertia and high torque/inertia ratio, the winding losses only appear in the stator because there is no winding in the rotor side. SRM has rigid structure and absence of permanent magnets and rotor windings and SRM can be used in extremely high speed application and the maximum permissible rotor temperature is high, since there are no permanent magnets and rotor windings [21].

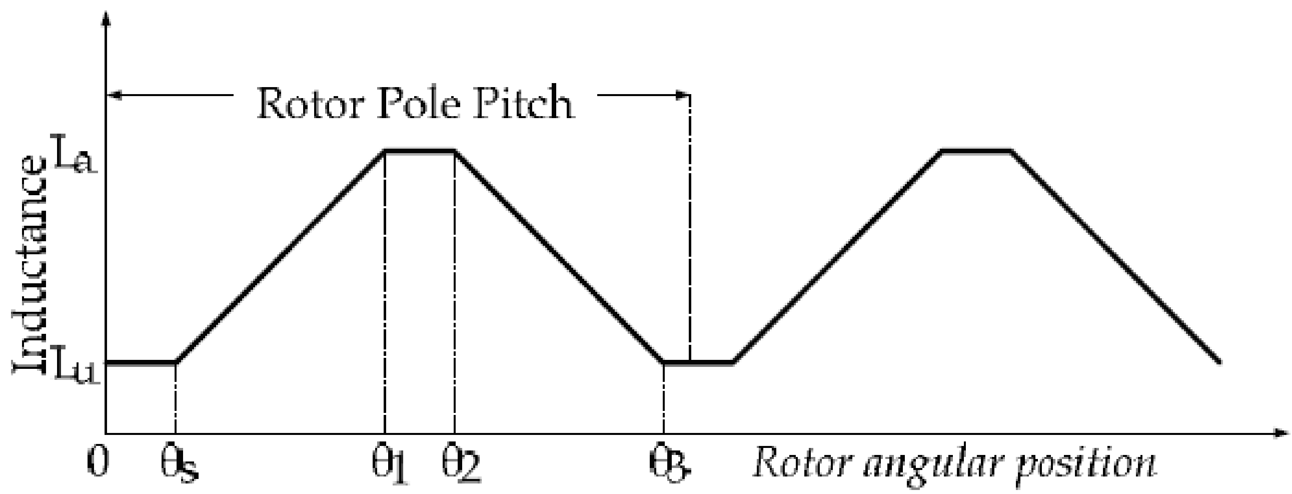
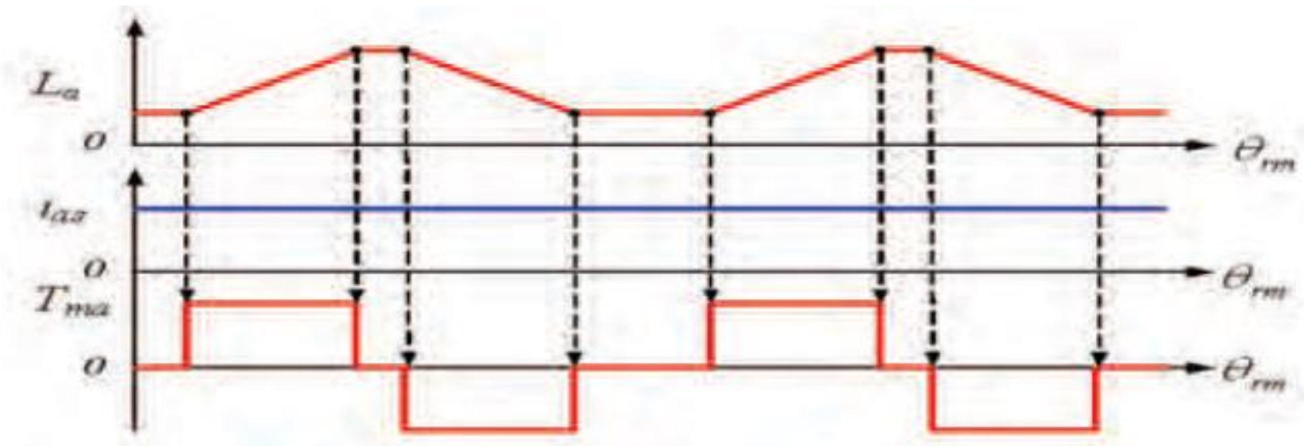


Figure 2.15a Inductance in switched reluctance motor

Constructions of SRM with no magnets or windings on the rotor also bring some disadvantage in SRM. Since there is only a single excitation source and because of magnetic saturation, the power density of reluctance motor is lower than PM motor. The construction of SRM is shown in figure 2.16. Switched reluctance motor has two different construction, singly salient construction and doubly salient construction. Stator and rotor magnetic circuits are laminated to reduce the core losses in both type of switched reluctance motor. A singly salient construction of SRM comprises of a non-salient stator and a salient two pole rotor. The rotor does not have any winding wound over it but the stator have two phase winding. The inductance is minimum when the rotor axis and stator phase winding axis coincides whereas it is maximum when both the axis are in quadrature. Unlike singly salient type, the stator of doubly salient switched reluctance motor is of salient construction and consists of four poles. The rotor do not carry any winding and is of salient construction but have two poles. Thus this type of SRM is a hetropolar motor where the numbers of stator and rotor poles are not same. A doubly salient type switched reluctance motor or variable reluctance motor produces more torque as compared to singly salient type for the same size. Therefore a doubly SRM is more common and widely used [8] [9].

The aligned position of a phase is defined to be the situation when the stator and rotor poles of the phase are perfectly aligned with each other , attaining the minimum reluctance position and at this position phase inductance is maximum . The phase inductance decreases gradually as the rotor poles move away from the aligned position in either direction. When the rotor poles are symmetrically misaligned with the stator poles of a phase, the position is said to be the unaligned position and at this position the phase has minimum inductance. Although the concept of inductance is not valid for a highly saturated machine like SR motor, the unsaturated aligned and unaligned incremental inductances are the two key reference positions for the controller. The relationship between inductance and torque production according to rotor position is shown in figure 2.15b.



(b)

Figure 2.15b Torque and inductance in switched reluctance motor

The dependence on magnetic saturation for torque production, coupled with the effects of fringing fields, and the classical fundamental square wave excitation result in nonlinear control characteristics for the reluctance motor. The double saliency construction and the discrete nature of torque production by the independent phases lead to higher torque ripple compared with other machines. The higher torque ripple, and the need to recover some energy from the magnetic flux, also cause the ripple current in the DC supply to be quite large, necessitating a large filter capacitor. The doubly salient structure of the SRM also causes higher acoustic noise compared with other machines. The main source of acoustic noise is the radial magnetic force induced. So higher torque ripple and acoustic noise are the most critical disadvantages of the SRM. The absence of permanent magnets imposes the burden of excitation on the stator windings and converter, which increases the converter KVA requirement. Compared with PM brushless machines, the per unit stator copper losses will be higher, reducing the efficiency and torque per ampere. However, the maximum speed at constant power is not limited by the fixed magnet flux as in the PM machine, and, hence, an extended constant power region of operation is possible in SRM [18].

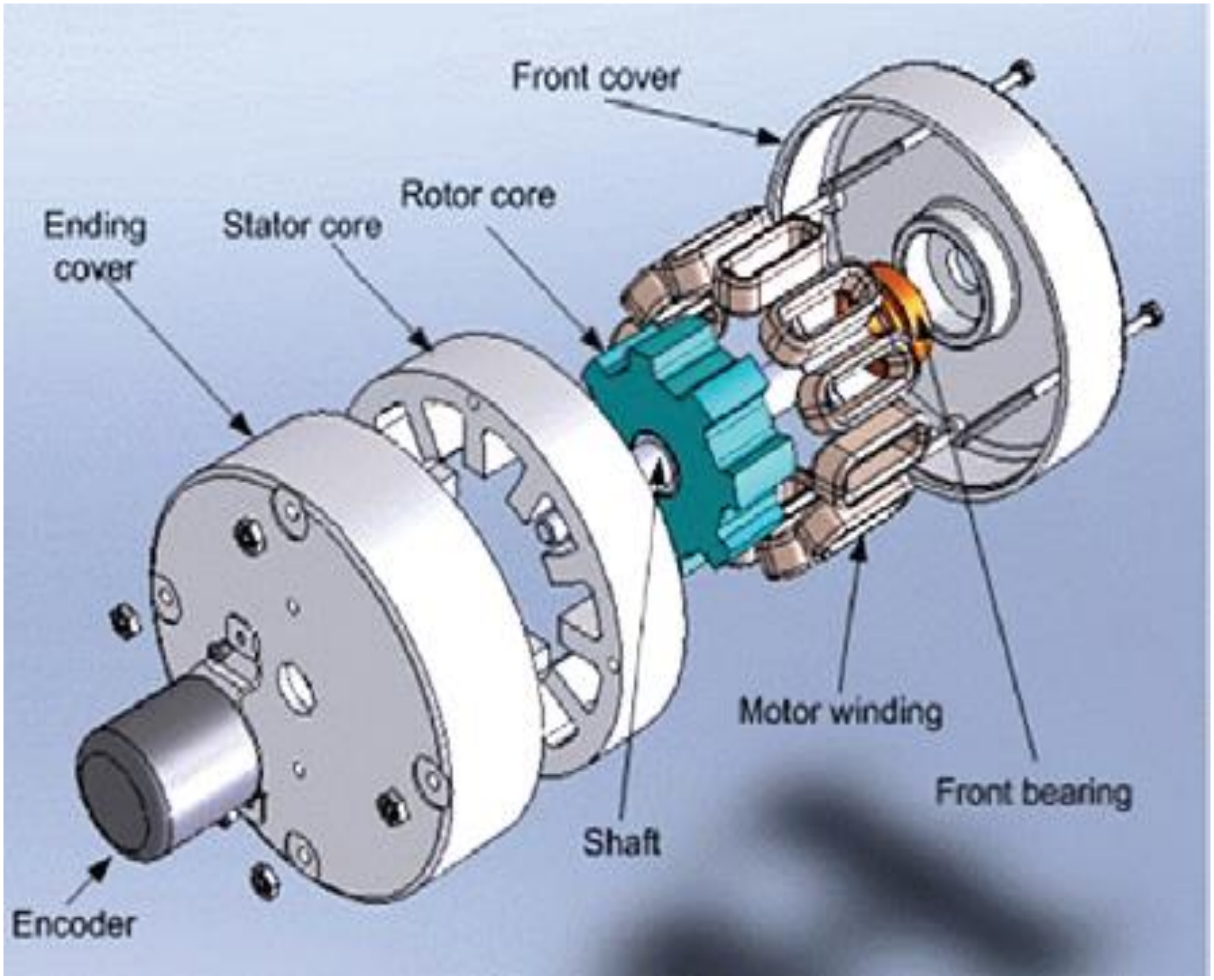


Figure 2.16 The construction of switched reluctance motor

2.11Torque speed characteristics of switched reluctance motor

The torque speed characteristics of an SRM are shown in figure 2.17. Based on different speed ranges, the motor torque generation has been divided into three different regions: constant torque, constant power and falling power region [24].

In the low-speed region of operation, the current rises almost instantaneously after turn-on, since the back-emf is small. The current can be set at any desired level by means of regulators, such as hysteresis controller or voltage PWM controller. As the motor speed increases, the back-emf soon becomes comparable to the DC bus voltage and it is necessary to phase advance-the turn-on angle so that the current can rise up to the desired level against a lower back-emf.. The phase excitation pulses are also needed to be turned off a certain time before the rotor passes alignment to allow the freewheeling current to decay so that no braking torque is produced.

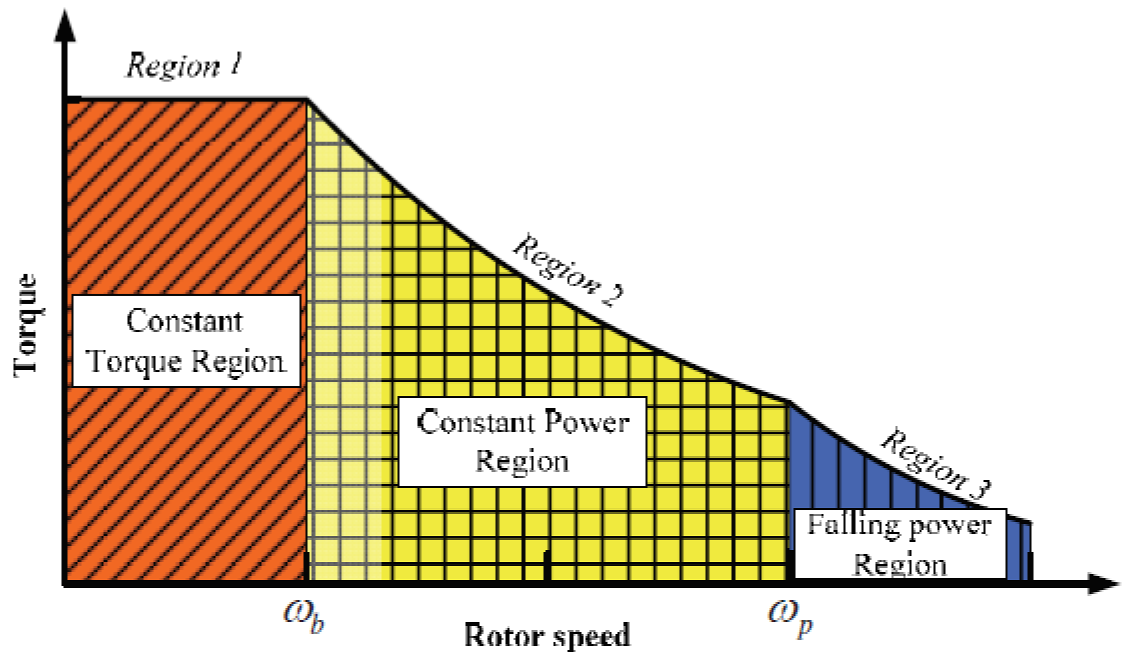


Figure 2.17 Torque speed characteristics of switched reluctance motor

The natural characteristic of the SRM, when operated with fixed supply voltage and fixed conduction angle θ_{dwell}(also known as the dwell angle), is that the phase excitation time falls off inversely with speed and so does the current. Since the torque is roughly proportional to the square of the current, the natural torque–speed characteristic can be defined by $T \alpha 1/\omega^2$. Increasing the conduction angle can increase the effective amps delivered to the phase. The torque production is maintained at a level high enough in this region by adjusting the conduction angle θ_{dwell} with the single-pulse mode of operation. The controller maintains the torque inversely proportional to the speed; hence, this region is called the constant power region. The conduction angle is increased by advancing the turn-on angle until the θ_{dwell} reaches its upper limit at speed ω_p. The medium speed range through which constant power operation can be maintained is quite wide and very high maximum speeds can be achieved [19] [20].

The θ_{dwell} upper limit is reached when it occupies half the rotor pole-pitch, i.e., half the electrical cycle. θ_{dwell} can not be increased further because otherwise the flux would not return to zero and the current conduction would become continuous. The torque in this region is governed by the natural characteristics, falling off as $1/\omega^2$. The torque speed characteristics of the SRM are similar to those of a DC series motor.

2.12 Mathematical modeling of multi-layer switched reluctance motor

The equivalent circuit for multi-layer switched reluctance motor can be consisting of resistance and inductance with some condition. The effects of magnetic saturation, fringing flux around the pole corners, leakage flux, and the mutual coupling of phases are not considered. The linear analytical model of the SRM can be described by three differential equations, which can as the voltage equation, the motional equation and the electromagnetic torque equation. The voltage equation is:

$$V = R.i + \frac{d\lambda(\theta, i)}{dt} \tag{2.26}$$

An equivalent circuit of the SRM is shown in figure 2.18. where V is the applied phase voltage to phase, R is the phase resistance, and e is back-emf. Ordinarily, e is the function of phase current and rotor position, and λ can be expressed as the product of inductance and winding current:

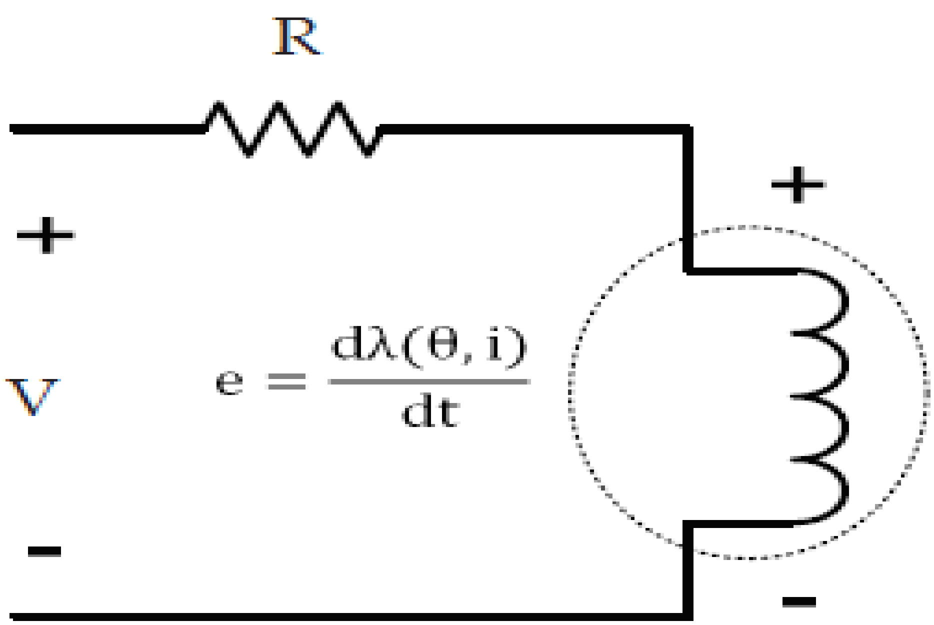


Figure 2.18 Equivalent circuit of multi-layer switched reluctance motor

From the above equivalent circuit the electromagnetic torque is given by:

$$T_e = \frac{1}{2} i^2 \frac{dL(\theta, i)}{d\theta} \tag{2.27}$$

The equations which have been mentioned above, can be combined together to build the simulation model for a SRM system. However, the function of inductance needs to be obtained by using a finite element method or by doing experiments with a prototype motor.

So, equation 2.27 shows that the electromagnetic torque is independent of current direction as T_e is directly proportional to i^2 . So, whatever may be the current value positive or negative the torque it will produce the unidirectional torque. But T_e is directly proportional to $\frac{dL(\theta,i)}{d\theta}$ So, if $\frac{dL(\theta,i)}{d\theta} > 0$ then, it will produce positive torque and electrical power is converted into mechanical power output (motoring) and if $\frac{dL(\theta,i)}{d\theta} < 0$ then, it will produce the negative torque and mechanical power is converted into electrical power (generating).This completes the development of the equivalent circuit and equation for evaluating electromagnetic torque and input power to the switched reluctance motor for both dynamic and steady state operation [1].

2.13 Description of multi-layer switched reluctance motor

Multi-layer switched reluctance motors offers a number of advantages including simplicity in construction, cooling, geometric versatility, durability, and higher permissible rotor temperature. In general, there are four distinct types of switched reluctance motors: namely, regular doubly salient cylindrical, disc-type, multi-layer, and linear motors [18]. This classification stems from the general shape of the motor means different types of switched reluctance motors with different geometries and then presents a new configuration for SR motor which is multi-layer switched reluctance motor [19].

The multi-layer switched reluctance motor structure consists of two magnetically isolated parts, and each part is known as a layer. The stator and rotor parts of each layer have six and four poles, respectively. So the MSRM is realized with the combination of a conventional 6/4 SRM with three phases. Each rotor part has a 15 angular shift in position from the next layer, while in the stator, the phases are on the same line. The three dimensional appearance of the proposed MSRM is illustrated in figure 2.19 [21].

The stator and the rotor poles are placed in two parts around the magnetic guide and the windings are stationary wrapped on the reels over the guide. When the stator poles are aligned with the rotor poles, the magnetic flux produced by the coils travels through the guide to the rotor and then to the stator poles and finally closes itself through the motor.

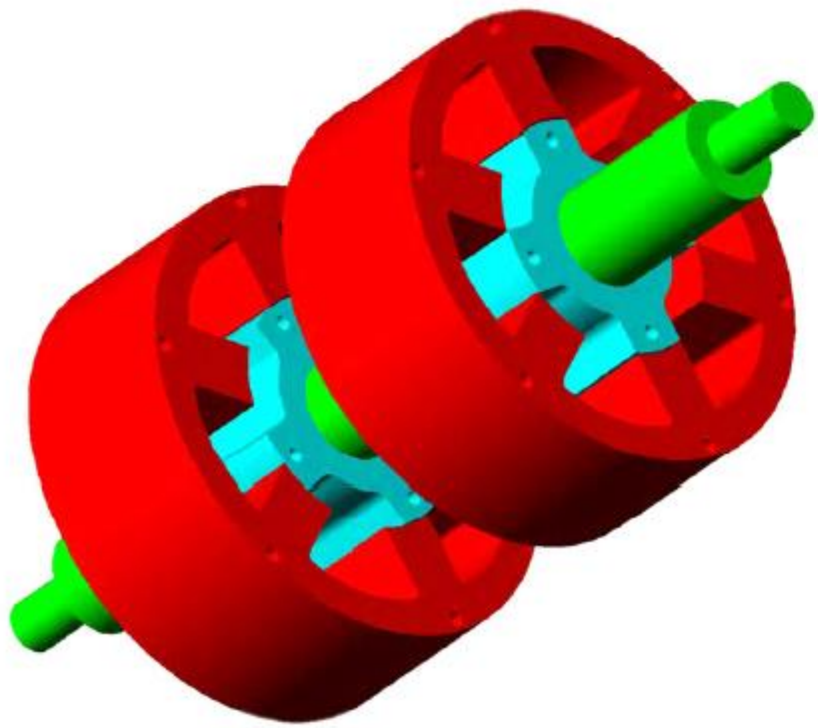


Figure 2.19 Multi-layer switched reluctance motor

To be able to compare performances between the classical SRM and the MSRM, the motors are designed in the same dimensions. All the laminated plates are produced using a standard press tool for fabrication of the motor. The mechanical and electrical parameters of each layer of the proposed MSRM are summarized in the appendix b. Each layer of the motor is energized individually or together with the other layer to obtain the maximum starting torque or reduce the torque ripple by using constructed control units according to the rotor position data.

2.14 Torque control strategy of multi-layer switched reluctance motor

The torque in multi-layer switched reluctance motor is generated toward the direction that the reluctance being to minimized. The magnitude of torque generated in each phase is proportional to the square of the phase current which controlled by the converter or drive circuit, and the torque control scheme. The drive circuit and torque control scheme directly affected to the performance and characteristic of the SRM. Many different topologies have emerged with a reduced number of power switch, faster excitation, faster demagnetization, high efficiency, high power factor and high power through continued research. Conventionally, there has always been a tradeoff between gaining some of the advantages and losing some with each new topology [10]. The torque is proportional to the square of current and the slope of inductance. Since the torque is proportional to the square of current, it can be generated regardless of the direction of the current. And also because the polarity of torque is changed due to the slope of inductance, a negative torque zone is formed according to the rotor position. To have a motoring torque, switching excitation must be synchronized with the rotor position angle. As shown in figure 2.20, an inductance profile is classified into three regions, increasing $\theta_{min1}\sim\theta_{max1}$, constant $\theta_{max1}\sim\theta_{max2}$ and decreasing $\theta_{max2}\sim\theta_{min2}$ period. If a constant exciting current flows through the phase winding, a positive torque is generated.

When that is operated in inductance increasing period $\theta_{min1}\sim\theta_{max1}$ and viceversa in inductance decreasing $\theta_{max2}\sim\theta_{min2}$. In the case of a constant excitation, it cannot be generated any torque, because a positive torque and negative one are canceled out, and the shaft torque becomes zero. As a result, to achieve an effective rotating power, switching excitation must be synchronized with the inductance profile. In order to derive the phase current exact information about the inductance profile of the SRM is essential. From the voltage equation the first term of the right side is voltage drops of winding resistance, the second term is the voltage drop of reactance and the last term is both the emf (electromotive magnetic force) and the mechanical output.

$$V = Ri + i(t)\frac{dL(\theta,i)}{d\theta}\omega + L(\theta,i)\frac{di(t)}{dt} \qquad (2.28)$$

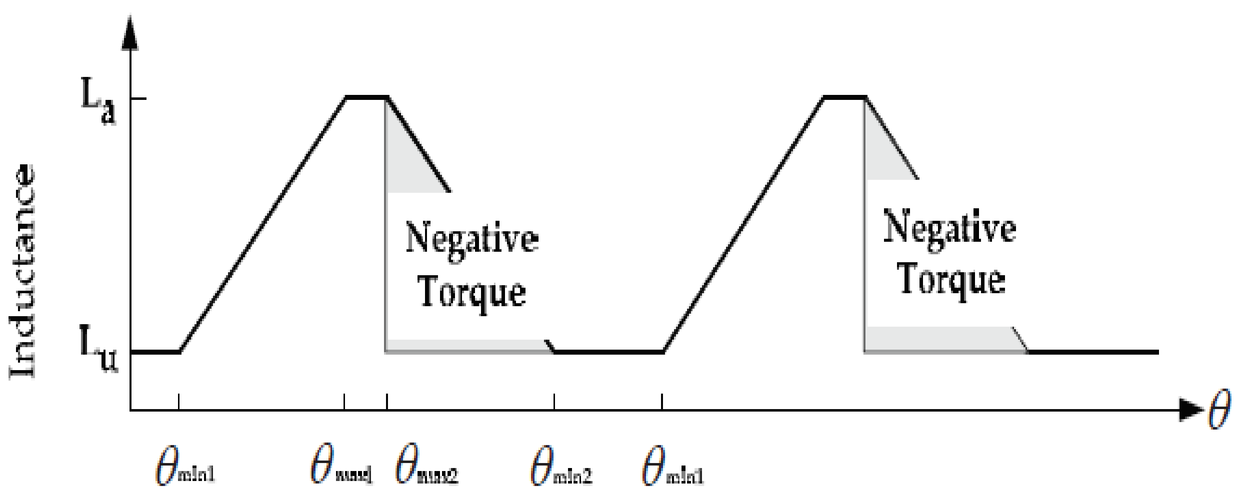


Figure 2.20a Inductance profile of multi-layer switched reluctance motor

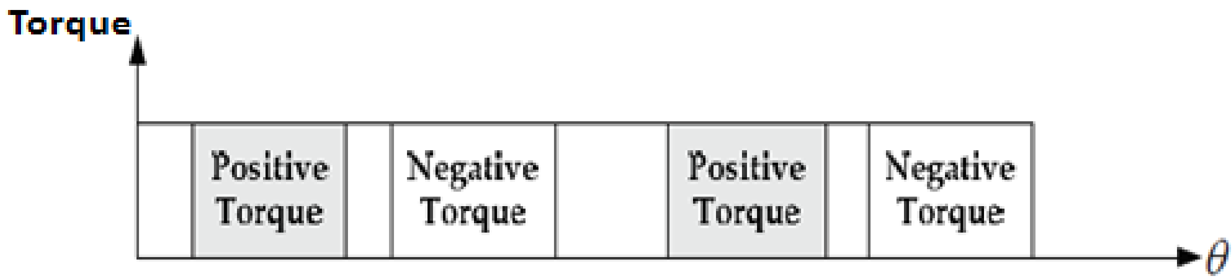


Figure 2.20b Torque control of multi-layer switched reluctance motor

Appropriate positioning of the phase excitation pulses relative to the rotor position is the key to obtaining effective performance from a multi-layer switched reluctance motor drive system. The turn-on time, the total conduction period, and the magnitude of the phase current determine torque, efficiency, and other performance parameters. The type of control to be employed depends on the operating speed of the multi-layer switched reluctance motor [11].

