Neural Network Based Space Vector Pwm Control Of Induction Motor

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ABSTRACT

The demand for high performance induction motor drives have been increasing at a steady rise in the industry and control techniques also have become sophisticated and it is a scope for implement controllers for ac drives. The conventional control methods need modeling and limited for linear systems. Most of controllers those are designed for drives are linearized near their operating points. Therefore there is scope to improve these using artificial intelligence techniques. Artificial intelligent system contains hard computation and soft computation. Artificial intelligent system has found high application in most nonlinear systems same as induction motors drive. Because artificial intelligent techniques can use as controller for any system without requirement to system mathematical model, it has been used in electrical drive control. Further, the necessity of intelligent controllers is to achieve the satisfactory dynamic performance of conventional methods.

This project considered two objectives: To understand and develop conventional SVPWM technique and the same is applied to induction motor drive; and To develop ANN model to realize the functionality of SVPWM. The performances of these methods are verified on induction motor drive in MATLAB/Simulink environment.

Keywords-artifical neuralnetwork,field oriented control,induction motor,neural based space vector pulse widh modulation, space vector pulse width modulation

1.1 INTRODUCTION

The control and estimation of induction motor drives constitute a vast subject, and the technology has further advanced in recent years. The control and estimation of ac drives in general are considerably more complex than those of dc drives, and this complexity increases substantially if high performances are demanded. The main reasons for this complexity are the need of variable-frequency, harmonically optimum converter power supplies, the complex dynamics of ac machines, machine parameter variations, and the difficulties of processing feedback signals in the presence of harmonics.

To limit the above problems, different types control strategies are introduced in recent years. In that, the control strategies are like

- Scalar control
- Vector control etc.[3]
  - Direct Vector Control
  - Indirect Vector Control

This project emphasis indirect vector control strategy.The inverter place a vital role in drives system. For inverter the switching pulse pattern are generated by using Pulse Width Modulation (PWM) controller.

In a PWM control in order to synthesis the inverter switches a desired reference stator a voltage space vector need to fulfill few requirements like a constant switching frequency f_s, and smallest instantaneous deviation from its reference value. Minimum switching losses in the inverter and the lowest ripple current are also to be achieved. To meet these requirements an average voltage vector is synthesized by means of the two instantaneous basic non-zero voltage vector that form the sector (in which the average voltage vectors to be synthesized lies) and both the zero voltage vectors, such that each transition causes change of only one switch status to minimize the inverter switching loss.

Pulse Width Modulation variable speed drives are increasingly applied in many new industrial applications that require superior performance. Recently, developments in power electronics and semiconductor technology have lead improvements in power electronic systems. Hence, different circuit configurations namely multilevel inverters have become popular and considerable interest by researcher are given on them. Variable voltage and frequency supply to a.c drives is invariably obtained from a three-phase voltage source inverter. A number of Pulse width modulation (PWM) schemes are used to obtain variable voltage and frequency supply. The most widely used PWM schemes for three-phase voltage source inverters are carrier-based sinusoidal PWM and space vector PWM (SVPWM). There is an increasing trend of using space vector PWM (SVPWM) because of their easier digital realization and better dc bus utilization. Space vector modulation is based on representation of the three phase voltages as space vectors. Most space vector modulation schemes generate the same required output voltage but differ in their performance with respect to THD, peak-to-peak ripple and switching losses.

Space Vector Modulation (SVM) was originally developed as vector approach to Pulse Width Modulation (PWM) for three phase inverters. It is a more sophisticated technique for generating sine wave that provides a higher voltage to the motor with lower total harmonic distortion. The main aim of any modulation technique is to obtain variable output having a maximum fundamental component with minimum harmonics. Space Vector PWM (SVPWM) method is an advanced; computation intensive PWM method and possibly the best techniques for variable frequency drive application.In SVPWM methods, the voltage reference is provided using a revolving reference vector. In this case magnitude and frequency of the fundamental component in the line side are controlled by the magnitude and frequency, respectively, of the reference voltage vector. Space vector modulation utilizes dc bus voltage more efficiently and generates less harmonic distortion in a three phase voltage source inverter.

The application of artificial network networks (ANNs) is recently growing in the areas of power electronics and drives. Remarkable features of neural networks are both fast processing speed and fault tolerance to some overlook connections in the network system. Because of the parallel processing mechanism of neural networks, it is expected that the neural networks can execute the non-linear data mapping in short time and of the distributed network structure, the performance of the neural network may not be influenced by some miss connections in the network itself. A control system with multi input neural network may not be affected by partial fault in the system, because some other correct input data may compensate the influence of wrong input data.

1.2 LITERATURE SURVEY

In indirect vector control scheme applied for the control the induction machine to acquire desired performance. The dynamic modeling of induction machine [1] in synchronously rotating frame is applied to indirect vector control scheme. The fundamentals of vector control implementation are explained.