2.15 Advance angle calculation of multi-layer switched reluctance motor

Ideally, the turn-on angle is advanced such that the reference current level is reached just at the onset of pole overlap. In the unaligned position, phase inductance is almost constant, and, hence, during turnon back-emf can be neglected. Assuming magnetic linearity (Where $= L(\theta)i$) the voltage expression can be simplified as:

$$V_{ph} = iR + L(\theta)\frac{di}{dt} + i\frac{dL(\theta)}{dt}\ \omega \tag{2.29}$$

Also, assuming that the resistive drop is small can be written as

$$V_{ph}L(\theta)\frac{\Delta i}{\Delta\theta}\ \omega \tag{2.30}$$

Now , $\Delta i = i$ and $\Delta\theta = \theta_{overlap} - \theta_{on} = \theta_{adv}$ where $\theta_{overlap}$ is the position where pole overlap begins, θ_{on} is the turn-on angle and θ_{adv} is the requred phase turn-on advanced angle. Therefore, we have

$$\theta_{adv} = L_u\omega\frac{i}{V_{dc}} \tag{2.31}$$

MacMinn and Sember [10] have described a more sophisticated method of controlling the advance angle, which accounts for the errors due to neglecting the back-emf and the resistive drop in the calculation of θ_{adv} .

2.16 Control Parameters of multi-layer switched reluctance motor

The control parameters for a MSRM drive are the turn-on angle (θ_{on}), turn-off angle (θ_{off}), and the phase current. The conduction angle is defined as $\theta_{dwell} = \theta_{on} - \theta_{off}$. The complexity of determination of the control parameters depends on the chosen control method for a particular application. The current command can be generated for one or more phases depending on the controller. In voltage-controlled drives, the current is indirectly regulated by controlling the phase voltage. At low speeds, the current rises almost instantaneously after turn-on because of the negligible back emf, and the current must be limited by either controlling the average voltage or regulating the current level. The type of control used has a marked effect on the performance of the drive. As the speed increases, the back-emf increases as explained before and opposes the applied bus voltage. Phase advancing is necessary to establish the phase current at the onset of rotor and stator pole overlap region [19].

Voltage PWM or chopping control is used to force maximum current into the motor to maintain the desired torque level. Also, the phase excitation is turned off early enough so that the phase current decays completely to zero before the negative torque-producing region is reached. At higher-speeds, the SRM enters the single-pulse mode of operation, and control is achieved by advancing the turn-on angle and adjusting the conduction angle. At very high speeds, the back-emf will exceed the applied bus voltage once the current magnitude is high and the rotor position is appropriate, which causes the current to decrease after reaching a peak even though a positive bus voltage is applied during the positive $dL/d\theta$. The control algorithm outputs θ_{dwell} and θ_{on} according to the speed at the end of θ_{dwell} the phase switches are turned off so that negative voltage is applied across the phase to commutate the phase as quickly as possible. The back-emf reverses polarity beyond the aligned position and may cause the current to increase in this region if the current does not decay to insignificant levels. Therefore, the phase commutation must precede the aligned position by several degrees so that the current decays before the negative $dL/d\theta$ region is reached [12].

In the high-speed range of operation, when the back-emf exceeds the DC bus voltage, the conduction window becomes too limited for current or voltage control and all the chopping or PWM has to be disabled. In this range, θ_{dwell} and θ_{adv} are the only control parameters and control is accomplished based on the assumption that approximately θ_{dwell} regulates torque and θ_{adv} determines efficiency.

2.16.1 Voltage controlled drive strategies

In low-performance drives, where precise torque control is not a critical issue, fixed-frequency PWM voltage control with variable duty cycle provides the simplest means of control of the SRM drive. The early proponents of SRM drives were driven by the fact that a highly efficient variable-speed drive having a wide speed range can be achieved with this motor by optimum use of the simple voltage feeding mode with closed loop position control only. The block diagram of the voltage-controlled drive is shown in figure 2.21. The angle controller generates the turn-on and turn-off angles for a phase depending on the rotor speed, which simultaneously determines the conduction period, θ_{dwell}. The duty cycle is adjusted according to the voltage command signal. The electronic commutator generates the gating signals based on the control inputs and the instantaneous rotor position. A speed feedback loop can be added on the outside as shown when precision speed control is desired. The drive usually incorporates a current sensor typically placed on the lower leg of the DC-link for over current protection. A current feedback loop can also be added, which will further modulate the duty cycle and compound the torque–speed characteristics just like the armature voltage control of a DC motor [13] [14].

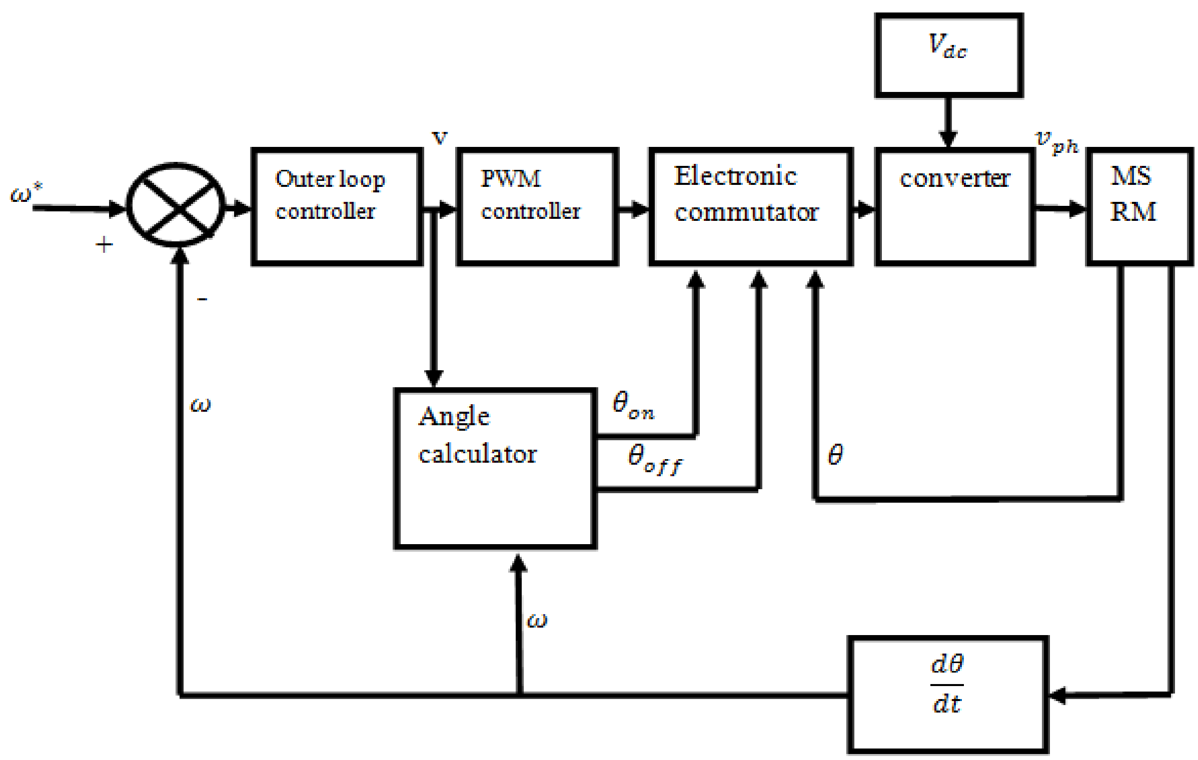


Figure 2.21 Voltage controlled drive of multi-layer switched reluctance motor

2.16.2 Current controlled drive strategies

In torque-controlled drives, such as in high-performance servo applications, the torque command is executed by regulating the current in the inner loop as shown in figure 2.22. The reference current i for a given operating point is determined from the load characteristics, the speed, and the control strategy. A wide-bandwidth current transducer provides the current feedback information to the controller from each of the motor phases. This mode of control allows rapid resetting of the current level and is used where fast motor response is desired. For loads whose torque increases monotonically with speed such as in fans or blowers, speed feedback can be introduced in the outer loop for accurate speed control. The simpler control strategy is to generate one current command to be used by all the phases in succession. The electronic commutator selects the appropriate phase for current regulation based on θ_{on}, θ_{off}, and the instantaneous rotor position. The current controller generates the gating signal for the phases based on the information coming from the electronic commutator. The current in the commuated phase is quickly brought to zero applying negative V_{dc}, while the incoming phase assumes the responsibility of torque production based on the commanded current. The phase transition in these drives is not very smooth, which tends to increase the torque ripple of the drive [14][15].

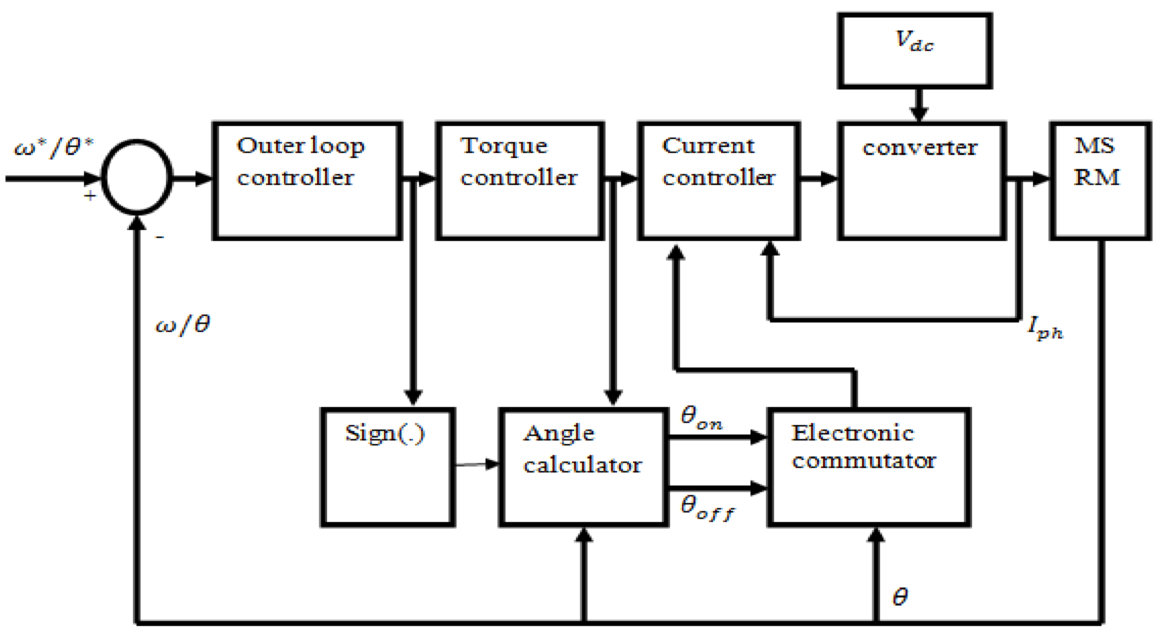


Figure 2.22 Current-controlled drive of multi-layer switched reluctance motor

2.17 Torque ripple minimization using the advanced control strategies

A higher performance index, such as torque/ampere maximization, efficiency maximization, or torque ripple minimization can be required in certain applications. For example, in direct drive or traction applications, the efficiency over a wide speed range is critical. For such applications as electric power steering in automobiles, the torque ripple is a critical issue. Hence intelligent (advanced) controllers such as fuzzy logic controller (FLC) and adaptive neuro fuzzy inference system (ANFIS) based current compensating techniques are employed for minimizing the torque ripples in switched reluctance motor [21].

The high-performance drives will typically be current-controlled drives with sophistication added to the controller as discussed earlier. For efficiency maximization, the key issue is the accurate determination of θ_{on} and θ_{off}, which may require modeling of the MSRM and online parameter identification [22]. The modeling issue is equally important for torque ripple minimization, where the overlapping phase currents are carefully controlled during commutation. In these sophisticated drives, the electronic commutator works in conjunction with the torque controller to generate the gating signals. The torque controller will include either a model or tables describing the characteristics of the MSRM [3]. Figure 2.23 shows the basic theory for the proposed ripple compensation scheme. The initial phase current is constant in steady state but produce the significant ripple. The resulted current i is determined by the compensated current and reference current i_{ref}, so the ideal waveforms of T is produced, which is the ripple free torque [9].

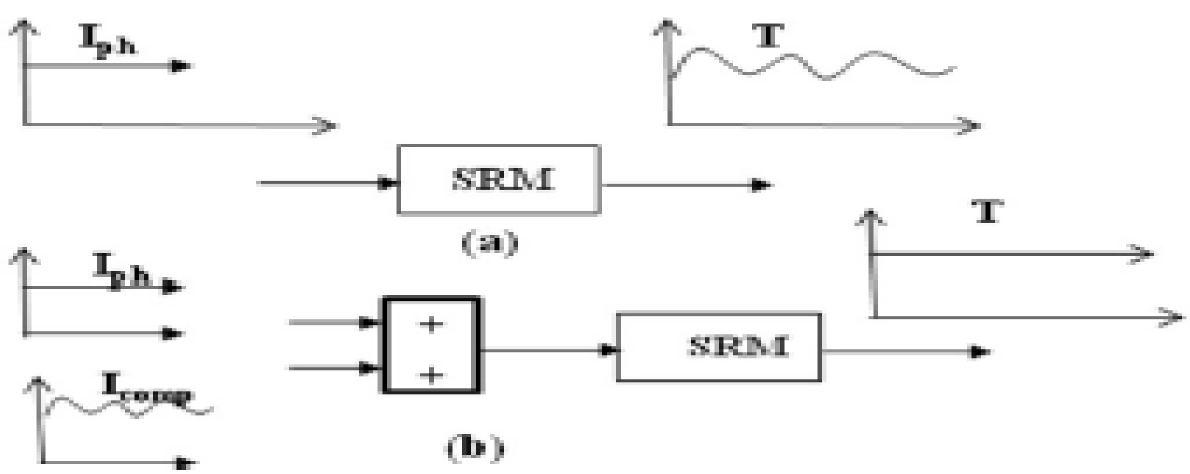


Figure 2.23 Torque ripple compensation technique (a) Torque ripple produced by reference current (b) Ripple free torque by compensated reference current

To attenuate the torque ripple, it is proposed to add a compensating signal as shown in figure 2.23. This signal can be dependent of the rotor position, the current, the motor speed, and the torque load value. In fact, it is a function that possesses high mathematical complexity and therefore the production of this signal is quite complicated. This new methodology to control a MSRM drive consists on the use of a fuzzy logic current controller and the supervision of a neuro-fuzzy block responsible of torque ripple reduction.

First, compensated current is injected in each phase by using fuzzy logic controller. Then by the learning capabilities of the compensator, the control shows large operation flexibility. The learning mechanism makes the compensator more independent of the motor characteristics. If the system has some load modification and/or change of speed, the compensator will have the ability of to adapt itself to this new operating point, searching for the required torque ripple minimization. The strategy to produce the compensating signal is done by learning mechanism through the new "intelligent" methodologies as the adaptive neuro-fuzzy inference systems.

2.18 The overall block diagram representation of multi-layer switched reluctance motor torque control

This will give the closed loop control of multi-layer switched reluctance motor. So, the torque ripple will be reduced than that of reference torque. So, machine will always remain in synchronism. For three-phase machine we are using three half bridge converters, for four-phase ‘four’ and for five-phase ‘five’ half bridge converters are used in order to get required amount of input to the multi-layer switched reluctance motor. From above equations of multi-layer switched reluctance motor the model for simulation is developed in figure 2.24 below.

Fuzzy logic can be used to design nonlinear controllers which are well justified by the universal approximation theorem [21]. The fuzzy logic system can, in principle, approximate relations between variables, regardless of their analytic dependence. Therefore, it can be thought of as a model free estimator. Also, fuzzy controllers are easy to implement and with adaptive schemes these controllers can be made robust. Fuzzy control is one of the appropriate control schemes for torque control of switched reluctance drives. Figure 2.24 shows a block diagram of a proposed control scheme. The controller uses the rotor position and reference current as inputs and compensated current as the output. The input is divided into membership functions which are designed to give an optimum number of rules and allow the switched reluctance to conduct over the entire positive torque producing area. Max-product rule of inference scheme is used and the output is determined using the center of average for defuzzification.

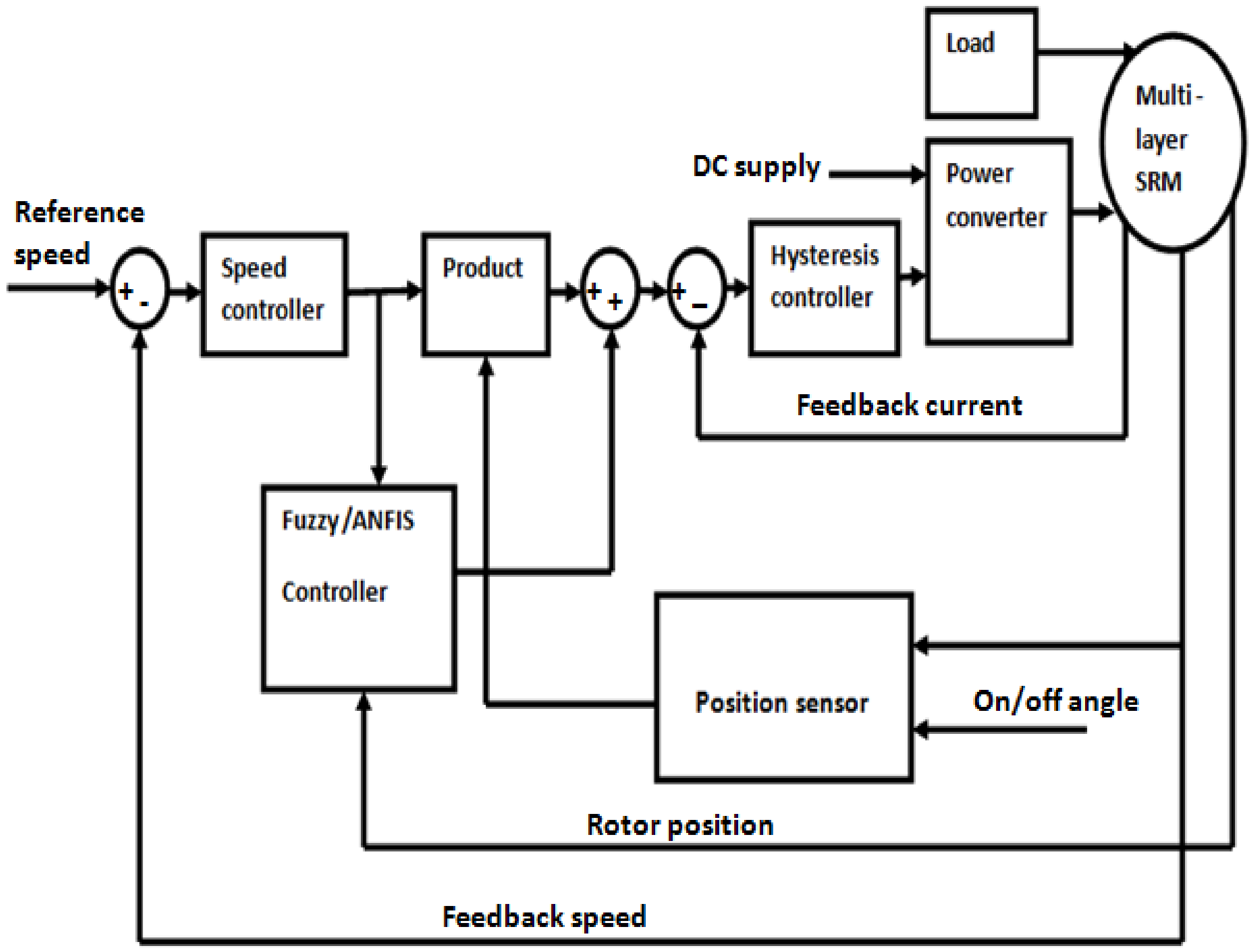


Figure 2.24 The overall block diagram of multi-layer switched reluctance motor torque control

The whole model is divided into several independent blocks, such as position sensor block, converter block, fuzzy / ANFIS controller block and current controller block etc. Detailed implementation of the various subsystems blocks are introduced in as follows.

2.18.1 Position sensor block

By using a position sensor attached to the rotor, the turn-on and turn-off angles of the motor phases can be accurately imposed. The switching angle can be used to control the developed torque waveforms. The function of this block is to work out the angle of rotor position angle relative to reference zero angle in an electric cycle. For a three-phase 6/4 switched reluctance motor, each phase inductance has a periodicity of 90 degrees. Therefore, it is appropriate to transform the rotor position angle coming from the mechanical equation so that it is modulo 90 . Here, modulo 90 is realized by virtue of rem function in MATLAB/ SIMULINK as shown in figure 2.25.

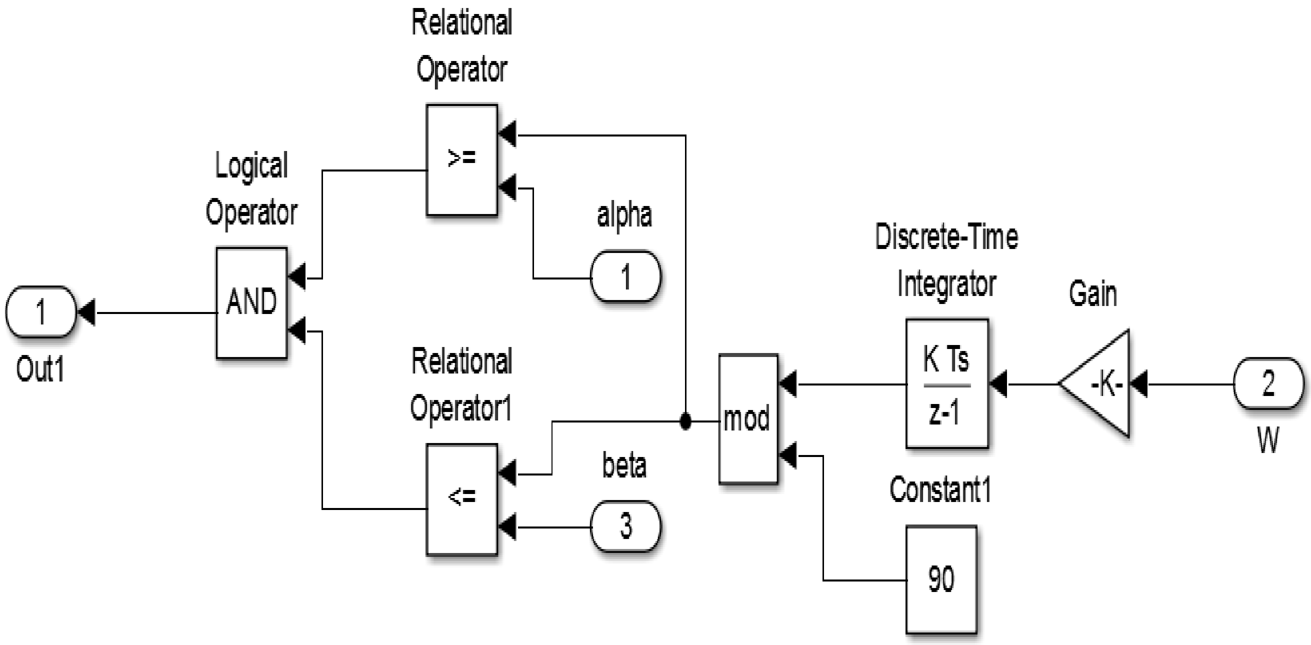


Figure 2.25 Inside of postion sensor block

2.18.2 Converter block

An asymmetric bridge converter is adopted here, its function is implemented by using MATLAB/SIMULINK. The simulation model of converter block for one phase is shown as figure 2.26. It has two power switches and two diodes. Step motion of multi-layer switched reluctance motor is realized by switching on or off phase windings. The choosing of conduction angle is crucial to the power and torque ripple of the switched reluctance motor. The switched reluctance motor is fed by a three-phase asymmetrical power converter having three legs, each of which consists of two IGBTs and two free-wheeling diodes. During conduction periods, the active IGBTs apply positive source voltage to the stator windings to drive positive currents into the phase windings. During free-wheeling periods, negative voltage is applied to the windings and the stored energy is returned to the power DC source through the diodes. The fall time of the currents in motor windings can be thus reduced.

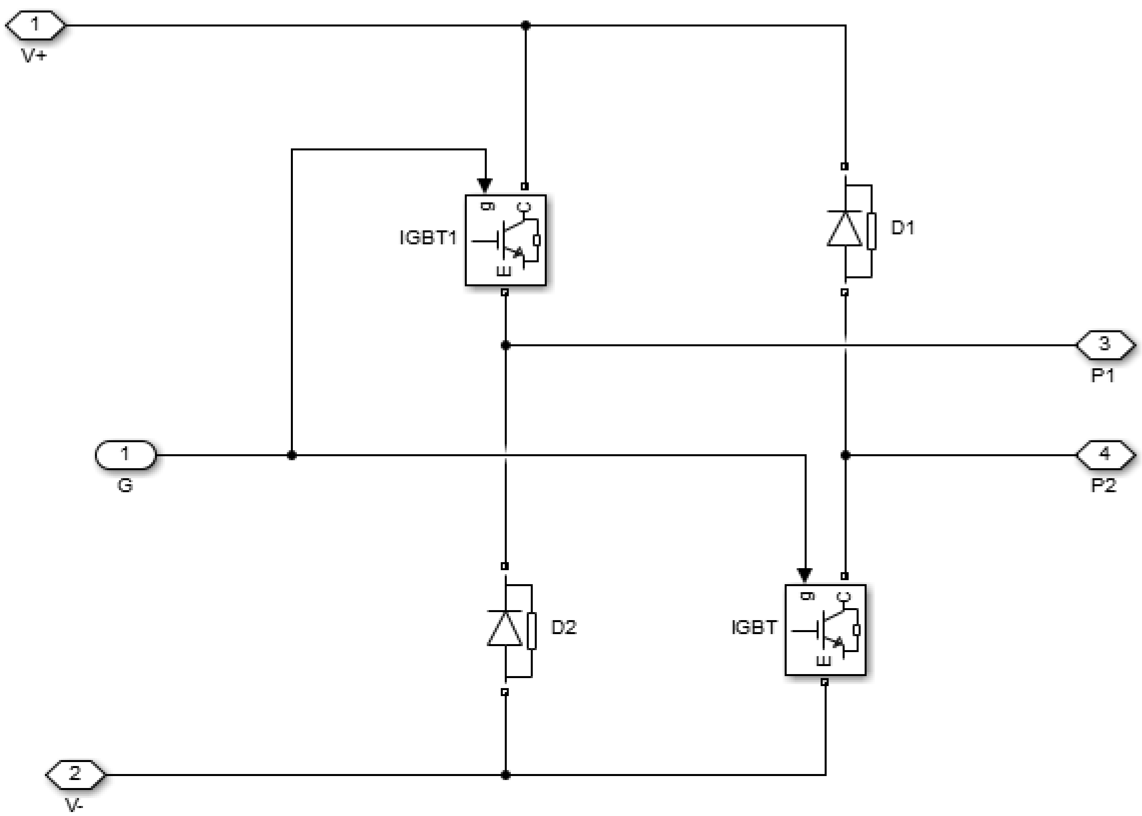


Figure 2.26 Inside of asymmetric-bridge converter for one leg.

2.18.3 Fuzzy /ANFIS controller block

In this block the use of intelligence, learning and adaptation capability in the control methods discussed in general control scheme, revealed the need for continuous expert intervention for the control of non-linear systems. During the past few years we have witnessed a rapid growth in the number and variety of applications of fuzzy logic and neural networks, ranging from consumer electronics and industrial process control to decision support systems and financial trading. The combination of fuzzy logic and neural network which is adaptive neuro fuzzy inference system is used to reduce the torque ripples in this block [19].

2.18.4 Current command generator and controllers block

The phase currents are independently controlled by three hysteresis controllers which generate the IGBTs drive signals by comparing the measured currents with the references. The IGBTs switching frequency is mainly determined by the hysteresis band. The current error existing between the reference current and its command is regulated by the controller to yield the current command magnitude, and then multiplied by the commutation timing signal S1 to generate the current command for phase one. Current controller [20] regulates the current feedback error to yield the control voltage for phase one which is compared with a triangular wave to create the PWM switching signal. Although any types of controller can be simulated by the proposed simulation environment, the hysteresis type is adopted here.

2.19 Simulation model of multi-layer switched reluctance motor

In this thesis, a DC supply voltage of 240 V is used. The converter turn-on and turn-off angles are kept constant at 45 deg and 75 deg, respectively becase the range of rotor postion for both controllers is from 0 deg to 90 deg the step angle for multilayer switched reluctance motor is given by $\frac{2\pi}{3N_r}$ where $N_r = no\ of\ rotorpoles = 4$, which is equal to 30deg. Hence it is possible to select the turn on and turn off angle in the range whose difference is 30 deg over the rotor position range. The reference speed is 200 Rad/s and the hysteresis band is chosen as between -10 and +10 A. The switched reluctance motor is started by applying the step reference to the regulator input. The acceleration rate depends on the load characteristics. To shorten the starting time, a very light load was chosen. Since only the currents are controlled, the motor speed will increase according to the mechanical dynamics of the system. The switched reluctance motor drive waveforms (phase voltages, magnetic flux, windings currents, motor torque, motor speed) are displayed on the scope. As shown in figure in figure 2.28c, the switched reluctance motor torque has a very high torque ripple component which is due to the transitions of the currents from one phase to the following one. This torque ripple is a particular characteristic of the switched reluctance motor and it depends mainly on the converters turn-on and turn-off angles. In observing the drive's waveforms, we can remark that the switched reluctance motor operation speed range can be divided into two regions according to the converter operating mode that is current-controlled and voltage-fed.

In current controlled mode from stand still up to about 3000 rpm, the motor's emf is low and the current can be regulated to the reference value. In this operation mode, the average value of the developed torque is approximately proportional to the current reference. In addition to the torque ripple due to phase transitions, we note also the torque ripple created by the switching of the hysteresis regulator. This operation mode is also called constant torque operation. But for speeds above 3000 rpm, the motor's emf is high and the phase currents cannot attain the reference value imposed by the current regulators. The converter operation changes naturally to voltage-fed mode in which there is no modulation of the power switches. This results in linear varying flux waveforms as shown on the scope. In voltage-fed mode, the SRM develops its 'natural' characteristic in which the average value of the developed torque is inversely proportional to the motor speed. Since the hysteresis regulator is inactive in this case, only torque ripple due to phase transitions is present in the torque waveforms.

In the MATLAB simulation of multi-layer switched reluctance motor the following specification are used based on the matlab code in the appendix. Number of stator and rotor poles = 6/4, Frequency [F] = 50 Hz, Number of phases = 3, Friction = 0.02 N.m.s, Unaligned inductance = 0.7 mH, Aligned Inductance = 20 mH, Stator resistance = 0.05 ohms/phase, Moment of inertia [J] = 0.05 $K.g\ m^2$.

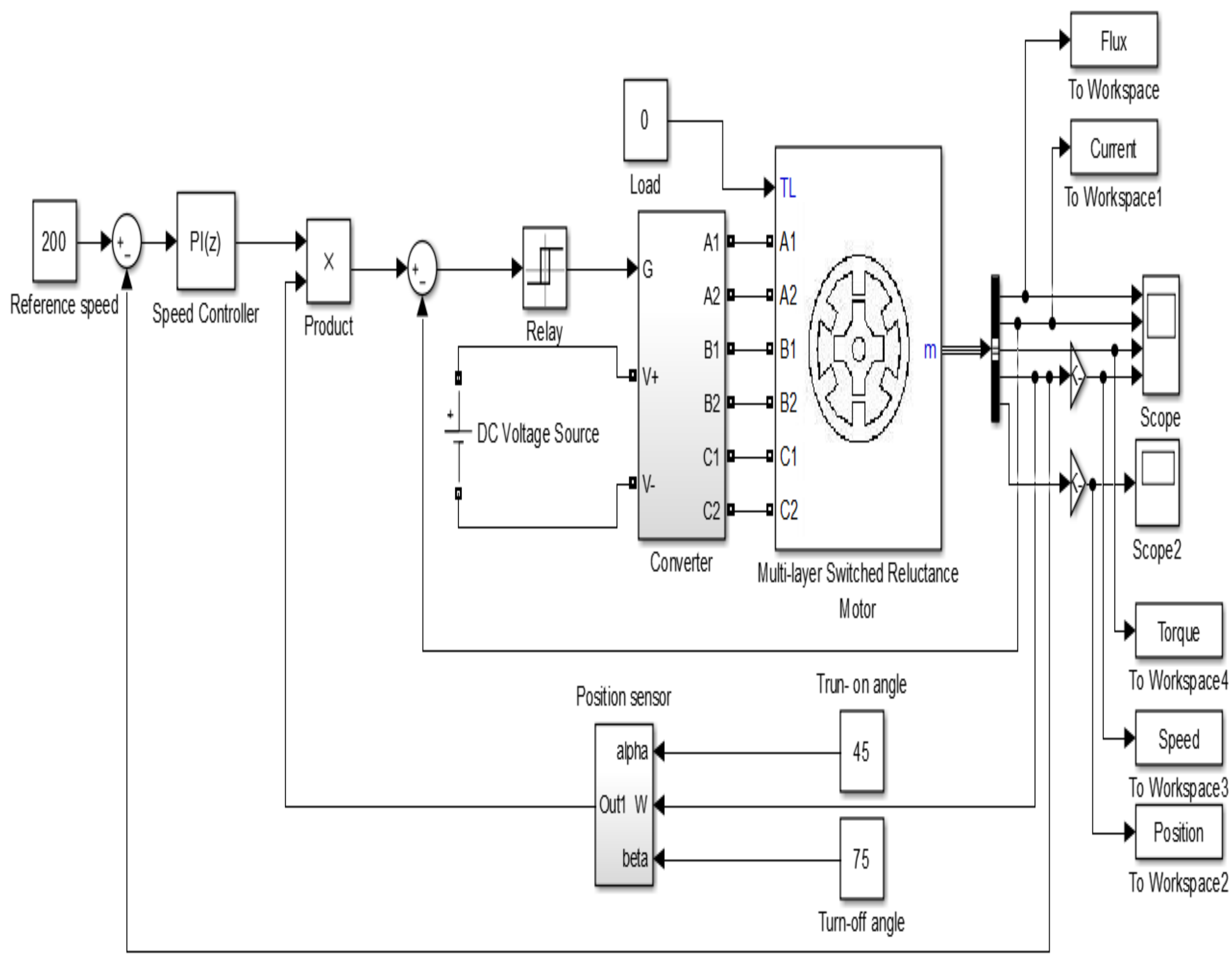


Figure 2.27 Matlab simulink model of multi-layer switched reluctance motor without controller

2.20 Simulation studies

A three phase 6/4 multi-layer switched reluctance motor is used for simulation using matlab/simulink with the parameters stated above. Figure below shows the simulation results of phase current of all the three phases, magnetic flux, torque, speed and rotor position of the switched reluctance motor parameters without any controller. From figure 3.28a and figure 3.28c it is observed that the torque is directly proportional to the square of current as current decrease the torque also decreases, therefore the torque of the switched reluctance motor is independent of current direction but it depends on $\frac{dL(\theta,i)}{d\theta}$ value. If this value is positive then the torque of switched reluctance motor is also positive. In case if it is negative then torque of the switched reluctance motor is negative. But this torque contains lot of torque ripples, noise and harmonics. Thus it needs control. The output shown below is at no load. The reference speed is $200\,{}^{rad}/_{sec}$ when amplify it by $30/pi$ it will be $1911\,{}^{rad}/_{sec}$ as shown in figure 2.28d.

A. Current

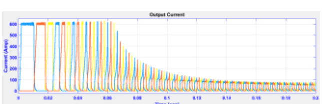


Figure 2.28a Simulation result of current.

B. Magnetic flux

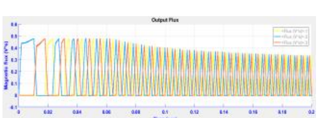


Figure 2.28b Simulation result of magnetic flux

C. Torque

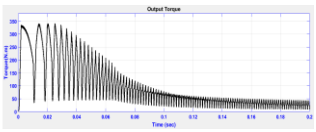


Figure 2.28c Simulation result of torque

D. Speed

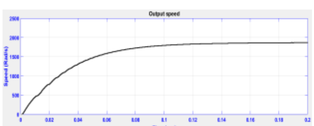


Figure 2.28d Simulation result of speed

E. Rotor position

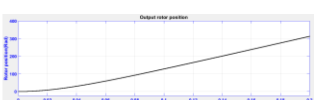


Figure 2.28e Simulation result of rotor position

CHAPTER THREE

Fuzzy logic controller for multi-layer switched reluctance motor

3.1 Introduction

Fuzzy logic is a powerful problem solving methodology with a lot of applications in embedded control and information processing. Fuzzy logic provides a remarkably simple way to draw definite conclusions from vague, ambiguous or imprecise information. In a sense, fuzzy logic resembles human decision making with its ability to work from approximate data and find precise solutions. Unlike classical logic which requires a deep understanding of a system, exact equations, and precise numeric values, fuzzy logic incorporates an alternative way of thinking, which allows modelling complex systems using a higher level of abstraction, originating from our knowledge and experience. In 1965 Lotfi A. Zadeh published his seminal work "fuzzy sets" which described the mathematics of fuzzy set theory, and by extension fuzzy logic. This theory proposed making the membership function (or the values false and true) operate over the range of real numbers [19].

New operations for the calculus of logic were proposed, and showed to be in principle at least a generalization of classic logic. Areas in which fuzzy logic has been successfully applied are often quite concrete. The first major commercial application was in the area of cement kiln control, an operation which requires that an operator monitor four internal states of the kiln, control four sets of operations, and dynamically manage 40 or 50 "rules of thumb" about their inter relationships, all with the goal of controlling a highly complex set of chemical interactions. One such rule is "If the oxygen percentage is rather high and the free-lime and kiln-drive torque rate is normal, decrease the flow of gas and slightly reduce the fuel rate. The objection has been raised that utilizing fuzzy systems in a dynamic control environment raises the likelihood of encountering difficult stability problems. Since in control conditions the use of fuzzy systems can roughly correspond to using thresholds, there must be significant care taken to insure that oscillations do not develop in the "dead 103 spaces" between threshold triggers. This seems to be an important area for future research. Other applications, which have benefited through the use of fuzzy systems theory, have been information retrieval systems, a navigation system for automatic cars, a predictive fuzzy-logic controller for automatic operation of trains, laboratory water level controllers, feature-definition controllers for robot vision, and more [20] [21].

3.2 Fuzzy block at the matlab prompt

The MATLAB fuzzy logic toolbox library contains the fuzzy logic controller with rule viewer blocks. It also includes a membership functions sub library that contains SIMULINK blocks for the built-in membership functions. Figure 3.1 shows the fuzzy logic controller with rule viewer block is an extension of the fuzzy logic controller block. Starting to build the fuzzy controller with rule viewer block or to initialize the fuzzy logic controller blocks (with or without the rule viewer), by entering the name of the structure variable describing FIS (fuzzy inference system). This variable must be located in the MATLAB workspace. For most fuzzy inference systems, the fuzzy logic controller block automatically generates a hierarchical block diagram representation of your (Fuzzy Inference System) FIS. This automatic model generation ability is called the fuzzy wizard. The block diagram representation only uses built-in SIMULINK blocks and therefore allows for efficient code generation. The fuzzy wizard cannot handle FIS with custom membership functions or with AND, OR, IMP and AGG functions outside of the following list: or method: max, and method: min, prod, imp method: min, prod and agg Method: max. In these cases, the fuzzy logic controller block uses the S-function to simulate the FIS [21] [22].

Fuzzy theory holds that all things are matters of degree, and also reduces black-white logic and mathematics to special cases of grey relationships. The multi-valued fuzziness corresponds to degrees of indeterminacy or ambiguity, partial occurrence of events or relations. Zadeh extended the bivalent indicator function I_A of non fuzzy subset A of X,

$$I_A = \begin{Bmatrix} 1\ if\ X \in A \\ 0\ if X \notin A \end{Bmatrix} \tag{3.1}$$

Sometimes this function is called a discrimination function, because it discriminates the elements of the universal set which belong to the set from those which do not. Determining the discrimination function, we divide the universal set into two parts. So we have the certain discrimination and the certain border between these two parts [23].

To a multi-valued indicator or membership functions $\mu_A : X \to [0, 1]$. This allows combining such multi valued or fuzzy sets with the point wise operators of indicating functions, as:

$$\mu_A : X \to [0, 1] \tag{3.2}$$

Figure 4.1 shows the membership function (MF): A MF is a curve that defines how each point in the universe of discourse is mapped to a value between 0 and 1. This value is known as degree of membership or membership value.

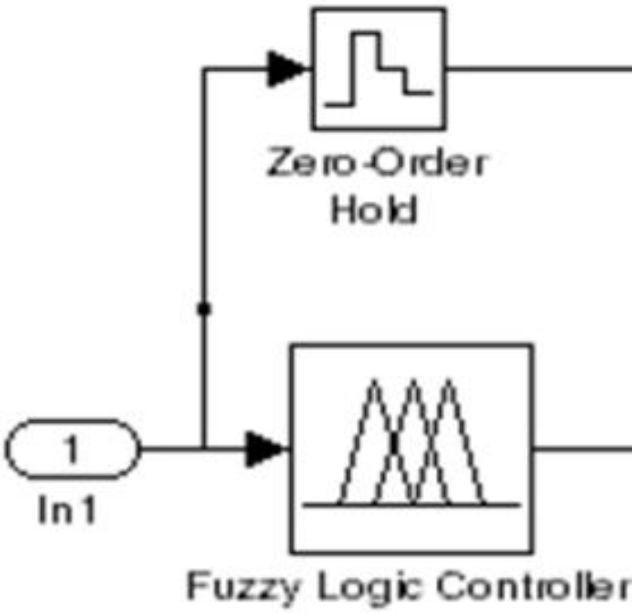


Figure 3.1The fuzzy logic controller block at the matlab prompt

If-Then rules will be used to make something useful with fuzzy logic. A single fuzzy If-Then Rule assumes the appearance: IF (x is A) THEN (y is B), where A and B are linguistic values defined by fuzzy sets in the ranges X and Y (universes of discourses). The 'IF' part is called the antecedent while 'THEN' part is called the consequent or conclusion. The antecedent is an assumption that returns a single number between 0 and 1. The consequent is an assignment that brings up the entire fuzzy set B to the output variable y. Interpreting an If-Then rule implies different parts: first evaluating the antecedent which involves fuzzifying the input and applying any fuzzy operator, and second, applying that result to the consequent (implication) [24].

Table 3.1: If - then rules

Antecedent:	“IF x is A THEN y is B”
Consequent:	“y is B”

3.3 Basic fuzzy logic controller structure

Fuzzy logic control mainly depends upon the rules formed by the linguistic variables. Fuzzy logic control is free of complex numerical calculations, unlike other methods. It only uses simple mathematical calculations to control the model. Despite relying on basic mathematical analysis it provides good performance in a control system. Hence, this method is one of the best methods available and also easier one to control a plant. Figure 3.2 shows how the fuzzy logic controllers (FLC) use fuzzy logic as a process of mapping from a given input (crisp numerical value) to an output (signal control). This process has a basic structure that involves a fuzzifier, an inference engine, a knowledge base (rule data base), and a deffuzzifier, which transforms fuzzy sets into real numbers to provide control signals [23].

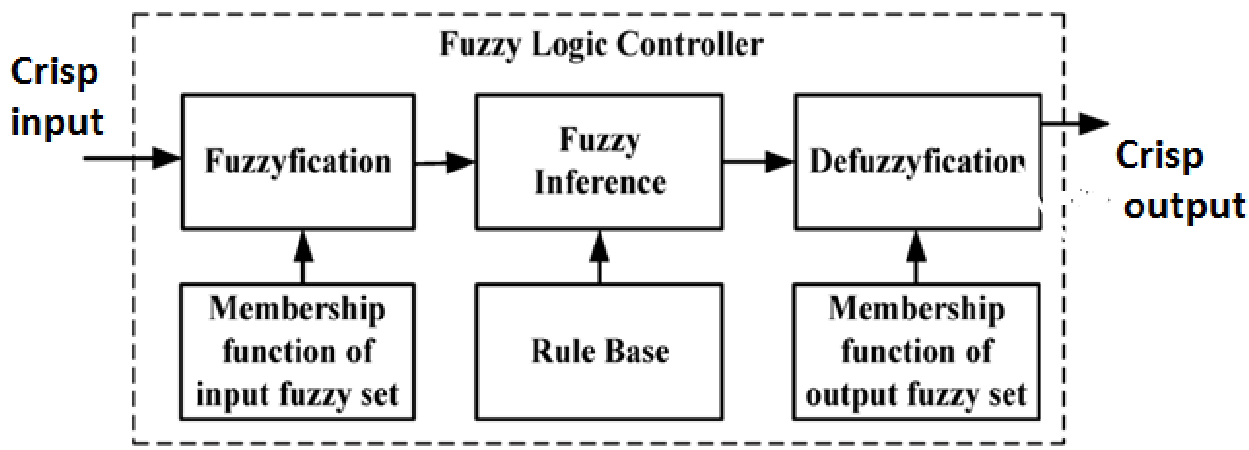


Figure 3.2 The block diagram of the fuzzy logic controller

The backbone of the fuzzy logic controller (FLC) is embodied in a set of fuzzy rules, not an elaborated set of equations. The success of the fuzzy logic controller is mainly due to their ability to cope with knowledge represented in a linguistic form instead of representation in the conventional mathematical framework. The main advantage is being their ability to incorporate experience, intuition and heuristics into the system instead of relying on mathematical models. Fuzzification plays important role in dealing with uncertain information, which might be objective or subjective in nature. The fuzzification block in the fuzzy logic controller represents the process of making crisp quantity into fuzzy. In fact, the fuzzifier converts the crisp input to a linguistic variable using the membership functions stored in the fuzzy knowledge base. Fuzziness in a fuzzy set is characterized by the membership functions [21] [23].

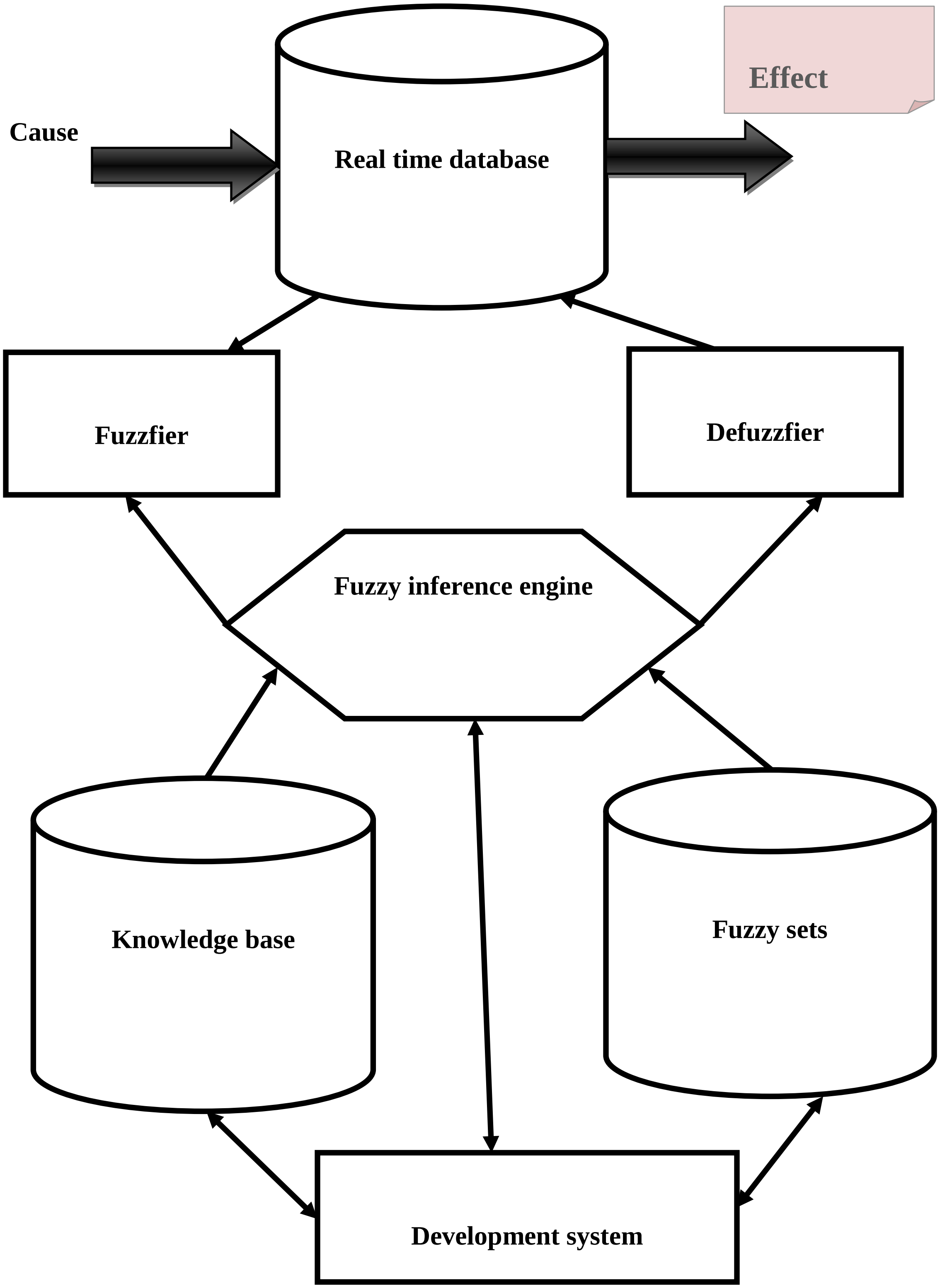


Figure 3.3 Elements of a fuzzy logic controller

3.4 Membership function

We already know that fuzzy logic is not logic that is fuzzy but logic that is used to describe fuzziness. This fuzziness is best characterized by its membership function. In other words, we can say that membership function represents the degree of truth in fuzzy logic.