The machine model is represented in a synchronously rotating reference frame. The machine terminal parameters are transformed from 3-$\emptyset$ to 2-$\emptyset$ according to the principle of vector control [2]. There are essentially two general methods of vector control. One, called the direct or feedback method, was invented by Blaschke, and the other, known as the indirect or feed forward method, was invented by Hasse. The methods are different essentially by how the unit vector ($\cos\theta_e$,$\sin\theta_e$) is generated for the control. The indirect vector control method is essentially the same as direct vector control, except the unit vector signals ($\cos\theta_e$,$\sin\theta_e$) are generated in feed forward manner [3].

Inverter requires the pulse pattern for the switching the switches according to the indirect vector control signal. The Pulse Width Modulation (PWM) techniques have given advantages like harmonic reduction and lower switching losses etc for the inverter. One of the most efficient techniques is Space Vector Pulse Width Modulation (SVPWM) technique [4]

The switching frequency of the inverter is limited in Space Vector Pulse Width Modulation (SVPWM). By using the intelligent techniques like Neural Networks [5], the switching frequency is easily extended to higher levels.In existing literature on Neural Network based SVPWM, the Space Vector PWM inverter is studied along with the modeling of SVPWM based inverter, vector control of induction motor, indirect vector control of induction motor and Kohonen’s competitive layer in Neural Network is studied along with its modeling [6].

1.3 PROBLEM FORMULATION

In aspect of drive systems, the conventional control methods need modeling and limited for linear systems. Most of controllers those are designed for drives are linearized near their operating points. Therefore there is scope to improve these using artificial intelligence techniques. The necessity of intelligent controllers is to achieve the satisfactory dynamic performance of conventional methods.

1.4 OBJECTIVES OF THE THESIS

This project considered two objectives:

(i) To understand and develop conventional SVPWM technique and the same is applied to induction motor drive; and

(ii) To develop ANN model to realize the functionality of SVPWM. The performances of these methods are verified on induction motor drive in MATLAB/Simulink environment.

II VECTOR CONTROL OF INDUCTION MOTOR

2.1 INTRODUCTION

An Induction motor (IM) is a type of asynchronous AC motor where power is supplied to the rotating device by means of electromagnetic induction. Other commonly used name is squirrel cage motor due to the fact that the rotor bars with short circuit rings resemble a squirrel cage. An electric motor converts electrical power to mechanical power in its rotor.

There are several ways to supply power to the rotor. In a DC motor this power is supplied to the armature directly from a DC source, while in an induction motor this power is induced in the rotating device. An induction motor is sometimes called a rotating transformer because the stator (stationary part) is essentially the primary side of the transformer and the rotor (rotating part) is the secondary side. Induction motors are widely used, especially poly phase induction motors, which are frequently used in industrial drives.

The Induction motor is a three phase AC motor and is the most widely used machine. Its characteristic features are-

- Simple and rugged construction
- Low cost and minimum maintenance
- High reliability and sufficiently high efficiency
- Needs no extra starting motor and need not be synchronized
- An Induction motor has basically two parts – Stator and Rotor

The Stator is made up of a number of stampings with slots to carry three phase windings. It is wound for a definite number of poles. The windings are geometrically spaced 120 degrees apart. Two types of rotors are used in Induction motors - Squirrel-cage rotor and Wound rotor.

The following sections describe the dynamic modeling of induction motor and different types of control strategies of induction motor drives. The vector control is one of the most important control strategies. Direct vector control and indirect vector control techniques are given in detail.

2.2 WORKING PRINCIPLE OF INDUCTION MOTOR

As a general rule, conversion of electrical power into mechanical power takes place in the rotating parts of an electrical motor. In dc motor, the electrical power is conducted directly in armature the rotating part of the motor through brush or commutates and hence dc motor called as conduction motor but in case of induction motor the motor does not receive the electrical power by conduction but by induction in exactly same way as the secondary of a 2-winding transformer receives its power from the primary. That is why such motor known as induction motor.In fact, an induction motor can be treated as a rotating transformer i.e. one in which primary winding is stationary but the secondary is free to rotate. Of all the a.c. motors, the poly phase induction motor is the one which is extensively used for various kinds of industrial drives.

When a three-phase supply is connected to the stator windings, a rotating magnetic field is produced. As the magnetic flux cuts a bar on the rotor, an E.M.F. is induced in it and since it is joined, via the end conducting rings, to another bar one pole pitch away, current flows in the bars.

The magnetic field associated with this current flowing in the bars interacts with the rotating magnetic field and a force is produced, tending to turn the rotor in the same direction as the rotating magnetic field. Similar forces are applied to all the conductors on the rotor, so that a torque is produced causing the rotor to rotate.