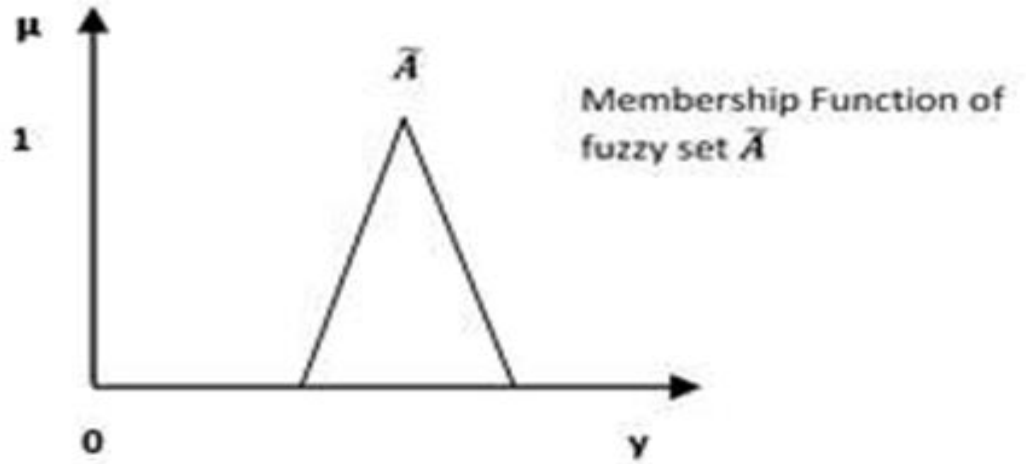


Figure 3.4 Membership function representation

Following are a few important points relating to the membership function [21]

- Membership functions were first introduced in 1965 by Lofti A. Zadeh in his first research paper "fuzzy sets".
- Membership functions characterize fuzziness (i.e., all the information in fuzzy set), whether the elements in fuzzy sets are discrete or continuous.
- Membership functions can be defined as a technique to solve practical problems by experience rather than knowledge.
- Membership functions are represented by graphical forms.
- Rules for defining fuzziness are fuzzy too.

3.4.1 Triangular membership functions

Though a membership function can be an arbitrary curve, there are eleven standard membership functions that are commonly used in engineering applications. These membership functions can be built from several basic functions. The simplest membership functions can be formed using straight lines. They may be triangular membership function which is a collection of three points forming a triangle or trapezoidal membership function which has a flat top and is just a truncated triangle curve. These membership functions built out of straight lines have the advantage of simplicity. A triangular MF is specified by three parameters {a, b, c} as follows:

$$triangle(x; a, b, c) = \left\{ \begin{array}{cc} 0, & x \leq a. \\ \dfrac{x-a}{b-a}, & a \leq x \leq b. \\ \dfrac{c-x}{c-b}, & b \leq x \leq c. \\ 0, & c \leq x. \end{array} \right\} \tag{3.3}$$

By using min and max, we have an alternative expression for the preceding equation:

$$triangle(x; a, b, c) = max\left(min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right) \tag{3.4}$$

The parameters {a, b, c} (with a < b < c) determine the x coordinates of the three corners of the underlying triangular MF.

3.4.2 Trapezoidal membership functions

A trapezoidal MF is specified by four parameters {a, b, c, d} as follows

$$trapezoid(x; a, b, c, d = \left\{ \begin{array}{cc} 0, & x \leq a. \\ \dfrac{x-a}{b-a}, & a \leq x \leq b. \\ 1, & b \leq x \leq c. \\ \dfrac{d-x}{d-c}, & c \leq x \leq d. \\ 0, & d \leq x. \end{array} \right\} \tag{3.5}$$

An alternative concise expression using min and max is:

$$trapezoid(x; a, b, c, d) = max\left(min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right) \tag{3.6}$$

The parameters {a, b, c, d} (with a < b <= c < d) determine the x coordinates of the four corners of the underlying trapezoidal MF. Note that a trapezoidal MF with parameter {a, b, c, d} reduces to a triangular MF when b is equal to c.

Due to their simple formulas and computational efficiency, both triangular MFs and trapezoidal MFs have been used extensively, especially in real-time implementations. However, since the MFs are composed of straight line segments, they are not smooth at the corner points specified by the parameters. In the following we introduce other types of MFs defined by smooth and nonlinear functions.

3.4.3 Gaussian membership functions

A gaussian MF is specified by two parameters

$$gaussian(x; c, \sigma) = e^{-\frac{1}{2}(\frac{x-c}{\sigma})^2} \tag{3.7}$$

A gaussian MF is determined complete by c and σ; c represents the MFs centre and σ determines the MFs width.

3.4.4 Generalized bell membership functions

A generalized bell MF (or Bell-shaped Function) is specified by three parameters {a, b, c}:

$$bell(x; a, b, c) = \frac{1}{1 + \left|\left(\frac{x-c}{a}\right)^{2b}\right|} \tag{3.8}$$

Where the parameter b is usually positive. (If b is negative, the shape of this membership function becomes an upside down bell). Note that this membership function is a direct generalization of the cauchy distribution used in probability theory, so it is also referred to as the Cauchy membership function.

Because of their smoothness and concise notation, gaussian and bell membership functions are becoming increasingly popular for specifying fuzzy sets. Gaussian functions are well known in probability and statistics, and they possess useful properties such as invariance under multiplication (the product of two gaussians is a gaussian with a scaling factor) and fourier transform (the fourier transform of a gaussian is still a gaussian). The bell membership function has one more parameter than the gaussian membership function, so it has one more degree of freedom to adjust the steepness at the crossover points.

Although the gaussian membership functions and bell membership functions achieve smoothness, they are unable to specify asymmetric membership functions, which are important in certain applications.

3.5 Fuzzy inference engine of fuzzy logic controller

Fuzzy inference is the process of converting fuzzy input to fuzzy output according to fuzzy rules in the knowledge base. Two types of fuzzy inference mechanisms are commonly used. We have already studied that a fuzzy set $\tilde{A}$ in the universe of information U can be defined as a set of ordered pairs and it can be represented mathematically as shown in figure 3.9.

$$A = \{(y,\ \mu_A(y))\ |y \epsilon U\} \tag{3.9}$$

Here $\mu_A(y) =$ membership function of A; this assumes values in the range from 0 to 1, i.e.,$\mu_A(y)\epsilon[0,1]]$. The membership function $\mu_A(y)$ maps U to the membership space. The y in the membership function described above, represents the element in a fuzzy set; whether it is discrete or continuous [21] [23].

3.5.1 Mamdani type fuzzy inference system

The most commonly used fuzzy inference technique is the so-called Mamdani method is used in fuzzy logic controller (Mamdani & Assilian, 1975) which was proposed, by Mamdani and Assilian, as the very first attempt to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators. Their work was inspired by an equally influential publication by Zadeh (Zadeh, 1973). Interest in fuzzy control has continued ever since, and the literature on the subject has grown rapidly. In Mamdani's model the fuzzy implication is modeled by Mamdani's minimum operator, the conjunction operator is min, the t-norm from compositional rule is min and for the aggregation of the rules the max operator is used.

3.5.2 Segno-type fuzzy inference system

Sugeno, or Takagi-Sugeno-Kang, method of fuzzy inference is used while using adaptive neuro fuzzy inference system controller. It was introduced in 1985 [19], it is similar to the Mamdani method in many respects. The first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator, are exactly the same. The main difference between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant. A typical rule in a Sugeno fuzzy model has the form: If Input 1 = x and Input 2 = y, the output is z = ax+by+c for a zero-order Sugeno model, the output level z is a constant (a=b =0). The output level z_i of each rule is weighted by the firing strength w of the rule. For example for an AND rule $\text{with input one} = \text{x and input two} = \text{y},$ the firing strength $\text{w}_\text{i} = \text{andmethod}\left(\mu_1(\text{x}),\, \mu_2(\text{y})\right)$ where $\mu_{1,2}(.)$ are the membership functions for inputs one and two. The final output of the system is the weighted average of all rule outputs, computed as

$$Final\ out = \frac{\sum_{I=1}^{N} w_i z_i}{\sum_{i-1}^{N} w_i} \tag{3.10}$$

3.6 Torque control model using fuzzy logic controller technique

The modeling process for estimation of torque starts from analyzing data from plotted curve and will be continued by fuzzy rule base and FIS structure and ends in mapping surface. By considering 6/4 MSRM's torque profile and fuzzy logic approach will explain as stated below.

3.6.1 Formation of fuzzy inference system (FIS)

For the formation of the fuzzy inference system, fuzzy logic toolbox of MATLAB is used. Figure 3.5 shows the FIS structure that current and rotor angle are the inputs and compensated current is the output.

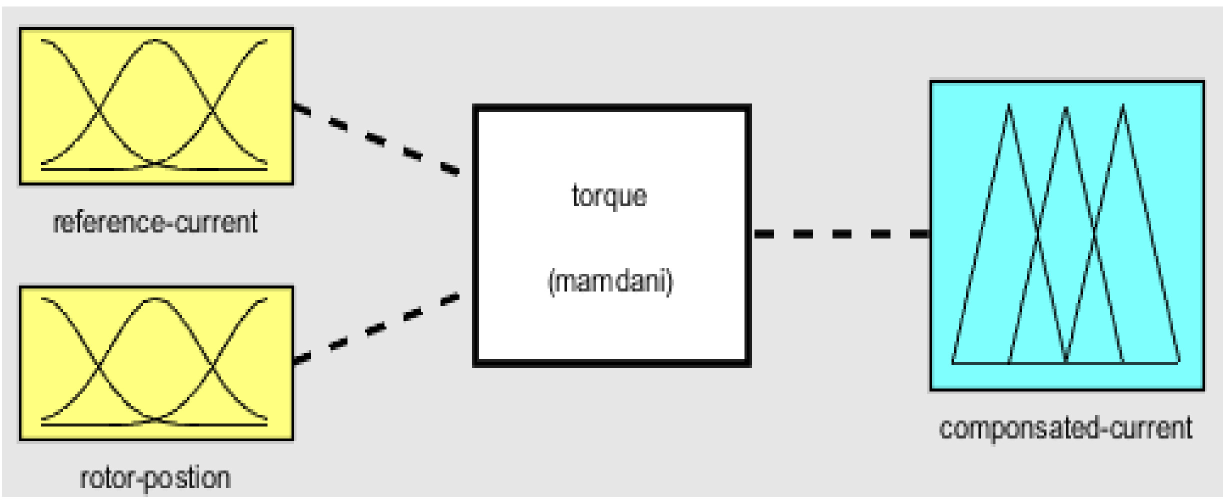


Figure 3.5 Mamdani fuzzy inference system structure of multi-layer switched reluctance motor.

3.6.2 Assigning the fuzzy inference system membership functions

Once the FIS structure is completed, membership functions for each of the inputs and the output will be formed. Toolbox of MATLAB has 11 built-in membership functions which some of those are trimf, gbellmf, gaussmf, gauss2mf, sigmf, psigmf. One of these membership functions that are formed by straight lines is called triangular membership functions. These membership functions are used in this thesis in account of simple structure and well suited for the modeling. Reference current and rotor angle as the inputs have seven membership functions and compensated current as the output has seven membership functions for 6/4 MSRM. Figure 3.6, figure 3.7 and figure 3.8 shows the membership function for reference current, rotor angle and compensated current, respectively.

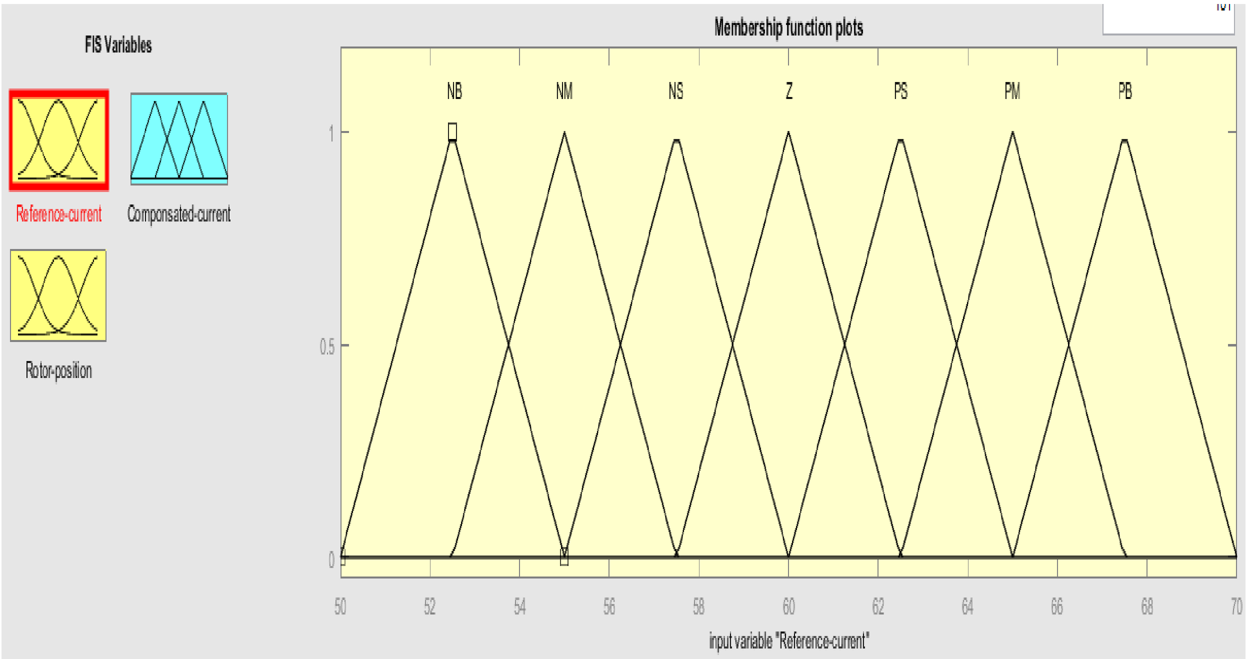
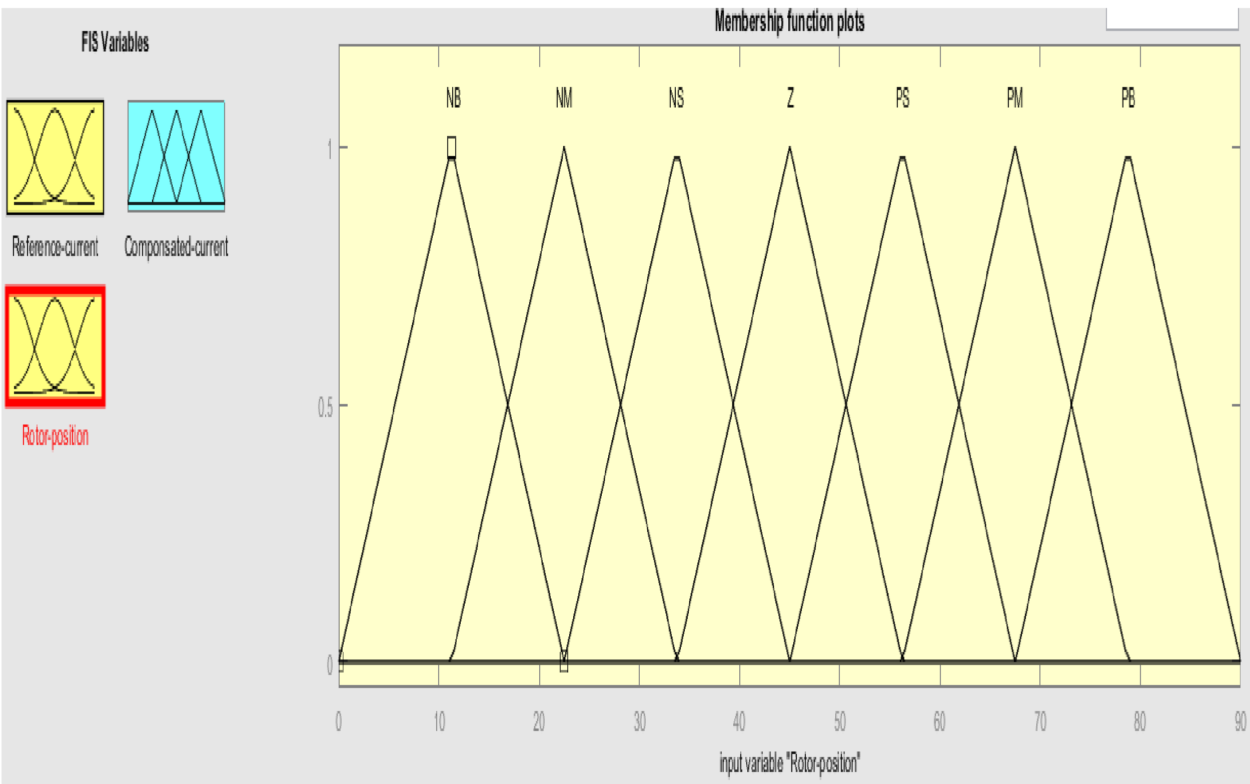


Figure 3.6 Membership functions for reference current



. **Figure 3.7 Membership functions for rotor angle**

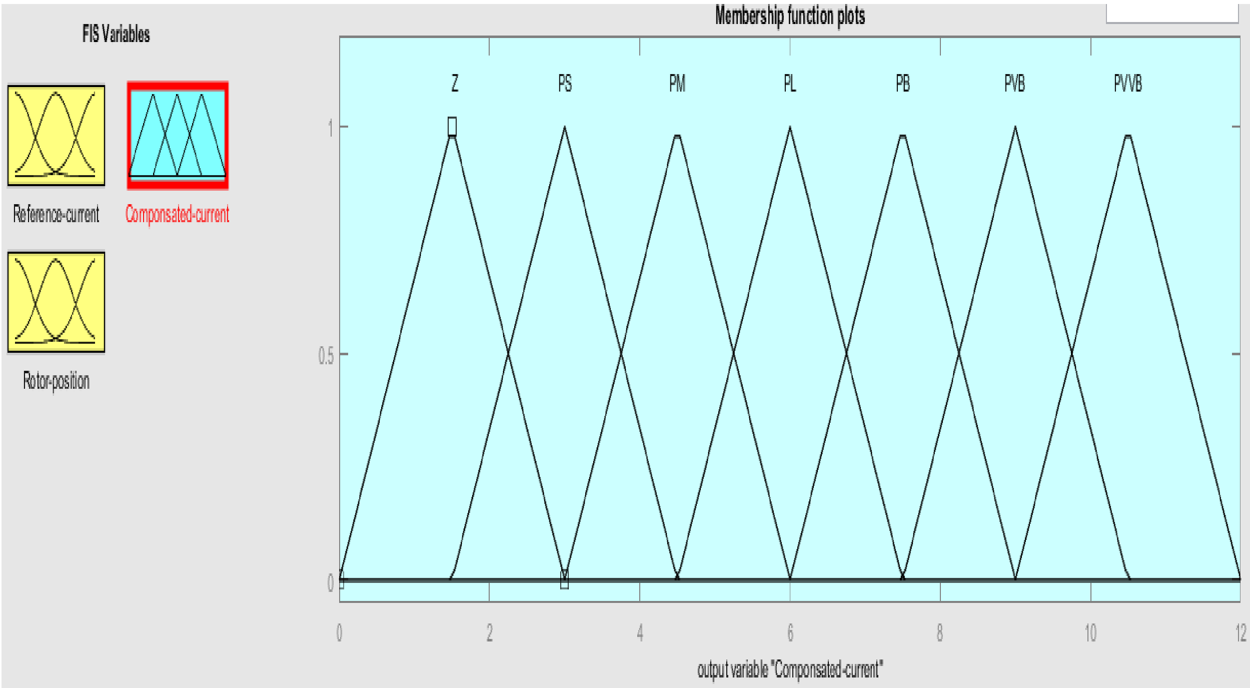


Figure 3.8 Membership functions for the compensated current

3.6.3 Establishing the fuzzy rules table

In the first step, from plotted curve, exact data should be extracted. For the torque estimation model, current and rotor angle are defined as inputs and compensated current is output. Based on analyzing the findings data from plotted curve minimum and maximum of each those inputs and output should be determined. Based on the division each of those inputs and output which is called fuzzy region, number of regions will determine and also, related linguistic variable will be assigned in order to settle the obstacle in establishing the fuzzy rule table. Table 3.2 show the input and output domain for 6/4 MSRM. This table shows the inputs and output variable with their respective number of region and linguistic variable assigned for the region.

Table 3.2 Input and output domains for 6/4 MSRM

Input/output	Range	No of regions	Variable
Reference current	50-70	7	NB,NM,NS,Z,PS,PM,PB
Rotor position	0-90	7	NB,NM,NS,Z,PS,PM,PB
Compensated current	0-12	7	Z,PS,PM,PL,PB,PVB,PVVB

Once domains are determined, forming fuzzy rule base table starts. To convert the torque profile characteristics to fuzzy rule base table, right interpret from the extracted data to linguistic variable is very important. Table 3.3 shows the fuzzy rule base table for 6/4 MSRM. According to the number of the fuzzy region and the linguistic variable, this table is established.

Table 3.3 Fuzzy rule base table for 6/4 MSRM

Reference current (A) / Rotor position (θ)	**NB**	**NM**	**NS**	**Z**	**PS**	**PM**	**PB**
NB	**PVVB**	**PVB**	**PL**	**PM**	**PB**	**PVB**	**PVVB**
NM	**PVVB**	**PVB**	**PL**	**PS**	**PB**	**PL**	**PVVB**
NS	**PVVB**	**PVB**	**PB**	**Z**	**PM**	**PB**	**PVB**
Z	**PVVB**	**PB**	**PM**	**PB**	**PVB**	**PB**	**PM**
PS	**PVB**	**PB**	**PM**	**Z**	**PM**	**PB**	**PL**
PM	**PB**	**PS**	**PS**	**Z**	**PS**	**PM**	**PB**
PB	**PM**	**PS**	**PS**	**Z**	**PS**	**PM**	**PB**

Linguistic variables for inputs: NB-negative big; NM-negative medium; NS- negative small; Z-zero; PS-positive small; PM-positive medium; PB-positive big. Linguistic variables for output: Z-zero; PS-positive small; PM-positive medium; PL-positive large; PB-positive big; PVB-positive very big; PVVB-positive very very big. It should be noted that wrong interpretation of each of rules will influence on overall output and as a result, wrong model will come up. Therefore, this part of work should be done carefully and without any wrong rule. Fuzzy rules act on phase current (with seven member function for 50-70 Amp.) and angular position (with seven member function for 0-90*)* as inputs and compensated current (with seven member function for 0-12 Amp) as output. Consequently new phase current is the addition of phase current and compensating current. In the regions of NB, NM and PM, PB torque reduces at the large scale and for torque ripple minimization, fuzzy rules PVB or PVVB but in the NS and PS regions torque reduces by far slowly, consequently fuzzy rules PB and PVB have been determined.

3.6.4 Constructing fuzzy inference system rules

The most important part of the modeling is the constructing FIS rules because of the outcome of this part will define output fuzzy set. In other words, compensated current as the output is a fuzzy set that basically are formed by the results of the constructing FIS rules. Table

3.3 is used to constructing FIS rules. In Mamdani's type a set of if-then called rules. Thus, the conditional statements are formulated by if-then form. For instance,

Rule 1: If current is NB and rotor angle is NB then torque is PVVB degree of membership function is a value between 0 and 1 which is the output of the membership function. Now, degree of a rule can be defined the multiple of the degree of the inputs and output. For example, degree of the mentioned rule can be as following:

$Degree(Rule1) = \mu(NB).\mu(NB).\mu(PVVB)$ FIS editor is used to produce the rules which are shown in figure 3.9. Also, figure 3.9 shows apart of rules for 6/4 MSRM and the number of total rules are 49.

1. If (Reference-current is NB) and (Rotor-position is NB) then (Componsated-current is PVVB) (1)
2. If (Reference-current is NB) and (Rotor-position is NM) then (Componsated-current is PVVB) (1)
3. If (Reference-current is NB) and (Rotor-position is NS) then (Componsated-current is PVVB) (1)
4. If (Reference-current is NB) and (Rotor-position is Z) then (Componsated-current is PVVB) (1)
5. If (Reference-current is NB) and (Rotor-position is PS) then (Componsated-current is PVB) (1)
6. If (Reference-current is NB) and (Rotor-position is PM) then (Componsated-current is PB) (1)
7. If (Reference-current is NB) and (Rotor-position is PB) then (Componsated-current is PM) (1)
8. If (Reference-current is NM) and (Rotor-position is NB) then (Componsated-current is PVB) (1)
9. If (Reference-current is NM) and (Rotor-position is NM) then (Componsated-current is PVB) (1)
10. If (Reference-current is NM) and (Rotor-position is NS) then (Componsated-current is PVB) (1)
11. If (Reference-current is NM) and (Rotor-position is Z) then (Componsated-current is PB) (1)
12. If (Reference-current is NM) and (Rotor-position is PS) then (Componsated-current is PB) (1)
13. If (Reference-current is NM) and (Rotor-position is PM) then (Componsated-current is PS) (1)
14. If (Reference-current is NM) and (Rotor-position is PB) then (Componsated-current is PS) (1)
15. If (Reference-current is NS) and (Rotor-position is NB) then (Componsated-current is PL) (1)
16. If (Reference-current is NS) and (Rotor-position is NM) then (Componsated-current is PL) (1)
17. If (Reference-current is NS) and (Rotor-position is NS) then (Componsated-current is PB) (1)
18. If (Reference-current is NS) and (Rotor-position is Z) then (Componsated-current is PM) (1)
19. If (Reference-current is NS) and (Rotor-position is PS) then (Componsated-current is PM) (1)
20. If (Reference-current is NS) and (Rotor-position is PM) then (Componsated-current is PS) (1)
21. If (Reference-current is NS) and (Rotor-position is PB) then (Componsated-current is PS) (1)
22. If (Reference-current is Z) and (Rotor-position is NB) then (Componsated-current is PM) (1)
23. If (Reference-current is Z) and (Rotor-position is NM) then (Componsated-current is PS) (1)
24. If (Reference-current is Z) and (Rotor-position is NS) then (Componsated-current is Z) (1)
25. If (Reference-current is Z) and (Rotor-position is Z) then (Componsated-current is PB) (1)
26. If (Reference-current is Z) and (Rotor-position is PS) then (Componsated-current is Z) (1)
27. If (Reference-current is Z) and (Rotor-position is PM) then (Componsated-current is Z) (1)
28. If (Reference-current is Z) and (Rotor-position is PB) then (Componsated-current is Z) (1)
29. If (Reference-current is PS) and (Rotor-position is NB) then (Componsated-current is PB) (1)
30. If (Reference-current is PS) and (Rotor-position is NM) then (Componsated-current is PB) (1)

31. If (Reference-current is PS) and (Rotor-position is NS) then (Componsated-current is PM) (1)
32. If (Reference-current is PS) and (Rotor-position is Z) then (Componsated-current is PVB) (1)
33. If (Reference-current is PS) and (Rotor-position is PS) then (Componsated-current is PM) (1)
34. If (Reference-current is PS) and (Rotor-position is PM) then (Componsated-current is PS) (1)
35. If (Reference-current is PS) and (Rotor-position is PB) then (Componsated-current is PS) (1)
36. If (Reference-current is PM) and (Rotor-position is NB) then (Componsated-current is PVB) (1)
37. If (Reference-current is PM) and (Rotor-position is NM) then (Componsated-current is PL) (1)
38. If (Reference-current is PM) and (Rotor-position is NS) then (Componsated-current is PB) (1)
39. If (Reference-current is PM) and (Rotor-position is Z) then (Componsated-current is PB) (1)
40. If (Reference-current is PM) and (Rotor-position is PS) then (Componsated-current is PB) (1)
41. If (Reference-current is PM) and (Rotor-position is PM) then (Componsated-current is PM) (1)
42. If (Reference-current is PM) and (Rotor-position is PB) then (Componsated-current is PM) (1)
43. If (Reference-current is PB) and (Rotor-position is NB) then (Componsated-current is PVVB) (1)
44. If (Reference-current is PB) and (Rotor-position is NM) then (Componsated-current is PVVB) (1)
45. If (Reference-current is PB) and (Rotor-position is NS) then (Componsated-current is PVB) (1)
46. If (Reference-current is PB) and (Rotor-position is Z) then (Componsated-current is PM) (1)
47. If (Reference-current is PB) and (Rotor-position is PS) then (Componsated-current is PL) (1)
48. If (Reference-current is PB) and (Rotor-position is PM) then (Componsated-current is PB) (1)
49. If (Reference-current is PB) and (Rotor-position is PB) then (Componsated-current is PB) (1)

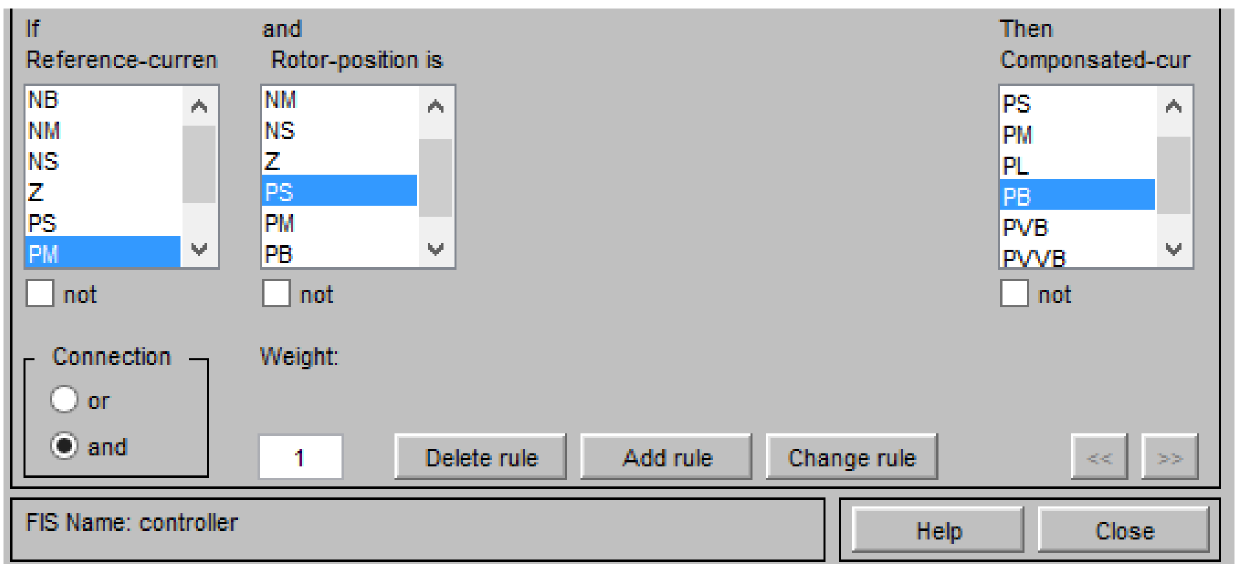


Figure 3.9 Constructing rules using rule editor

Figure 3.10 shows change of reference current (ΔI_{ref}) and rotor position ($\Delta\theta$) generation by fuzzy logic controller, as soon as any antecedent's linguistic variables change or both during the process, then the output compensated current (ΔI_{comp}) changes accordingly. The results appear at the bottom of the third columns.

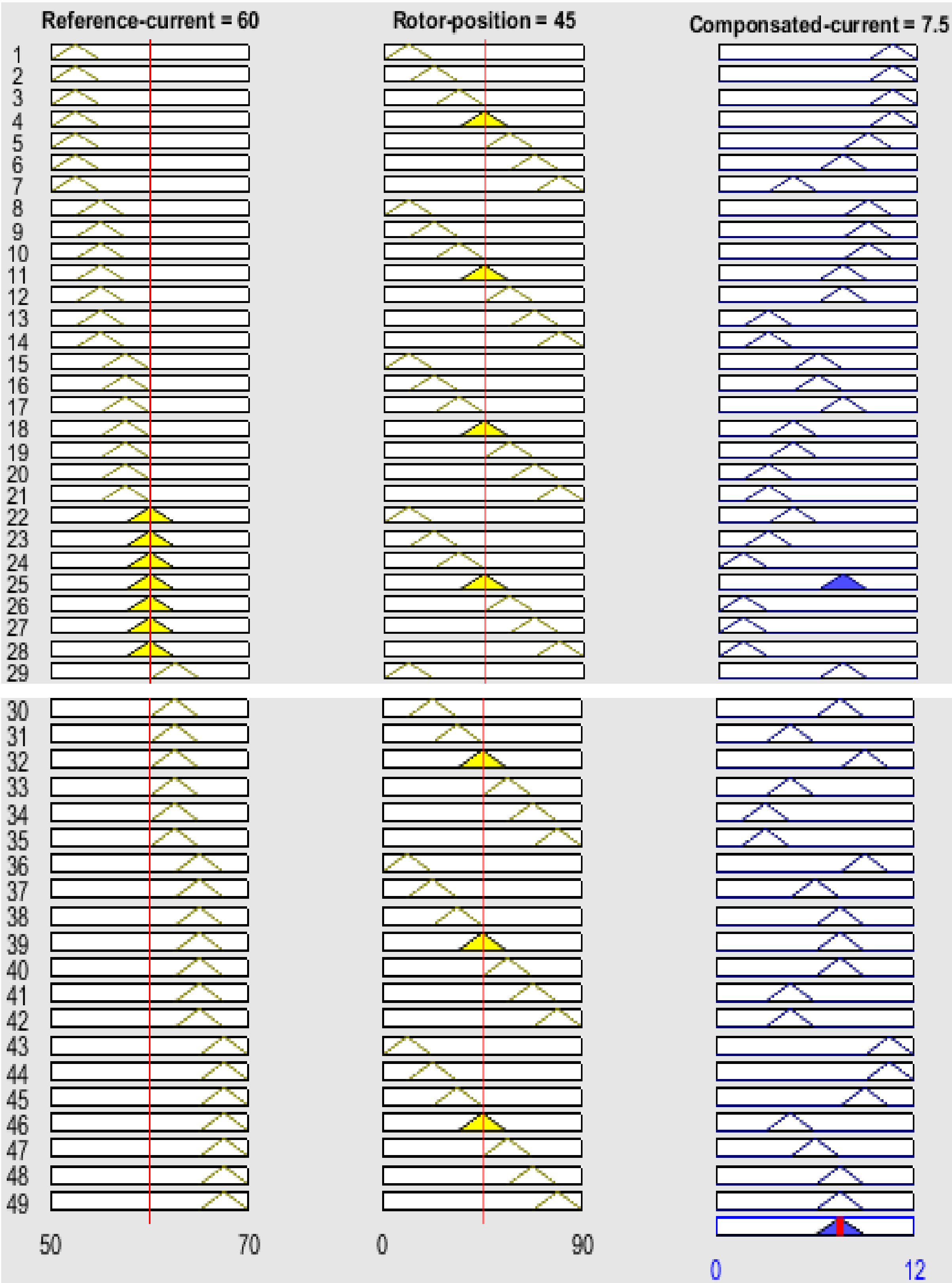


Figure 3.10 Rules Viewer for three phase 6/4 Poles MSRM using fuzzy logic controlle

3.6.5 Surface viewer of the controller

The surface viewer is used to show the dependency of the output to both of inputs. There for, it generates compensated current surface map. Figure 3.11 shows the compensated current surface for 6/4 mult-layer switched reluctance motor.

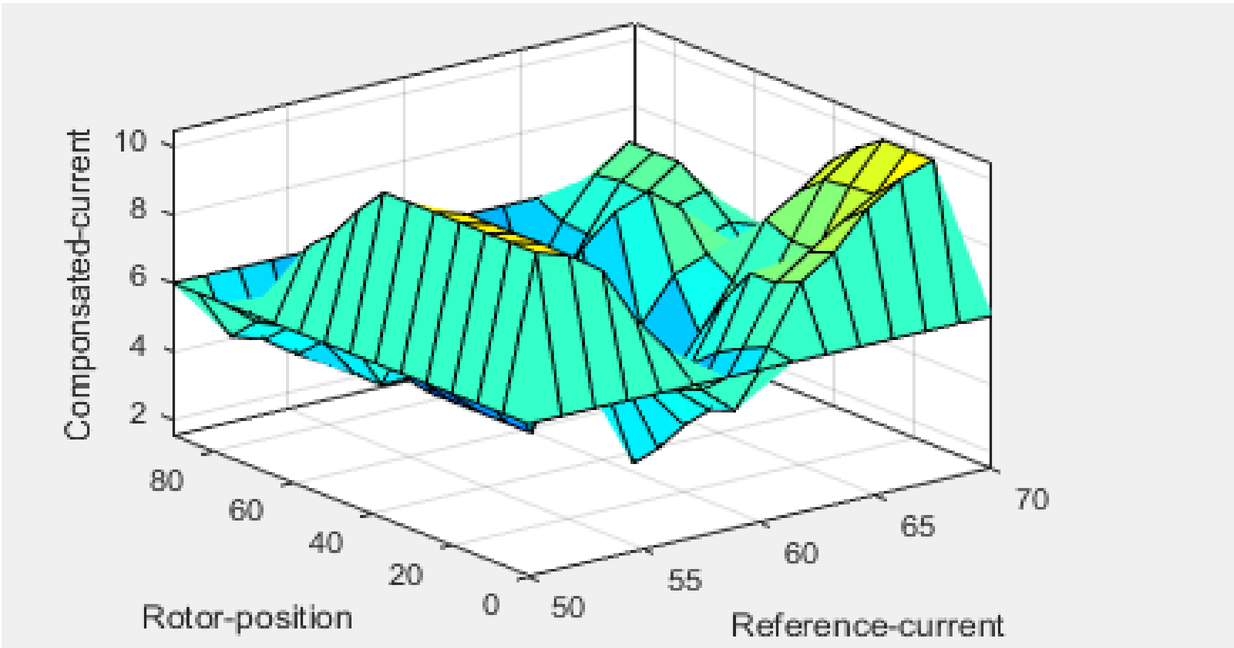


Figure 3.11 Surface viewer of the for three phase 6/4 MSRM using fuzzy logic controller

3.7 Implementation of fuzzy logic controller

For this model, a DC supply voltage of 240 V is used. The converter turn-on and turn-off angles are kept constant at 45 deg and 75 deg, respectively, over the speed ranges. The reference speed is limited to $200 Rad/s$ and the hysteresis band is chosen as ± 10 Amps. In fuzzy logic controller, reference current (I_{ref}), rotor position (θ) are considered as inputs and compensating current(I_{comp}) as output. The fuzzy rules act on reference current (with seven member functions for 50-70 Amps) and angular position (with seven member function for 0-90 Degrees) as inputs and compensating current (with seven member functions for 0 to 12 Amps) as output as shown in figure 3.8. In addition, fuzzy logic rules for maximum compensation in near zero speeds up to rated speed has been used. As well, in upper the rated speed, fuzzy logic rules for compensation current is limited to PB because high ripple in high current will damage the SRM.

The rule base developed for the control of MSRM drive is given in table 3.3. In the regions of NB, NM and PM, PB torque reduces at the large scale and for torque ripples minimization, fuzzy rules PVB or PVVB but in the NS and PS regions torque reduces by far slowly, consequently fuzzy rules PB and PVB have been determined. In addition, fuzzy logic rules for maximum compensation in near zero speeds up to rated speed has been used. As well, in upper the rated speed, fuzzy logic rules for compensation current is limited to PB because high ripple in high current will damage the MSRM.

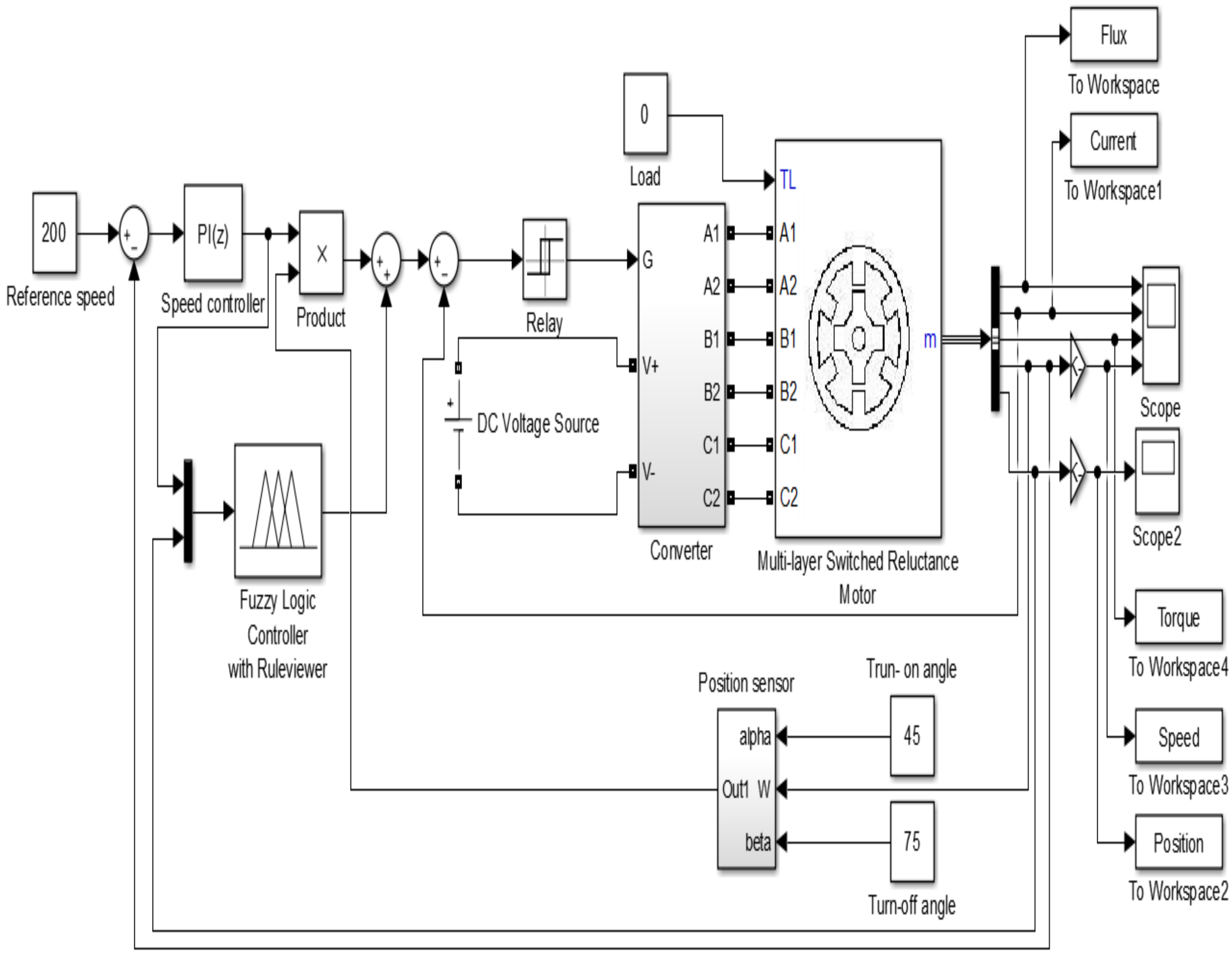


Figure 3.12 Matlab simulink model of multi-layer switched reluctance motor with fuzzy logic controller.

3.7.1 Simulation result and discussion

The torque control using figure 3.12 is the simulink model of multi-layer switched reluctance motor with fuzzy logic controller. The new compensation mechanism using fuzzy logic controller with closed loop control is used to compensate the phase current to get a reduced torque ripple by adding this compensated current. Torque is generated over the maximum torque producing region of the phases, thus increasing the torque density under a multi-layer switched reluctance motor system simulation environment. Using matlab the test is implemented and the simulation result have shown torque ripple reduction when compare with that of without controller that is obtained by adding the compensating current signal. When we compare without controller and with fuzzy logic controller in figure 3.13 there is reduction of the torque ripple, hence the fuzzy logic controller give reduced toque ripple with the limitation to adapt itself with motor speed and torque changes.

Figure 3.13 Torque characteristic of multi-layer switched reluctance motor without controller and with fuzzy logic controller

From the simulation result above the output torque without controller has torque ripple given by

$$T_{ripple} = \frac{T_{max} - T_{min}}{T_{avg}} \quad \text{where}$$

$$T_{max} = 250 \quad T_{min} = 50 \quad T_{avg} = 150$$

But with fuzzy logic controller

$$T_{max} = 150 \quad T_{min} = 45 \quad T_{avg} = 97.5$$

Torque ripple reduction in percentage = (torque ripple without controller- torque ripple with fuzzy logic controller)*100

$$\boldsymbol{torque\ ripple\ reduction\ in\ percentage = (1.33 - 1.11) * 100 = 22\%}$$

Hence using fuzzy logic controller is reduced by twenty two percent than using without any controller.

CHAPTER FOUR

Adaptive neuro fuzzy inference system controller (ANFIS) of multi-layer switched reluctance motor

4.1 Introduction to artificial neural network

An artificial neural network is a system based on the operation of biological neural networks, in other words, is an emulation of biological neural system. Why would be necessary the implementation of artificial neural networks. Although computing these days is truly advanced, there are certain tasks that a program made for a common microprocessor is unable to perform; even so a software implementation of a neural network can be made with their advantages and disadvantages [19].

Neural networks may have various advantages over traditional control techniques that be trained to perform definite tasks based on experimental or real time data. It exhibits capability of artificial neural networks to organize information received during runtime to approximate functions. It endows with parallel computation through multiple output architectures. Artificial neural networks are used in system identification, adaptive control, modeling, optimization, and motion control. In comparison, analytical models fall short due to the complexity required to appropriately model those systems. Artificial neural network's are ideal for controlling discrete-time, non-linear systems with large non-linear variations in their states due to their extreme non-linearity. Artificial neural networks have successfully modeled highly complex, non-linear systems, due to their unparalleled ability to recognize complex patterns in seemingly random data. Artificial neural network’s architectures are primarily designed in two fashions. The first one is the time-delay is more suitable for dynamic non-linear systems. But, they are inherently more difficult to implement due to the architectural complexity required to achieve estimation accuracy. Typically, the feed-forward type of neural net is most utilized in control problems. The second one is a feed-forward neural network, development information from input to output through one or more layers of neurons. Feed-forward networks exhibit the greatest compatibility for the position estimation problem in switched reluctance motors [19] [20].

A completely associated neural net has all of the inputs connected to each neuron in the input layer. A partially connected network is a fully connected network with some of the synaptic weights set to zero. The neural network with a reduced amount of input neurons and a single output neuron is also referred to as a multi-layer perceptron. Artificial neural networks ease the control burdens, yet there are several outstanding issues that may present obstacles for a system designer.

(i) Artificial neural network's maintain their accuracy through the force of large number of neurons. If accuracy is critical, a successful neural network implementation may require a large amount of memory to contain all the synaptic weights.

(ii) The number of connections between layers can be problematic (depends on the size of the network). The calculations required to process the network can not be implemented with other control functions on most common microprocessors.

(iii) Most Artificial neural network designers then tradeoff performance versus neural size, thus, accepting more estimation error for the ability to capture some of the benefits artificial neural network's provide.

(iv) Estimation error is dependent upon both the number of neurons in the hidden layer and the number of samples in the training data set.

(v) Training data is highly effective in the performance of the network and perform for small conduction angles that are strongly affected by the chosen training set.

4.2 Biological neurons

In the human brain, there are neurons that are interconnected to one another. These neurons act as a tool that can perform processing of information of human senses. Haykin (2009) described that a biological neuron consists of a cell body, where conditions are covered by the cell membrane as shown in the figure 4.1. Each cell has branches called dendrites. Dendritic play a role in receiving the information into the cells of the body through the axon. The axon is a long single fiber that can carry the signal from the cell body toward the neuron the next neuron. The meeting point between neurons with the next neuron found in a small space between dendrites and axons is known as a synapse. The space of synapses is applicable for shipping and receiving all information processes from the senses. Any information entered will be encoded in the form of electrical signals. All electrical signals into the synapses are counted and calculated. When the number of electrical signals regardless of the limits or thresholds specified in the synapse, the synapses react to a new electrical signal input to be used by the next neuron. If the electrical signals cannot be separated from the predetermined threshold, then the synapses will be retarded. Retardation of synapses causes obstruction of the relationship between the two neurons. [21]

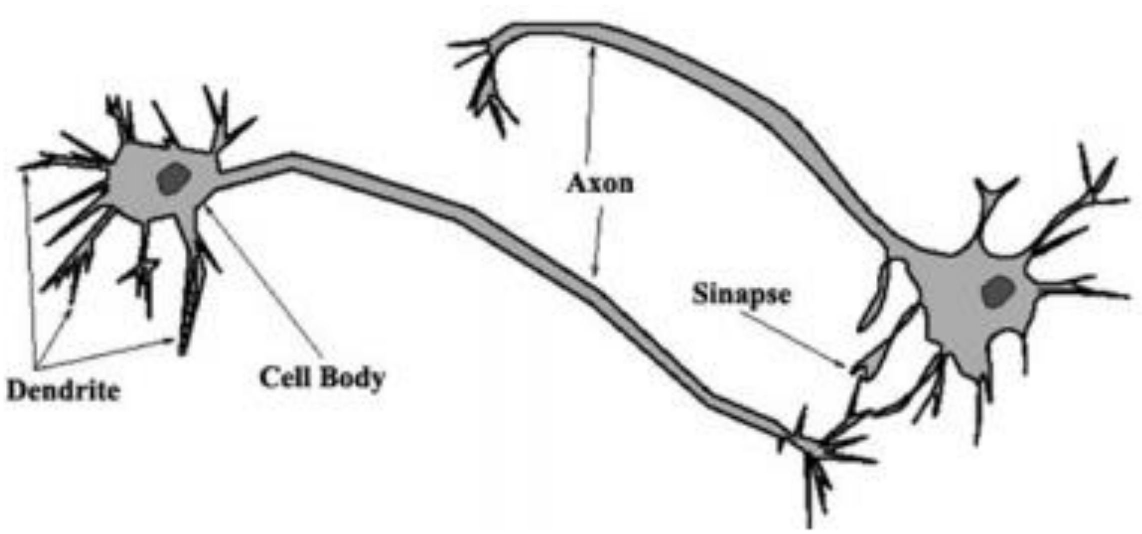


Figure 4.1 Schematic diagrams of biological neurons

Artificial neural networks may be thought of as simplified models of the networks of neurons that occur naturally in the animal brain. From the biological viewpoint the essential requirement for a neural network is that it should attempt to capture what we believe is the essential information processing features of the corresponding real network [21].

4.3 History of neural networks

The idea of neural networks began unsurprisingly as a model of how neurons in the brain function termed ‘connectionism’ and used connected circuits to simulate intelligent behaviour. In 1943, portrayed with a simple electrical circuit by neuro physiologist Warren McCulloch and mathematician Walter Pitts. Donald Hebb took the idea further in his book, the organization of behaviour (1949), proposing that neural pathways strengthen over each successive use, especially between neurons that tend to fire at the same time thus beginning the long journey towards quantifying the complex processes of the brain. Two major concepts that are precursers to neural networks are [20] [22].

- Threshold Logic:- converting continuous input to discrete output
- ‘Hebbian Learning:- a model of learning based on neural plasticity, proposed by Donald Hebb in his book “The Organization of Behaviour” often summarized by the phrase: “Cells that fire together, wire together.

Both proposed in the 1940's. In 1950s, as researchers began trying to translate these networks onto computational systems, the first Hebbian network was successfully implemented at MIT in 1954.

4.4 Neurons mathematical model

In line with the biological neuron model, McCulloch and Pitt (1943) proposed a model neuron that has the characteristics of the transmission and receipt of information process that is similar to the process that occurs in biological neurons. This neuron modeling was becoming a reference in the development of artificial neural network model at current state. A neuron plays a role in determining the function and operation of the network. The mathematical models of neurons, which are commonly used in the artificial neural network model is shown in figure 4.2. Neuron modeling based on figure 4.2 can be represented by the following mathematical equation: [22]

$$u(k) = \sum_{j=1}^{n} W_{kj} X_j \ \ and \ \ Y(k) = \varphi\big(u(k)\big) + b(k) \tag{4.1}$$

Where $u(k)$ is the output of the adder function neuron model, X_j is data or input signal on path synapse j, and W_{kj} is the weighted in the path of synapse j to k neuron. The output of the neuron is represented by $Y(k)$, where it is dependent on the activation function $\varphi(.)$ and the bias (k). There are several types of activation functions that were used in modeling neurons, some of them are fixed limiter function, linear function, sigmoid function, and bipolar sigmoid function.

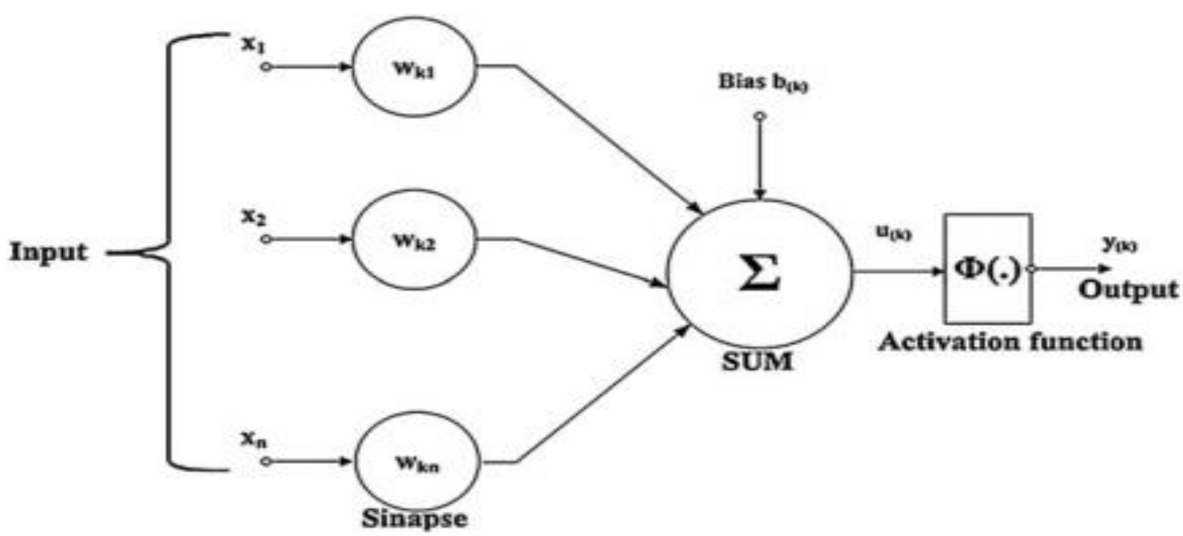


Figure 4.2 Mathematical modeling of neuron

4.4.1 Neural networks topologies

A neural network topology represents the way in which neurons are connected to form a network. In other words, the neural network topology can be seen as the relationship between the neurons by means of their connections. The topology of a neural network plays a fundamental role in its functionality and performance. The generic terms `structure' and `architecture' are used as synonyms for network topology. However, caution should be taken when using these terms since their meaning is not well defined as they are also often used in contexts where they encompass more than the neural network topology alone or refer to something deferent altogether. They are for example often used in the context of hardware implementations (`computer architectures') or their meaning includes, besides the network topology, also the learning rule [2]. More precisely, the topology of a neural network consists of its frame or framework of neurons, together with its interconnection structure or connectivity [21].

Another aspect of the artificial neural networks is that there are different architectures, which consequently requires different types of algorithms, but despite to be an apparently complex system, a neural network is relatively simple. Basically, an artificial neural network is a system. A system is a structure that receives an input, process the data, and provides an output. Commonly, the input consists in a data array which can be anything such as data from an image file, a wave sound or any kind of data that can be represented in an array. Once an input is presented to the neural network, and a corresponding desired or target response is set at the output, an error is composed from the difference of the desired response and the real system output.

A neural network is an interconnected assembly of simple processing elements, units or nodes, whose functionality is loosely based on the animal neuron. The processing ability of the network is stored in the inter unit connection strengths, or weights, obtained by a process of adaptation to, or learning from, a set of training patterns. The neural network shown below has three layers as input, hidden and output layers respectively. An input layer is connected to the three neurons in the hidden layer through different weights. The outputs of the hidden layer are connected to the output layer through weights as shown in figure 4.3. In this thesis we have two inputs (reference current and rotor position) and one output which is compensated current. Each of input and output has seven membership functions with different connections (weights) [22].

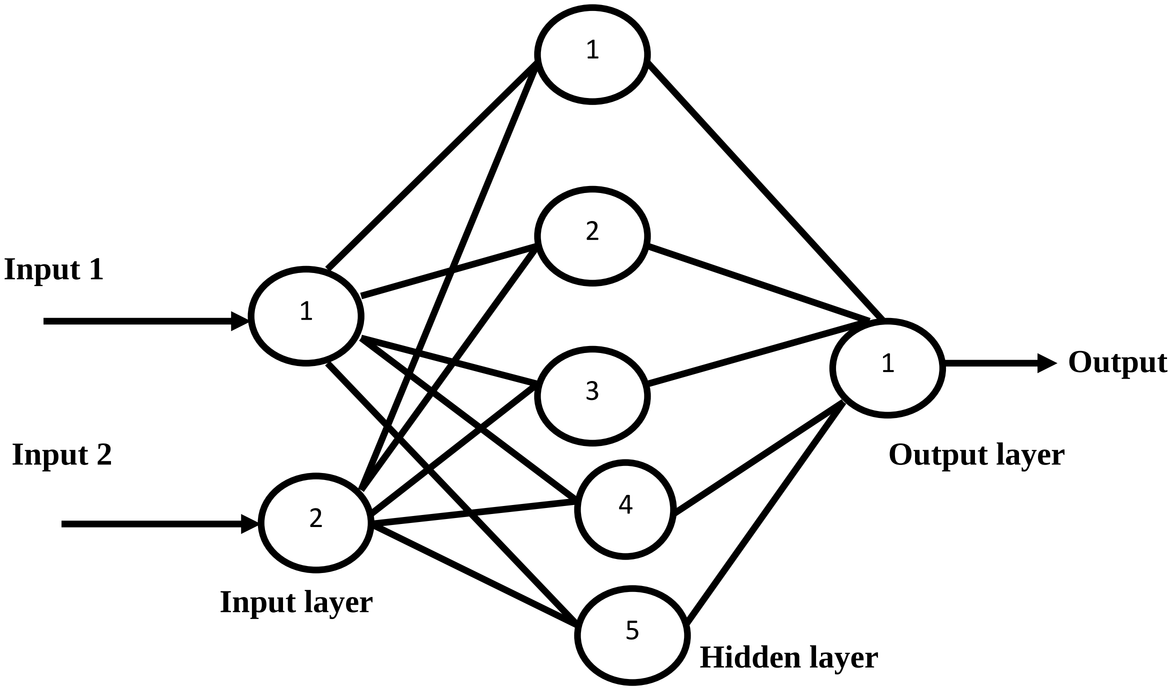


Figure 4.3 The layout of the neural network

The output of a single neuron can be represented by the following equation:

$$a_i \; = f_i(\sum_{j=1}^{n} w_{ij} x_j(t) + b_i \qquad (4.2)$$

Where f_i is the activation function, w_{ij} is the weighting factor, x_j is the input signal, and b_i is the bias. The most commonly used activation functions are non-linear, continuously varying types between two asymptotic values -1 and +1. This is known as sigmoid function. The artificial neural networks are the best way to implement a solution" this motivated by their simplicity, design and universality. Nowadays, neural network technologies are emerging as the technology choice for many applications, such as patter recognition, prediction, system identification and control. The learning process of an ANN is based on the training process. This learning process is then followed by supplying with the real input power and the ANN then produces the required output data [2] [21].

4.4.2 Back propagation algorithm

Back propagation neural (BPN) is a multilayer neural network consisting of the input layer, at least one hidden layer and output layer. As its name suggests, back propagating will take place in this network. The error which is calculated at the output layer, by comparing the target output and the actual output, will be propagated back towards the input layer.

As shown in the diagram, the architecture of BPN has three interconnected layers having weights on them. The hidden layer as well as the output layer also has bias, whose weight is always one, on them. As is clear from the diagram, the working of BPN is in two phases. One phase sends the signal from the input layer to the output layer, and the other phase back propagates the error from the output layer to the input layer [23].

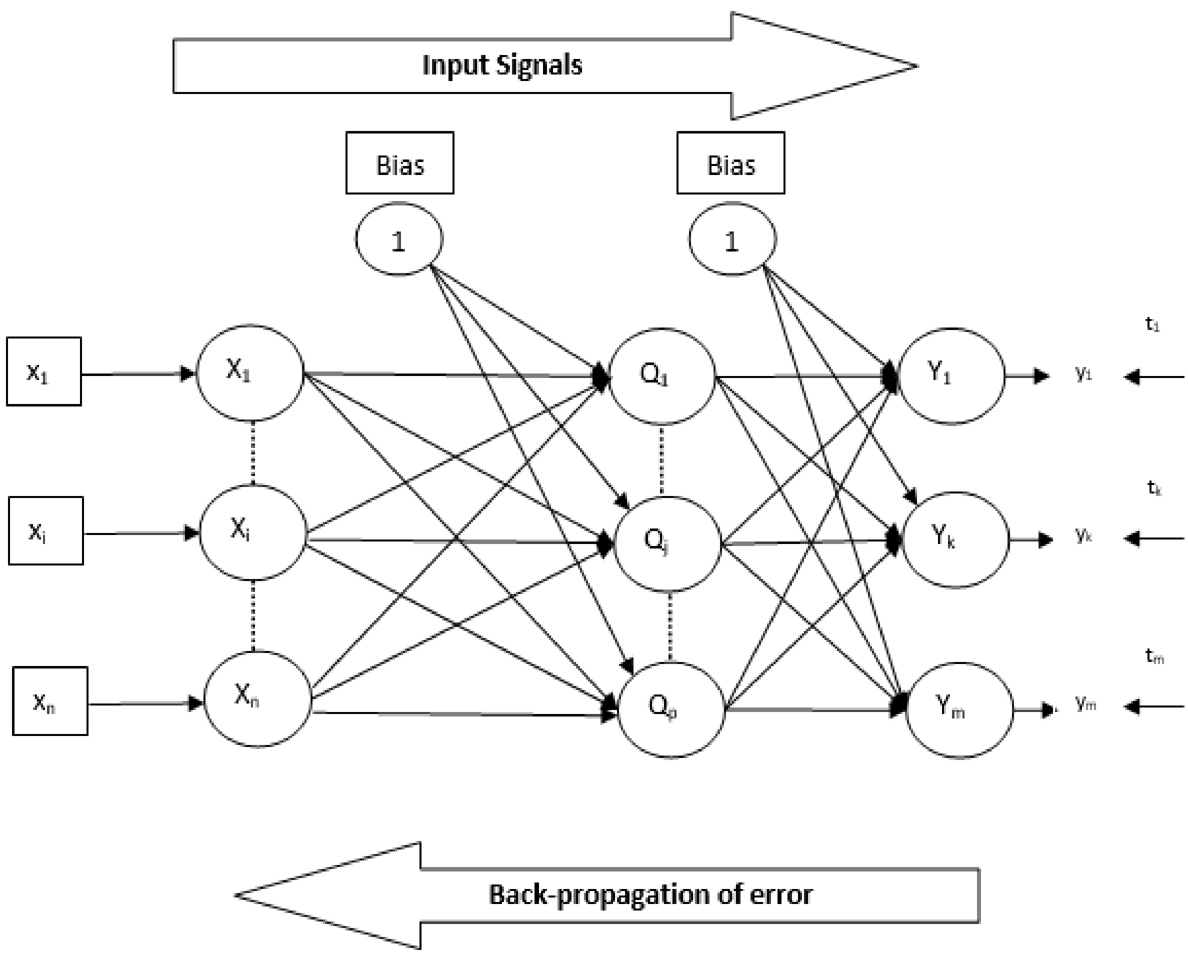


Figure 4.4 Back-propagation algorithm

4.5 Artificial neural network design steps

At this time, there is no exact design to implement intelligent control. However, it achieves neural design implementation to include some steps. They are [23]

(i) Designer should define the number of input, hidden, output layers.

(ii) The activation functions that are suited for application should be chosen. (i.e. match the function to data space dynamic range). Non-linear activation functions should comprise the majority of the neurons while the output neurons can be linear.

(iii) The neural network weights should be initialized to random, small values to ensure that the network is not saturated by large values of weights. Also if the initial weights are identical, the neural network would not be trainable.

(iv) The designer should collect, select the data set for training. The training data should include both the input and output spaces.

(v) A training supervisory algorithm should be chosen based on the type of neural architecture that was chosen. Generally, a back-propagation type algorithm is sufficient for feed-forward networks.

(vi) The neural net should then be trained by adapting the weights using the supervisory algorithm. The algorithm should minimize the error between the neural output calculated from the input space and the associated target value.

(vii) The designer should verify the network with data pairs not from the original data set. The test data is an extraction from the original data set, yet the test data is never presented to the network during training.

4.6 The main advantages and disadvantage of using the artificial neural network (ANN) controller

The main advantages of using the artificial neural network (ANN) controller

- A neural network can perform tasks that a linear program can not.
- When an element of the neural network fails, it can continue without any problem by their parallel nature.
- A neural network learns and does not need to be reprogrammed.

- It can be implemented in any application.
- It can be implemented without any problems
- They may require less tuning effort than conventional controller

The main disadvantages of using the artificial neural network (ANN) controller

- The neural network needs training to operate.
- The architecture of a neural network is different from the architecture of microprocessors therefore needs to be emulated.
- Requires high processing time for large neural networks.

4.7 Adaptive neuro fuzzy inference system (ANFIS) controller

An adaptive neuro-fuzzy inference system or adaptive network based fuzzy inference system is a kind of artificial neural network that is based on takagi-sugeno fuzzy inference system. The technical was developed in the early 1990s**.** Since it integrates both neural networks and fuzzy logic principles, it has potential to capture the benefits of both in a single framework. Fuzzy inference system forms a useful computing framework based on the concepts of fuzzy set theory, fuzzy if–then rules and fuzzy reasoning. ANFIS is a fuzzy inference system implemented in the framework of an adaptive fuzzy neural network [24] [25].

The main objective of ANFIS is to optimize the parameters of the equivalent FIS by applying a learning algorithm using input–output data sets. The parameter optimization is done in a way such that the error measure between the target and the actual output is minimized. A typical architecture of an ANFIS for two inputs is shown in figure 4.5, in which a circle indicates a fixed node whereas a square indicates an adaptive node. Considering two inputs x, y and one output z and a Sugeno-fuzzy model. Among many FIS models, the Sugeno fuzzy model is the most widely applied one for its high interpretability, computational efficiency, and built-in optimal and adaptive techniques.

For simplicity, we assume that the fuzzy inference sytem under consideration has two inputs x and y and one output z. For a first-order Takagi-Sugeno fuzzy model, a common rule set with two fuzzy if-then rules is the following rule set: [22]

$$Rule\ 1: If\ x\ is A_1 and\ y\ is\ b_1, then, f_1 = p_1x + q_1y + r_1$$

$$Rule\ 2: If\ x\ is\ A_2 and\ y\ is B_2, then, f_2 = p_2x + q_2y + r_2$$

Most of the fuzzy logic applications involve construction and processing of fuzzy rules. Fuzzy rules serve to describe, in linguistic terms, a qualitative relationship between two or more variables. Processing of fuzzy rules or fuzzy reasoning provides a mechanism for using fuzzy rules to compute the response to a given fuzzy controller input. So we can measure outputs of a plant and calculate a control action according to this rules table. The result is a fuzzy set. The inputs of the inference engine are fuzzy sets and the output is also a fuzzy set.

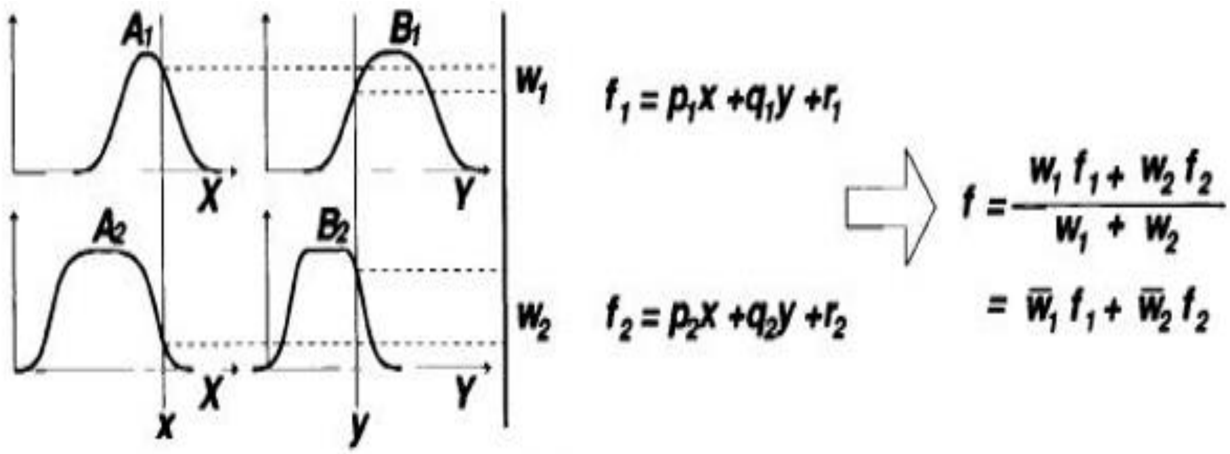


Figure 4.5 A two inputs first order Takagi-Sugeno fuzzy model with two rules

Corresponding equivalent ANFIS architecture will be as shown below:-

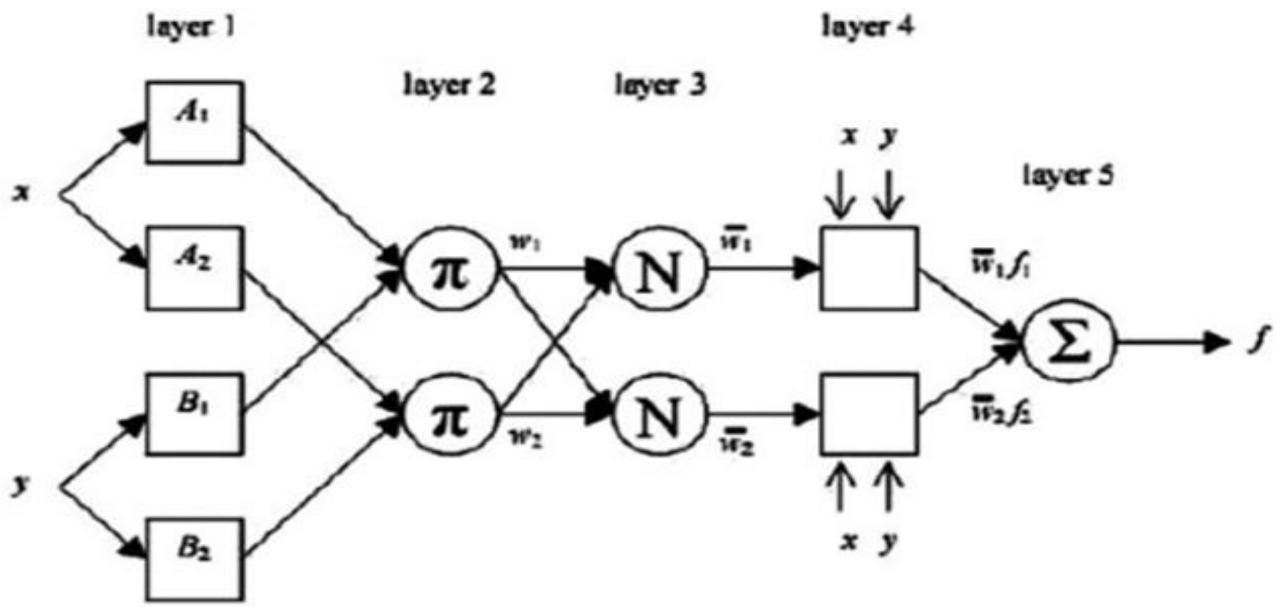


Figure 4.6 Architecture of adaptive neuro fuzzy inference system (ANFIS)

ANFIS consists of five layers the description of these layers is as follow:

Layer 1: Every node i in the first layer employ a node function given by:

$$O_{1,i} = \mu_{Ai}(x), i = 1,2 \tag{4.3}$$

$$O_{1,i} = \mu_{Bi}(y), i = 3,4 \tag{4.4}$$

Where $\mu_{Ai}(x)$ and $\mu_{Bi}(y)$ can adopt any fuzzy membership function (MF). Where x or y is the input to node i and Ai or Bi is a linguistic label (such as "small" or "large") associated with this node. In other words, $O_{1,i}$ is the membership grade of a fuzzy set $A = A1, A2, or\ B1, B2$ and it specifies the degree to which the given input x or y satisfies the quantifier A.

$$\mu_A(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b}} \tag{4.5}$$

Where $\{a_i, b_i, c_i\}$ is the parameter set. As the values of these parameters change, the bell-shaped function varies accordingly, thus exhibiting various forms of membership function for fuzzy set A. Parameters in this layer are referred to as premise parameters.

Layer 2: Every node in this layer is a fixed node labeled anfis, whose output is the product of all the incoming signals:

$$O_{2,i} = w_i = \mu_{Ai}(x)\ \mu_{Bi}(y), i = 1,2 \tag{4.6}$$

Each node output represents the firing strength of a rule. In general, any other T-norm operators that perform fuzzy AND can be used as the node function in this layer.

Layer 3: Every node in this layer is a fixed node labeled N. The ith node calculates the ratio of the ith rule's firing strength to the sum of all rules' firing strengths:

$$O_{3,i} = w'_i = \frac{w_i}{w_1 + w_2}, i = 1,2 \tag{4.7}$$

For convenience, outputs of this layer are called normalized firing strengths.

Where w'_i is referred to as the normalized firing strengths.

Layer 4: Every node i in this layer is an adaptive node with a node function.

$$O_{4,i} = w'_i f_i = w'_i(p_i x + q_i y + r_i) \tag{4.8}$$

Where anfis is a normalized firing strength from layer three and $\{pi, qi, ri\}$ is the parameter set of this node. Parameters in this layer are referred to as consequent parameters.
Where w'_i is the output of layer three and $\{p, q, r\}$ are the parameter set. The parameters in this layer are referred to as the consequent parameters.

Layer 5: The single node in this layer computes the overall output as the summation of all incoming signals, which is expressed as:

$$overall\ output = O_{5,i} = \sum_i w'_i\, f_i = \frac{\sum_i w'_i\, f_i}{\sum_i w_i} = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} \tag{4.9}$$

Thus we have constructed an adaptive network that is functionally equivalent to a Sugeno fuzzy model.
The output f in figure 5.6 can be rewritten from equations above as:

$$f = (w'_1 x)p_1 + (w'_1 y)q_1 + (w'_1)r_1 + \left(w'_2 x\right)r_1 + (w'_2 x)p_2 + \left(w'_2 y\right)q_2 + (w'_2)r_2 \tag{4.10}$$

4.8 Learning scheme of adapative neuro fuzzy inference system

Basically, learning means to do and adapt the change in itself as and when there is a change in environment. Artificial neural network is a complex system or more precisely we can say that it is a complex adaptive system, which can change its internal structure based on the information passing through it. Being a complex adaptive system, learning in artificial neural network implies that a processing unit is capable of changing its input/output behavior due to the change in environment. The importance of learning in artificial neural network increases because of the fixed activation function as well as the input/output vector, when a particular network is constructed. Now to change the input/output behavior, we need to adjust the weights. Just as there are different ways in which we ourselves learn from our own surrounding environments, so it is with neural networks. In a broad sense, we may categorize the learning processes through which neural networks function as follows: learning with a teacher and learning without a teacher. By the same token, the latter form of learning may be subcategorized into unsupervised learning and reinforcement learning. These different forms of learning as performed on neural networks parallel those of human learning [25].

In the iterative training of the neuro-fuzzy controller the training data were obtained from simulations of fuzzy logic controller of the complete switched reluctance drive system. This data set is then passed to the training algorithm, so that the torque ripple is interpreted by the controller in terms of compensating current (I_{comp}) for each reference current (I_{ref}), rotor position (θ) pair. The controller output is then readjusted to reduce the torque ripple. The process is repeated until some minimum value torque ripple has been reached. The information about the adaptive neuro fuzzy inference system is given in table 4.1.

Table 4.1 Adaptive neuro fuzzy inference system (ANFIS) information.

Number of iterations	180
Number of nodes	113
Total number of parameters	189
Number of training data pairs	360
Number of fuzzy rules	49

When the iteration counter reaches maximum number of iterations, the learning process will stop. The choice of stopping criteria is very important for the stability of the method, since the converter may not be able to produce the required compensated currents at any speed or load. The main reason is that, after training, the controller can require current magnitudes that could not be reached by the converter. Therefore, a compromise between the converter capabilities and the currents required by the controller is needed. The optimization of the neuro-fuzzy system was performed by a hybrid technique that uses the back propagation and the mean-squared error method. The rule set was initially generated by the grid partition technique. After training, the controller signal may be generated and added to the phase current (I_{pha}) to produce new reference current (I_{ref}').

4.8.1Hybrid learning algorithm for adaptive neuro fuzzy inference system (ANFIS)

In the ANFIS architecture, the first layer and the fourth layer contain the parameters that can be modified over time. In the first layer, it contains a nonlinear of the premises parameter while the fourth layer contains linear consequent parameters. To update both of these parameters required a learning method that can train both of these parameters and to adapt to its environment. A hybrid algorithm proposed by Jang [2] will be used in this study to train of these parameters. The use of this algorithm is due to the backpropagation algorithm that was used to train the parameters that exist in the adaptive networks found problematic especially in a slow convergence rate and tend to be trapped in local minima [24] [25].

There are two parts of a hybrid learning algorithm, namely the forward path and backward path. In the course of the forward path, the parameters of the premises in the first layer must be in a steady state. A recursive least square estimator (RLSE) method was applied to repair the consequent parameter in the fourth layer. As the consequent parameters are linear, then RSLE method can be applied to accelerate the convergence rate in hybrid learning process. Next, after the consequent parameters are obtained, input data is passed back to the adaptive network input, and the output generated will be compared with the actual output. While backward path is run, the consequent parameters must be in a steady state [24].

The error occurred during the comparison between the output generated with the actual output is propagated back to the first layer. At the same time, parameter premises in the first layer are updated using learning methods of gradient descent or back propagation. With the use of hybrid learning algorithm that combines RSLE and the gradient descent methods, it can ensure the convergence rate is faster because it can reduce the dimensional search space in the original method of backpropagation. One level of hybrid learning is called epochs. Table 4.2 describes briefly a hybrid learning process in adaptive neuro fuzzy inference system (ANFIS) [25].

Table 4.2 Hybrid learning process

Type	**Path forwards**	**Path backwards**
Premise parameter	Fixed	Gradient descent
Consequent parameter	RSLE	Fixed
Signal	Node output	Error rate

4.9 Basic flow diagram of adaptive neuro fuzzy inference system (ANFIS)

ANFIS (adaptive neuro fuzzy inference system) method is used as a teaching method for sugeno-type fuzzy systems. System parameters are identified by the aid if ANFIS. Usually the number and type of fuzzy system membership functions are defined by user when applying ANFIS. ANFIS method is a hybrid method, which consists two parts gradient method is applied to calculation of input membership function parameters, and least square method is applied to calculation of output function parameters. The restrictions of matlab adaptive neuro fuzzy inference system method is [25]:-

- Only sugeno type decision method is available

➢ There can be only one output
➢ Defuzzification method is weighted mean value

In fuzzy control toolbox a useful command called anfis exists. This provides an optimization scheme to find the parameters in the fuzzy system that best fit the data. It is explained in the toolbox manual that since most (not all) optimization algorithms require computation of the gradient, this is done with a neural network. Then, in principle, any of the optimization schemes, say those in the MATLAB optimization toolbox, can be used.

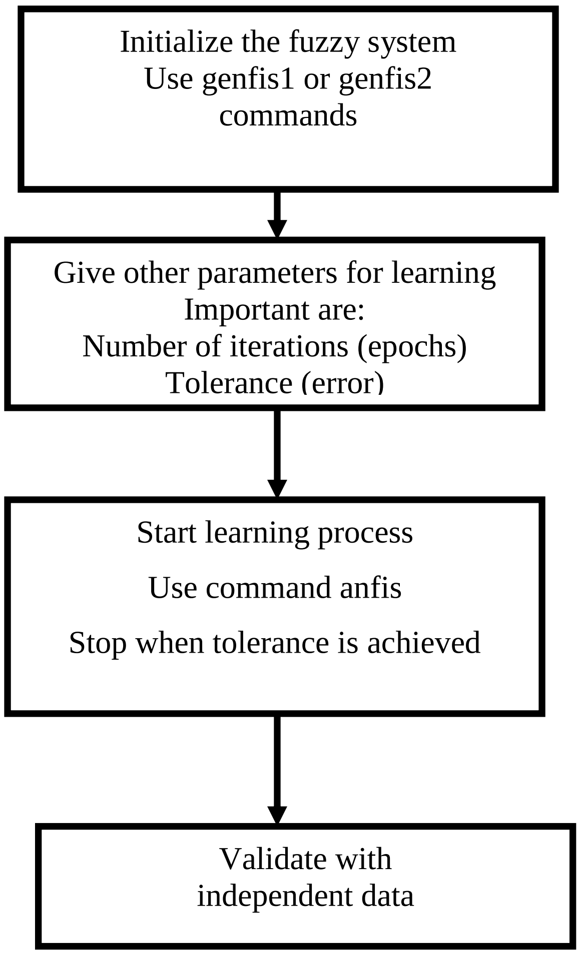


Figure 4.7 Basic flow diagram of adaptive neuro-fuzzy inference system

4.10 Torque control model using adaptive neuro fuzzy inference system (ANFIS) technique

The neural net is choosing the proper data set and performance limited use in estimating MSRM rotor position. ANN trained to estimate flux linkage performs much better estimation than the one that is trained to estimate rotor position. This should be taken into account when developing the data set to be used during training. To prevent poor position accuracy, the data set should be randomly distributed over the entire operating range and dimensional data reduction is done. Most neural training sets consist of data points of flux linkage, current and the corresponding rotor position. However, several ambiguities exist in the complete data set which should be considered by designers creating ANNs for MSRM's drives. Several values of current and rotor angle exist for a single torque value. To overcome this concurrency, quantities from at least two phases must be measured or the data set must be limited to the interested angular interval that produces positive torque. There are two possible ways to generate training data, model-based data generation, and experiment-based data generation [24] [25].

The compensated current values can be computed for randomly generated phase current and rotor position values. The resulting compensated current, reference current and rotor position values judiciously cover the intended operating region.

4.10.1 Forming adaptive neuro fuzzy inference system (ANFIS)

ANFIS is an acronym of adaptive neuro fuzzy inference system. Adaptive neuro fuzzy is a technique which provides a learning method from the desired input and output to adjust the membership functions parameters. During this process, back propagation and hybrid are two algorithms that are used so that the best parameters for the membership functions will be achieved. By considering the graphical representative of compensated current, rotor angle and reference current are defined as inputs and compensated current as output. Figure 4.8 shows the FIS editor for ANFIS that two inputs and one output has been shown clearly.

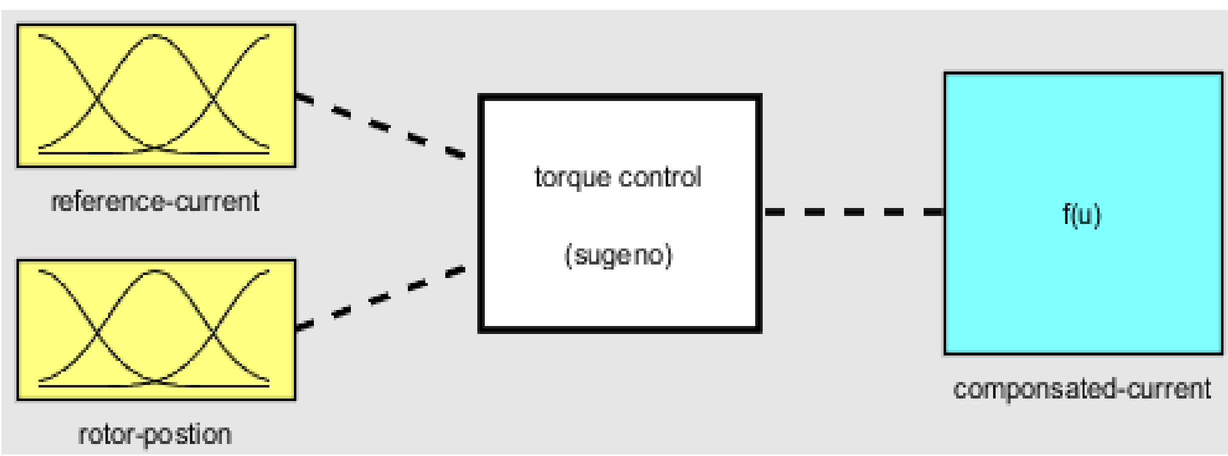


Figure 4.8 Sugeno fuzzy inference system structure of multi-layer switched reluctance motor

4.10.2 Loading dataset of adaptive neuro fuzzy inference system (ANFIS) controller

Once the data set are obtained from the torque curve, loading data starts. The loaded data set should be in three columns matrix format. First and second belong to the inputs and the third one present the torque data. The training data appears in the plot in center of the ANFIS editor as a set of circle as shown in figure 4.9 for 6/4 MSRM.

To load the data sets from the workspace into the neuro fuzzy designer open the neuro fuzzy designer by typing neuro Fuzzy Designer in the MATLAB command line. To load the training data set from the workspace in the load data portion of the designer, select the following options type training from workspace. The training data set is used to train a fuzzy system by adjusting the membership function parameters that best model this data, and appears in the plot in the center of the GUI as shown below as a set of circles.

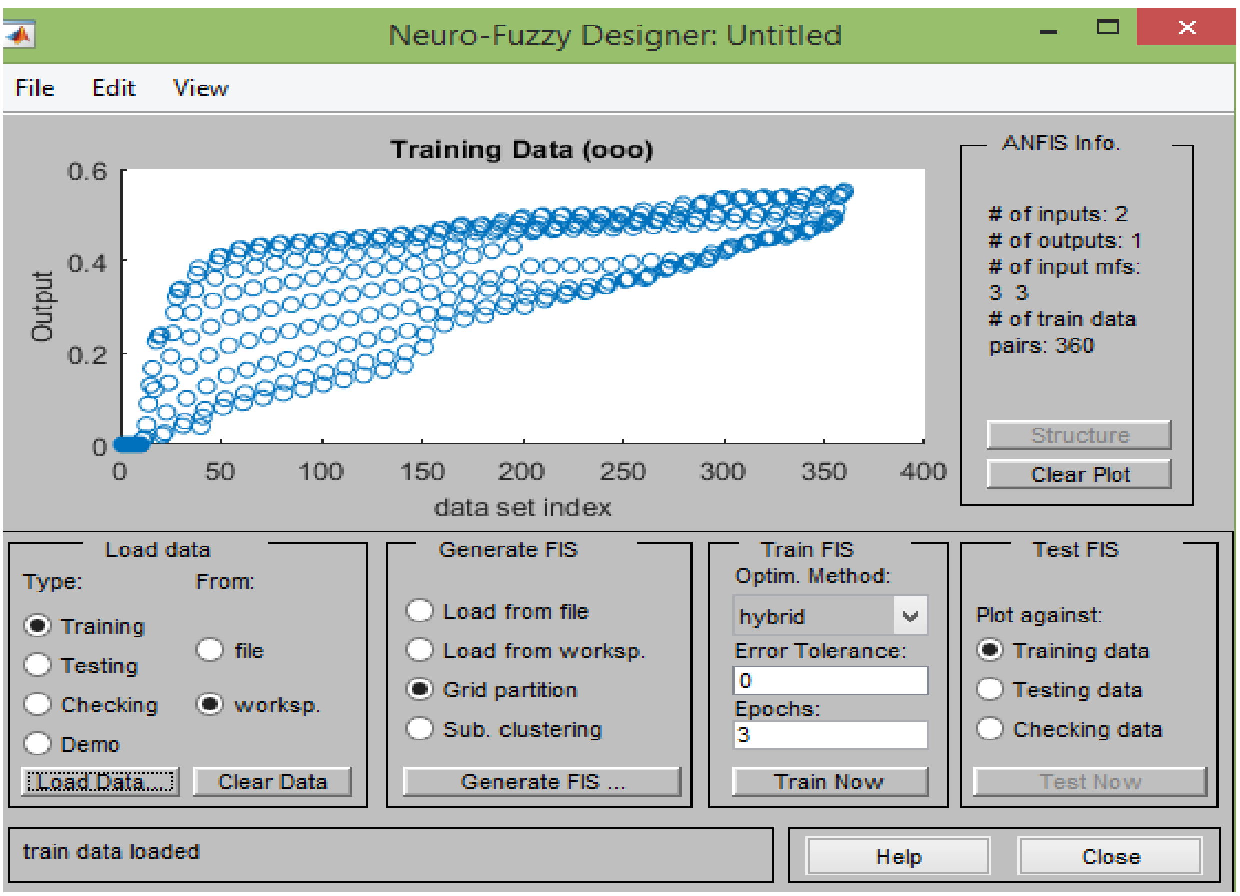


Figure 4.9 Loading the training data set of multi-layer switched reluctance motor

To load the checking data set from the workspace select checking from workspace and then loading data it will be as shown below.

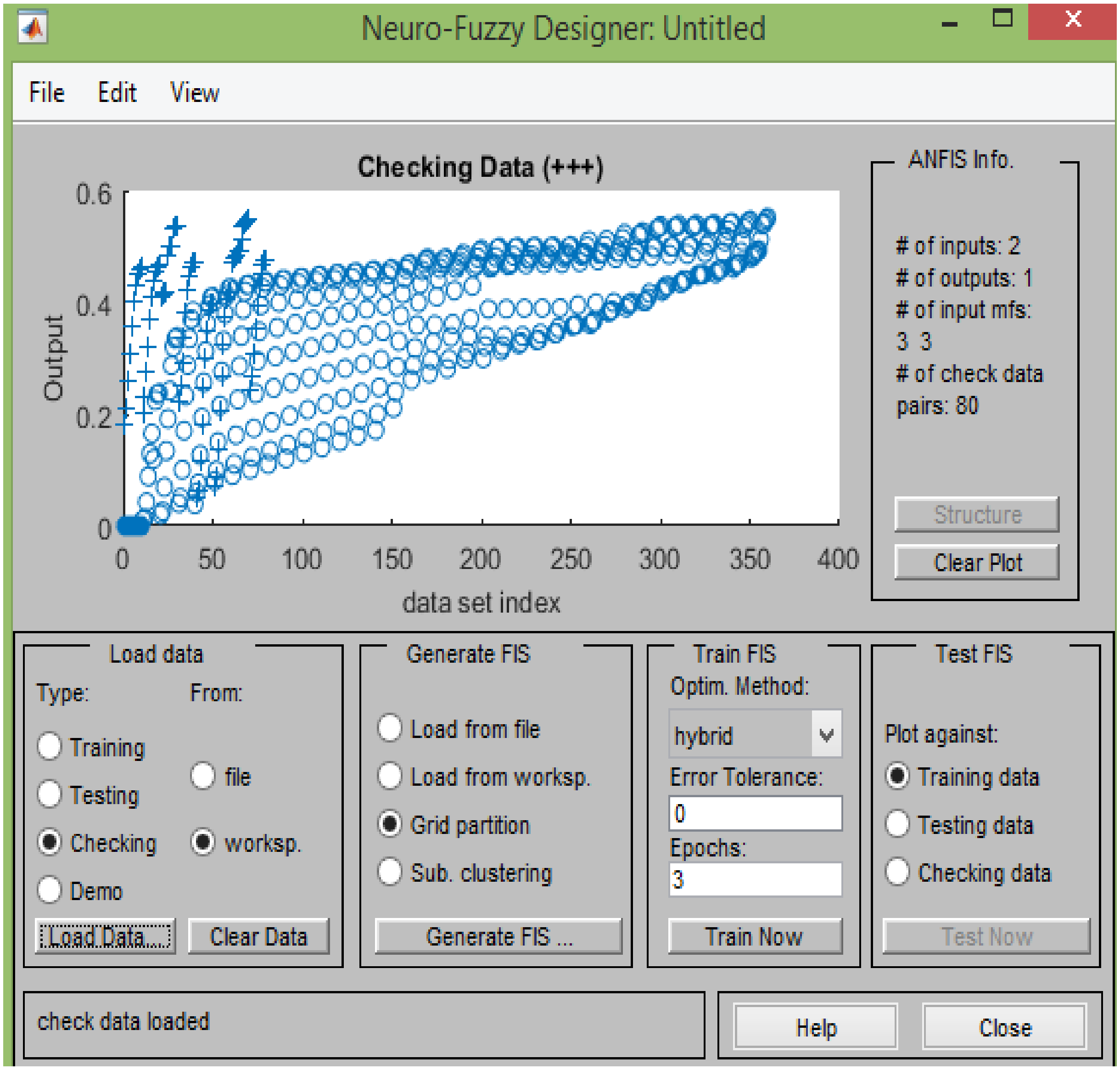


Figure 4.10 Loading checking dataset of multi-layer switched reluctance motor

Initializing and Generating the FIS parameters by specifying membership functions for ANFIS which is automatic FIS structure generation. To initialize fuzzy inference system using adaptive neuro fuzzy inference system click on the generate fuzzy inference system button of figure 4.10. Clicking this button displays a menu from which can choose the number of membership function, and the type of input and output membership functions. There are only two choices for the output membership function constant and linear. This limitation of output membership function choices is because ANFIS only operates on sugeno-type systems. Fill in the entries as shown in the following figure 4.11.

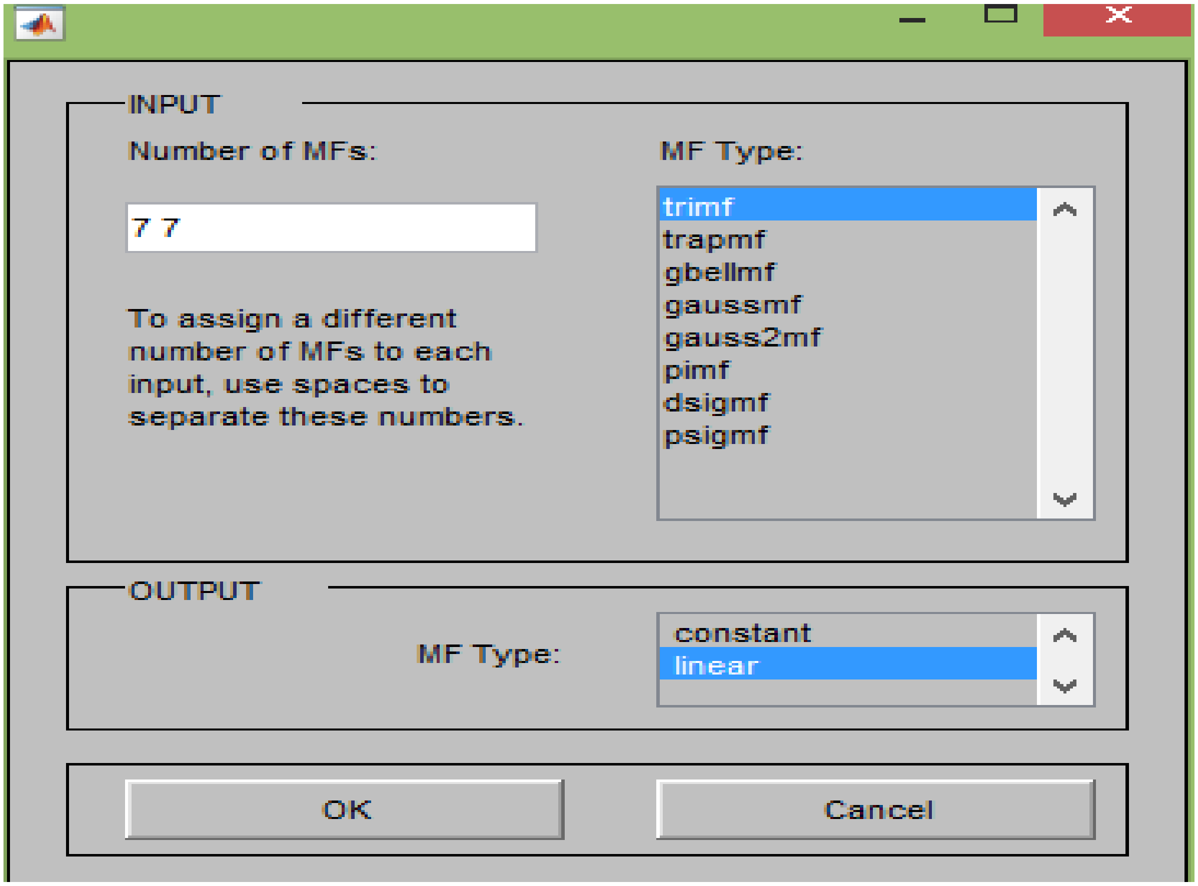


Figure 4.11 Initializing and generating the fuzzy inference system

4.10.3 Viewing adaptive neuro fuzzy inference system (ANFIS) structure

Adaptive neuro fuzzy inference system network structure, which maps the inputs by the membership functions and their associated parameters, and therefore through the output membership functions and corresponding associated parameters, is shown in figure 4.12. They are the synaptic weights and bias, being associated to the membership functions adjusted during the learning process. The computational work for the parameters acquisition and their adjustments is helped by the gradient descendent technique which shows how much the error decreases. When the gradient is obtained, any optimization routine may be applied to adjust the parameters and, therefore, decrease the error. The ANFIS neuro-fuzzy system operation may be summarized in two steps. The set of membership functions has to be chosen, i.e., their number and corresponding shape. The number and types of membership functions used in current research is seven and generalized traingular shape respectively. The input output training data are used by the ANFIS system.

Viewing the FIS Structure after you generate the fuzzy inference system, you can view the model structure by clicking the structure button in the middle of the right side of the editor. A new editor appears, as follows.

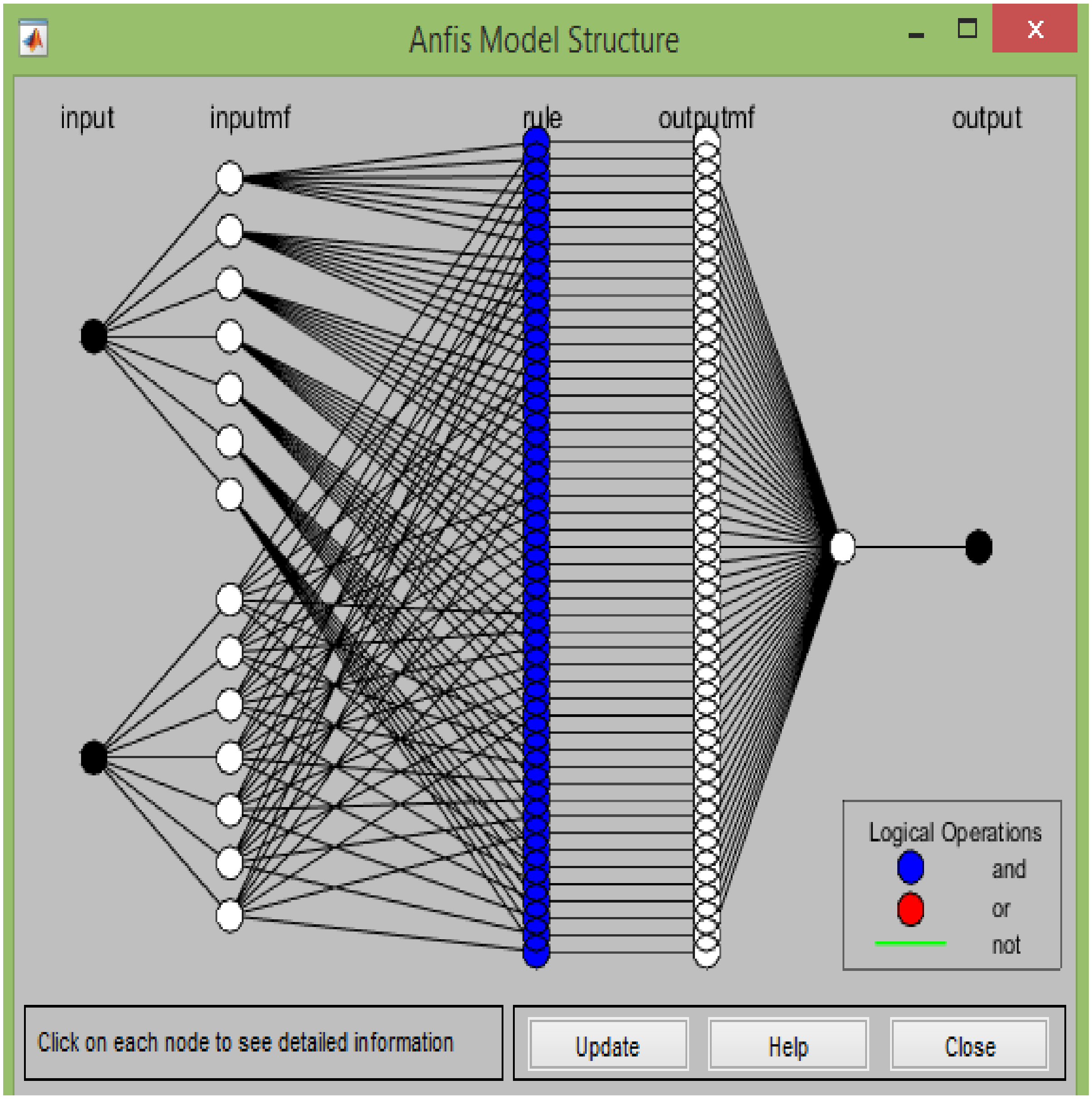


Figure 4.12 Adaptive neuro fuzzy inference system network structure of MSRM

The branches in this graph are color coded. Color coding of branches characterize the rules and indicate whether or not and, not, or or are used in the rules. The input is represented by the left-most node and the output by the right most node. The node represents a normalization factor for the rules. Clicking on the nodes indicates information about the structure. We can view the membership functions or the rules by opening either the membership function editor, or the rule editor from the edit menu.

4.10.4 Adaptive neuro fuzzy inference system training of multi-layer switched reluctance motor

In order to optimize the obtained parameters, two methods are available the hybrid method this method is a combination of least squares and back propagation method and back propagation this method consists of steepest descend method for membership functions. The first method is considered for data training. Error tolerance is established to create halt criterion. The error training will stop after certain epoch which is set. The number of epochs for training is 180. The final training error 0.0079514 is which is shown in figure 4.13 after 180 epochs.

The two anfis parameter optimization method options available for fuzzy inference system training are hybrid (the default, mixed least squares and back-propagation). Error Tolerance is used to create a training stopping criterion, which is related to the error size. The training will stop after the training data error remains within this tolerance. This is best left set to zero because we are unsure how the training error may behave.

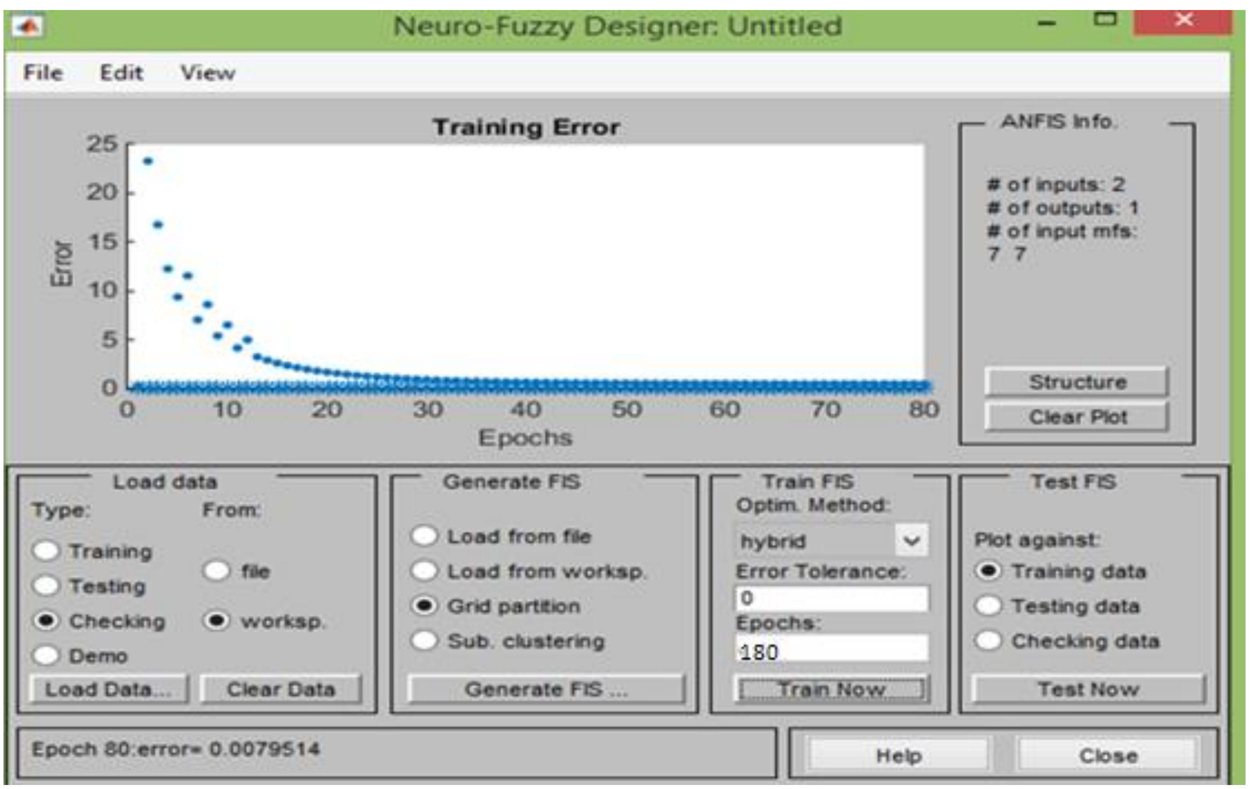


Figure 4.13 Training error of adaptive neuro fuzzy inference system

The plot shows the checking error as shown on the top and the training error appears as shown on the bottom. The checking error decreases up to a certain point in the training. This shows why the checking data option of adaptive neuro fuzzy inference system is useful.

4.10.5 Testing the data against the trained fuzzy inference system

To test the fuzzy inference system against the checking data, select checking data in the test fuzzy inference system portion of the Neuro-Fuzzy Designer, and click test now. When test the checking data against the fuzzy inference system, it looks satisfactory as shown in the figure 4.14 below. As a result, the trained FIS capture the features of this data set very well. Hence clearly this set of membership functions is the best choice for modeling the training data.

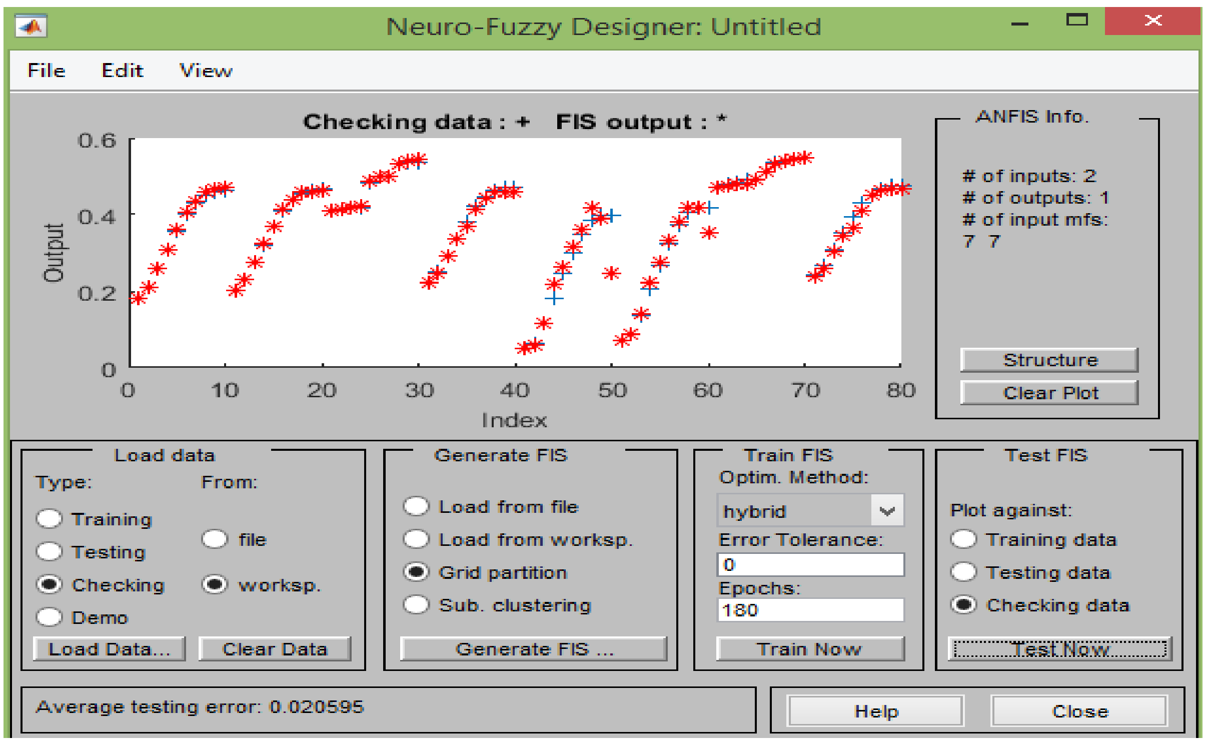


Figure 4.14 Testing data against the trained fuzzy inference system

4.11 Implementation of adaptive neuro fuzzy inference system (ANFIS)

The ANFIS is a Sugeno adaptive network based fuzzy inference system. In this thesis, the fuzzy inference system under consideration has two inputs, reference current (I_{ref}), rotor position (θ) and one output, compensating current (I_{comp}), by means of a relation such as $I_{comp} = f(\theta, I_{ref})$. The matlab simulation model of multi-layer switched reluctance motor with adaptive neuro fuzzy inference system is implemented as shown in figure 4.15.

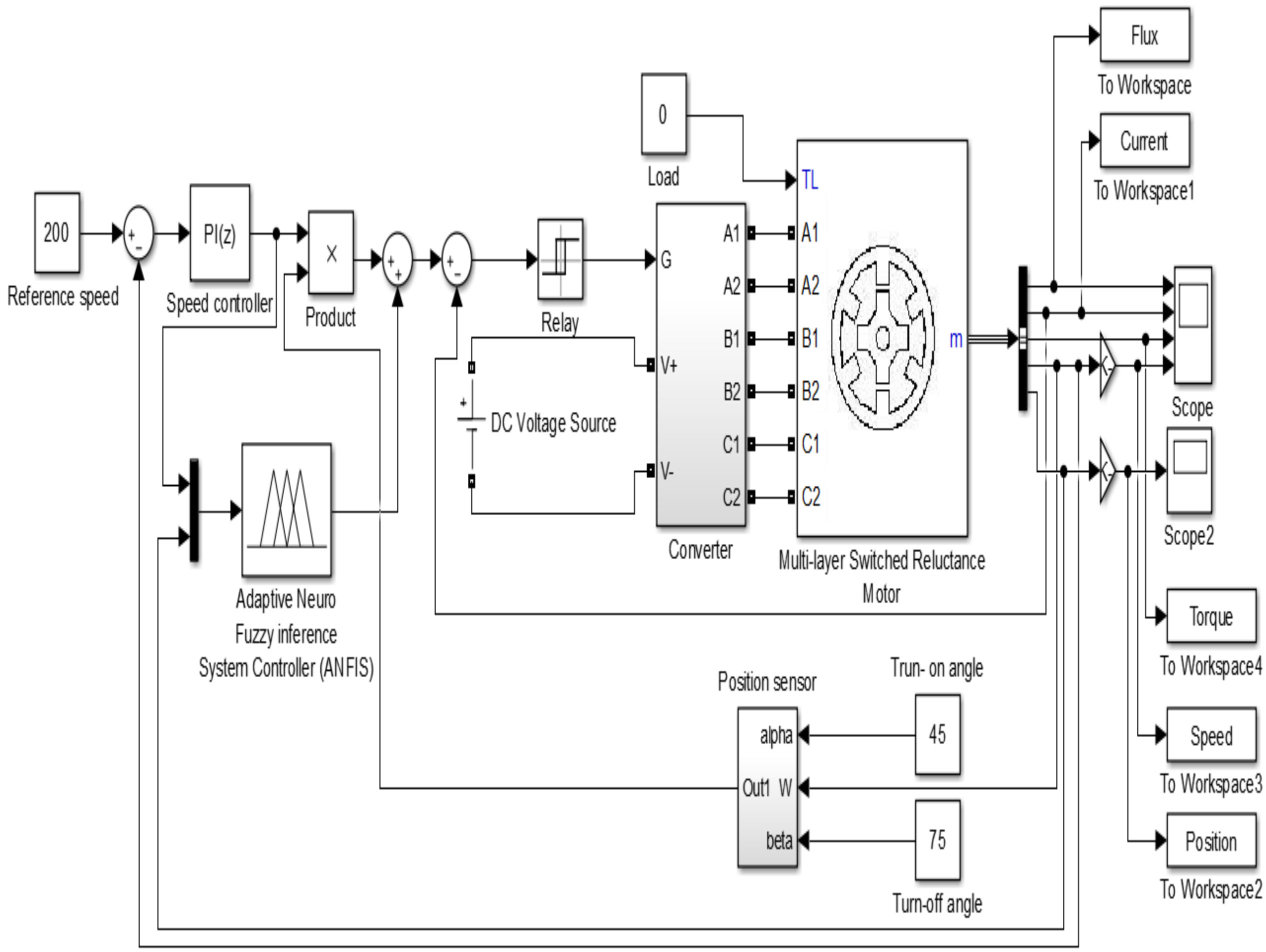


Figure 4.15 Matlab simulation model of multi-layer switched reluctance motor with adaptive neuro fuzzy inference system (ANFIS)

4.11.1 Simulation result and discussion

The reduction of the torque ripples is the main issue for an acceptable control strategy. In this case the simulation results with fuzzy logic controller is not enough because torque ripple changes with the switched reluctance motor speed and load changes. Hence it is advantages to include some learning mechanisms to the switched reluctance motor control to adapt itself to new dynamic condition that is adaptive neuro-fuzzy inference system (ANFIS) and the simulation result is with reduced torque ripple than that of fuzzy logic controller. When we compare figure 4.16 the torque ripple of the multi-layer switched reluctance motor is well reduced but it is not completely eliminated because the data set may not enough and moderate to train the multi-layer switched reluctance motor. Hence it will be eliminated when we use exact and moderate data set from experienced experts.

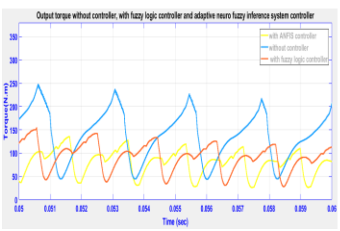


Figure 4.16 Matlab simulation result of multi-layer switched reluctance motor with adaptive neuro fuzzy inference system

From the simulation result above the output torque without controller has torque ripple given by

$$T_{ripple} = \frac{T_{max} - T_{min}}{T_{avg}} \quad \text{where}$$

$$T_{max} = 250 \quad T_{min} = 50 \quad T_{avg} = 150$$

But with adaptive neuro fuzzy inference system (ANFIS)

$$T_{max} = 140 \quad T_{min} = 42 \quad T_{avg} = 91$$

Torque ripple reduction in percentage = (torque ripple without controller- torque ripple with adaptive neuro fuzzy inference system (ANFIS))*100

$$\boldsymbol{torque\ ripple\ reduction\ in\ percentage} = (\mathbf{1.33 - 1.07}) * \mathbf{100} = \mathbf{26}\%$$

Hence using adaptive neuro fuzzy inference system the torque ripple is reduced by twenty six percent than using without any controller.

CHAPTER FIVE

Conclusions, recommendations and suggestions for future work

In this chapter, the conclusions, recommendations and suggestions for future work are presented as follows:

5.1 Conclusions

This thesis has presented two modeling techniques for a three phase, 6/4 pole multi-layer switched reluctance motor for obtaining the nonlinear torque model by means of fuzzy logic and adaptive neuro fuzzy inference system (ANFIS) techniques. Fuzzy logic controller (FLC) and adaptive neuro fuzzy inference system (ANFIS) based current compensating techniques are employed for minimizing the torque ripples in multi-layer switched reluctance motor. Simulation results show that both fuzzy logic controller (FLC) and adaptive neuro fuzzy inference system (ANFIS) controllers give reduced torque ripple than without controller. Among the intelligent controllers, ANFIS improves the torque ripples of MSRM drives better than fuzzy logic controller, due to its good learning and generalization capabilities. From the simulation results fuzzy logic controller reduces twenty two (22%) percent and adaptive neuro fuzzy inference system (ANFIS) reduces twenty six (26%) of the torque ripple. During ANFIS first the fuzzy inference system (FIS) based torque model is built by using the magnetization characteristics of the multi-layer switched reluctance motor (MSRM) and the results of this model has shown a good agreement with the actual data set. The ANFIS torque model is then setup and trained with the same set of torque data of the motor. The results of adaptive neuro fuzzy inference system (ANFIS) model are in excellent and close agreement with the actual data yielding negligible error for the complete range of the test data. The first order sugeno type fuzzy inference system is used with seven membership triangular functions. The parameters are optimized by ANFIS and it shows improvement in steady state behavior of MSRM controlled by ANFIS through reduction in torque ripples.

5.2 Recommendations

The adaptive neuro fuzzy inference system controller uses data set for training. Hence it is better to use the data set generated from the built proto-type motor and tested in the laboratory rather than using the data generated from the Matlab Simulink model of the motor.

5.3 Suggestions for future work

One of the disadvantages of the multi-layer switched reluctance motors is acoustic noise which is not considered in this thesis. It is suggested that design and effectiveness of different types of intelligent controllers such as fuzzy logic controller and adaptive neuro fuzzy inference system controller for the reduction of acoustic noise may be investigated.

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Appendices

Appendix A: Multi-layer switched reluctance motor data

The multi-layer switched reluctance motor data utilized by the simulation program is obtained from reference [18]. This data is listed below. The torque versus reference current versus rotor position is given in the following table:-

Table: Multi-layer switched reluctance motor data

Current in [amp]	Rotor position in degree									
	45	50	55	60	65	70	75	80	85	90
0	0.0000	0.0000	0.0000	00000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
1	0.0102	0.0134	0.0429	0.0884	0.1292	0.1656	0.1996	0.2248	0.2357	0.2376
2	0.0204	0.0261	0.0697	0.1338	0.1918	0.2421	0.2873	0.3203	0.3352	0.3381
3	0.0306	0.0379	0.0853	0.1544	0.2171	0.2705	0.3165	0.3498	0.3656	0.3692
4	0.0404	0.0507	0.1005	0.1702	0.2331	0.2875	0.3356	0.3700	0.3845	0.0386
5	0.0500	0.0639	0.1148	0.1830	0.2450	0.3000	0.3498	0.3850	0.3980	0.3990
6	0.0601	0.0761	0.1270	0.1940	0.2567	0.3127	0.3618	0.3959	0.4087	0.4099
7	0.0704	0.0878	0.1386	0.2046	0.2672	0.3231	0.3716	0.4048	0.4174	0.4187
8	0.0806	0.0992	0.1503	0.2154	0.2765	0.3313	0.3794	0.4126	0.4248	0.4259
9	0.0908	0.1109	0.1624	0.2263	0.2861	0.3398	0.3871	0.4197	0.4313	0.4320
10	0.1010	0.1230	0.1746	0.2468	0.3034	0.3547	0.3997	0.4304	0.4406	0.4370
11	0.1106	0.1344	0.1861	0.2468	0.3034	0.3547	0.3997	0.4304	0.4406	0.4407
12	0.1204	0.1458	0.1973	0.2561	0.3114	0.3613	0.4049	0.4343	0.4440	0.4440
13	0.1306	0.1573	0.2080	0.2651	0.3195	0.3686	0.4102	0.4379	0.4474	0.4479
14	0.140	0.1683	0.2183	0.2737	0.3273	0.3755	0.4152	0.4411	0.4504	0.4511
15	0.151	0.1790	0.2281	0.2820	0.3348	0.3820	0.4197	0.4440	0.4531	0.4540

16	**0.1613**	**0.1899**	**0.2379**	**0.2898**	**0.3416**	**0.3881**	**0.4242**	**0.4471**	**0.4559**	**0.4571**
17	**0.1712**	**0.2005**	**0.2475**	**0.2978**	**0.3485**	**0.3940**	**0.4284**	**0.4498**	**0.4585**	**0.4599**
18	**0.1808**	**0.2106**	**0.2573**	**0.3062**	**0.3560**	**0.4001**	**0.4324**	**0.4522**	**0.4606**	**0.4622**
19	**0.1908**	**0.2209**	**0.2668**	**0.3142**	**0.3628**	**0.4057**	**0.4363**	**0.4546**	**0.4628**	**0.4647**
20	**0.201**	**0.2310**	**0.2759**	**0.3220**	**0.3694**	**0.4110**	**0.4399**	**0.4570**	**0.4650**	**0.4670**
21	**0.2112**	**0.2401**	**0.2846**	**0.3305**	**0.3763**	**0.4159**	**0.4437**	**0.4601**	**0.4673**	**0.4688**
22	**0.2214**	**0.2490**	**0.2929**	**0.3386**	**0.3829**	**0.4207**	**0.4471**	**0.4627**	**0.4694**	**0.4707**
23	**0.2317**	**0.2579**	**0.3008**	**0.3457**	**0.3892**	**0.4255**	**0.4501**	**0.4644**	**0.4713**	**0.4732**
24	**0.2414**	**0.2674**	**0.3091**	**0.3525**	**0.3945**	**0.4296**	**0.4529**	**0.4665**	**0.4736**	**0.4757**
25	**0.2510**	**0.2770**	**0.3175**	**0.3590**	**0.3993**	**0.4330**	**0.4557**	**0.4690**	**0.4759**	**0.4780**
26	**0.2611**	**0.2881**	**0.3185**	**0.3592**	**0.3997**	**0.4332**	**0.4572**	**0.4697**	**0.4760**	**0.4785**
27	**0.2727**	**0.2971**	**0.3285**	**0.3597**	**0.4101**	**0.4412**	**0.4611**	**0.4699**	**0.4772**	**0.4791**
28	**0.2811**	**0.2987**	**0.3384**	**0.3612**	**0.4214**	**0.4611**	**0.4675**	**0.4732**	**0.4812**	**0.4864**
29	**0.2995**	**0.3102**	**0.3392**	**0.3702**	**0.4295**	**0.4623**	**0.4685**	**0.4798**	**0.4902**	**0.4943**
30	**0.3001**	**0.3218**	**0.3391**	**0.3882**	**0.4621**	**0.4654**	**0.4694**	**0.4810**	**0.4961**	**0.4978**
31	**0.3142**	**0.3219**	**0.3392**	**0.3886**	**0.4662**	**0.4672**	**0.4710**	**0.4832**	**0.4972**	**0.4989**
32	**0.3253**	**0.3289**	**0.3398**	**0.3897**	**0.4682**	**0.4775**	**0.4781**	**0.4843**	**0.4981**	**0.4992**
33	**0.3321**	**0.3331**	**0.3440**	**0.3899**	**0.4693**	**0.4791**	**0.4799**	**0.4852**	**0.4985**	**0.4999**
34	**0.3445**	**0.3451**	**0.3541**	**0.3901**	**0.4701**	**0.4801**	**0.4841**	**0.4871**	**0.4992**	**0.5010**
35	**0.3578**	**0.3597**	**0.3601**	**0.3953**	**0.4721**	**0.4834**	**0.4862**	**0.4882**	**0.4997**	**0.5100**
36	**0.3609**	**0.3642**	**0.3671**	**0.3989**	**0.4753**	**0.4867**	**0.4874**	**0.4889**	**0.5011**	**0.5123**
37	**0.3701**	**0.3712**	**0.3724**	**0.3991**	**0.4785**	**0.4894**	**0.4896**	**0.4991**	**0.5018**	**0.5134**
38	**0.3821**	**0.3845**	**0.3862**	**0.3998**	**0.4791**	**0.4897**	**0.4899**	**0.4999**	**0.5142**	**0.5230**
39	**0.3905**	**0.3962**	**0.3972**	**0.4002**	**0.4795**	**0.4903**	**0.4912**	**0.5200**	**0.5221**	**0.5261**

40	**0.4014**	**0.4026**	**0.4076**	**0.4167**	**0.4824**	**0.4976**	**0.4980**	**0.5310**	**0.5335**	**0.5372**
41	**0.4111**	**0.4134**	**0.4182**	**0.4196**	**0.4836**	**0.4986**	**0.4992**	**0.5332**	**0.5349**	**0.5386**
42	**0.4207**	**0.4244**	**0.4291**	**0.4299**	**0.4852**	**0.4994**	**0.4998**	**0.5348**	**0.5356**	**0.5392**
43	**0.4349**	**0.4354**	**0.4398**	**0.4398**	**0.4864**	**0.4999**	**0.5007**	**0.5353**	**0.5367**	**0.5398**
44	**0.4489**	**0.4499**	**0.4501**	**0.4506**	**0.4887**	**0.5012**	**0.5074**	**0.5367**	**0.5384**	**0.5402**
45	**0.4521**	**0.4572**	**0.4582**	**0.4598**	**0.4896**	**0.5089**	**0.5174**	**0.5292**	**0.5420**	**0.5426**
46	**0.4620**	**0.4668**	**0.4689**	**0.4699**	**0.4900**	**0.5092**	**0.5328**	**0.5390**	**0.5443**	**0.5467**
47	**0.4734**	**0.4797**	**0.4847**	**0.4898**	**0.4912**	**0.5106**	**0.5383**	**0.5394**	**0.5468**	**0.5489**
48	**0.4802**	**0.4842**	**0.4863**	**0.4902**	**0.4931**	**0.5124**	**0.5398**	**0.5424**	**0.5479**	**0.5516**
49	**0.4920**	**0.4968**	**0.4989**	**0.5086**	**0.5098**	**0.5148**	**0.5420**	**0.5442**	**0.5497**	**0.5538**
50	**0.5041**	**0.5098**	**0.5124**	**0.5242**	**0.5284**	**0.5387**	**0.5466**	**0.5568**	**0.5624**	**0.5687**

Appendix B: Main dimensions of multi-layer switched reluctance motor

The main dimensions of multi-layer switched reluctance motor are provided in the following Table.

Table: Main dimensions of multi-layer switched reluctance motor

Parameter	**Values**
Number of layers	2
Number of stator poles	6
Number of rotor poles	4
Phase resistance (R)	0.05Ω
Reference speed	$200 Rad/s$
DC voltage	240V
Moment of inertia (J)	0.05 $k.g/m^2$
Friction (F)	0.02 N.m.s

Appendix C: Calculation of parameters and steady state response of multi-layer switched reluctance motors

% Initializing program

% This program allows to change certain parameter values without any change in the other matlab functions.

```
NS=6
NR=4
P=3;
BETAS=30*(pi/180);
BETAR=30*(pi/180);
TETAS=(2*pi)*((1/NR)-(1/NS))
TETAX=(pi/NR)-((BETAR+BETAS)/2)
TETAY=(pi/NR)-((BETAR-BETAS)/2)
BETAZ=(BETAR-BETAS)/2
TETAXY=(TETAY+TETAZ+TETAS)
TETAON=45*(pi/180)
TETAOFF=75*(pi/180)
TETAQ=60*(pi/180)
TETAIN=20.1*(pi/180)
V=150
R=1.30;
J=0.005;
F=0.02;
I=5;
DELTAI=0
% Program below computes from the giving minimum and maximum
inductance values, the equation of the linear inductance profile
for the increasing and decreasing part
G=(inv([TETAX 1;TETAY 1]))*([LMIN;LMAX]);
AUP=G(1);
BUP=G(2);
```

```
H=(inv([(TETAY+TETAZ) 1;TETAXY 1]))*([LMAX;LMIN]);
ADOWN=H(1);
BDOWN=H(2);
DL=AUP;
function s=f(e);
s=rem(e,pi/2);
function y =f(e);
a=(pi/180)*45;
b=(pi/180)*90;
if ((e >= 0) & (e <= a))
    y=((e*(180/pi))-45);
end;
if ((e>a) & (e <=b))
    y=(45-(e*(180/pi)));
end;
% Program used for the heysteresis current control
% This program allows to choose the commutation instances of the
semi conductors
function Va=f(TE);
E=TE';
e=E(1);
teta=E(2);
if ((TETAON <= teta) & (teta <= TETAOFF))
    Va=e;
end;
if ((TETAOFF < teta) & (teta <= TETAQ))
    Va=-V;
end;
if (teta >TETAQ)
    Va=0;
end;
% Inductance program
```

```
% This program gives the output current the input variables are
flux and teta
function U=f(TE);
E=TE';
flux=E(1);
teta=E(2);
if((0 <=teta & (teta <= TETAX))
    U=[flux/LMIN,LMIN];
end;
if ((TETAX < teta) & (teta <= TETAY))
    U=[flux/((AUP*teta) +BUP),((AUP*teta)+BUP)];
end
if ((TETAY < teta) & (teta <=TETAXY))
    U=[flux/((ADOWN*teta)+BDOWN),(ADOWN*teta)+BDOWN)];
end;
if (teta >TETAXY)
    U=[flux/LMIN,LMIN];
end;
% torque program
% This program computes the output torque produced in one phase
teta and current are the input variables
function T=f(TE);
E=TE ';
i=E(1);
teta=E(2);
if ((0<= teta) & (teta <=TETAX))
    T=[0,0];
end;
if ((TETAX < teta)& (teta <=TETAXY))
    T=[-0.5*(DL)*(i*i),-DL];
end;
if (teta >TETAXY)
```

```
    T=[0,0];
end;
% initializing program (non-linear model)
%This program builds the look-up tables used in the MSRM non-
linear model
load sr.dat; X=sr;
couple=X(:,10);
M1=X(:,5);M2=X(:,6);X(:,12)=[];X(:,11)=[];X(:,9)=[];X(:,8)=[];X(
:,7)=[];
tet=X(:,1);cour=X(:,2);flux=X(:,3);angl=-45:0; angle=angl';
% construction of the torque and mutual flux look-up tables
C=ones(21,46);
MU1=ones(21,46);
MU2=ones(21,46);
for i=1:21;
    for j=1:46;
        C(i,j)=couple(j+(i-1)*46);
        MU1(i,j)=M1(j+(i-1)*46);
        MU2(i,j)=M2(j+(i-1)*46);
    end;
end;
% Construction of of the current look up tables
A=zeros(21,46);
Bn=0:20;
for i=1:46;
    p=find(test==(1-i));
    for j=1:21;
        A(j,i)=flu(p(j));
    end;
end;
fluxmax=A(21,1); don=0:fluxmax/1000:fluxmax;
tailler=size(don,2);
```

```
res=zeros(taille,46);
for i=1:46;
    x=A(:,i);
    xi=0:A(21,i)/200:A(21,i);
    y=0:20;
   yi=interp1(x,y,xi);
   for j=1:taille;
       gg=find(xi>=don(j));
       if gg==[]
           res(j,(47-i))=20;
       else
           res(j,(47-i))=yi(gg(1));
       end;
   end;
end;
```