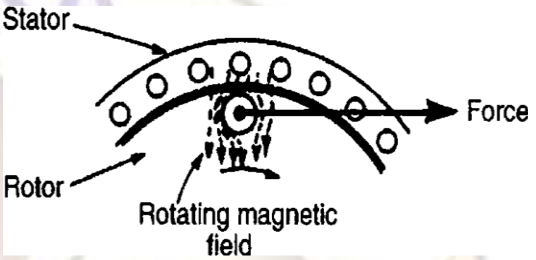

Fig 2.1 Production of Magnetic Field

They are widely used for different applications ranging from small induction motors in washing machines, household fans etc to vary large induction motors which are capable of tens of thousands of kW in output, for pipeline compressors, wind-tunnel drives and overland conveyor systems. Through electromagnetic induction, the rotating magnetic field induces a current in the conductors in the rotor, which in turn sets up a counterbalancing magnetic field that causes the rotor to turn in the direction the field is rotating.The rotor must always rotate slower than the rotating magnetic field produced by the poly phase electrical supply; otherwise, no counterbalancing field will be produced in the rotor.

2.3 MODELLING OF INDUCTION MOTOR

The dynamic model of the induction motor is derived by using a two phase motor in direct and quadrature axes. This approach is desirable because of the conceptual simplicity obtained with two sets of windings, one on stator and the other on the rotor. The equivalence between the three phase and two phase machine models is derived from simple observation, and this approach is suitable for extending it to model an n-phase machine by means of a two phase machine. The concept of power invariance is introduced: the power must be equal in the three phase machine and its equivalent two phase model. The modeling of induction motor considers the equivalent circuit as shown in Fig 2.2.

2.3.1 EQUIVALENT CIRCUIT

The induction motor D-Q axes equivalent circuit plays key role in design of Dynamical model. These circuits are shown in Fig.2.2

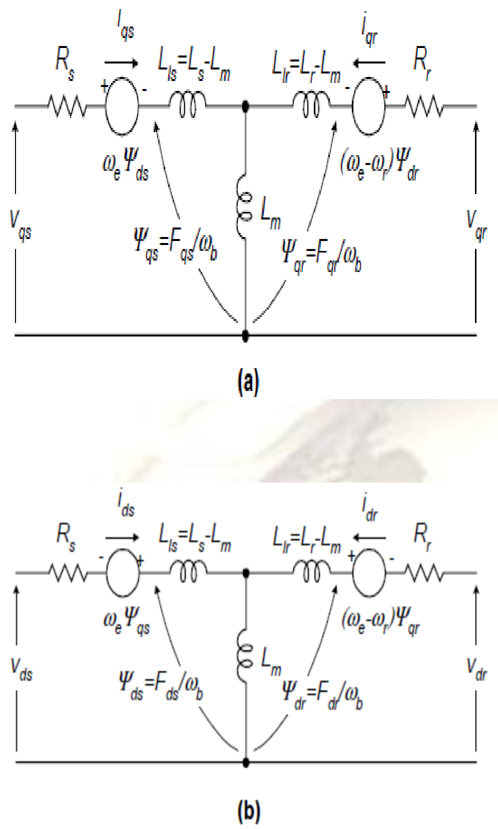

Fig 2.2 Dynamic or d-q equivalent circuit of an induction machine

The one of the popular induction motor models derived from Kron's Model. According to his model, the modeling equations in flux linkage form are as follows:

$$\frac{dF_{qs}}{dt} = \omega_b\left[v_{qs} - \frac{\omega_e}{\omega_b}F_{ds} + \frac{R_s}{x_{ls}}\left(F_{mq} + F_{qs}\right)\right] \quad 2.1$$

$$\frac{dF_{ds}}{dt} = \omega_b\left[v_{ds} - \frac{\omega_e}{\omega_b}F_{qs} + \frac{R_s}{x_{ls}}\left(F_{md} + F_{ds}\right)\right] \quad 2.2$$

$$\frac{dF_{qr}}{dt} = \omega_b\left[v_{qr} - \frac{(\omega_e-\omega_r)}{\omega_b}F_{dr} + \frac{R_r}{x_{lr}}\left(F_{mq} - F_{qr}\right)\right] \quad 2.3$$

$$\frac{dF_{dr}}{dt} = \omega_b\left[v_{dr} - \frac{(\omega_e-\omega_r)}{\omega_b}F_{qr} + \frac{R_r}{r}\left(F_{md} - F_{dr}\right)\right] \quad 2.4$$

$$F_{mq} = x_{ml}^{*}\left[\frac{F_{qs}}{x_{ls}} + \frac{F_{qr}}{x_{lr}}\right] \quad 2.5$$

$$F_{md} = x_{ml}^{*}\left[\frac{F_{ds}}{x_{ls}} + \frac{F_{dr}}{x_{lr}}\right] \quad 2.6$$

$$i_{qs} = \frac{1}{x_{ls}}\left(F_{qs} - F_{mq}\right) \quad 2.7$$

$$i_{ds} = \frac{1}{x_{ls}}\left(F_{ds} - F_{md}\right) \quad 2.8$$

$$i_{qr} = \frac{1}{x_{lr}}\left(F_{qr} - F_{mq}\right) \quad 2.9$$

$$i_{dr} = \frac{1}{x_{lr}}\left(F_{dr} - F_{md}\right) \quad 2.10$$

$$T_e = \frac{3}{2}\left(\frac{P}{2}\right)\frac{1}{\omega_b}\left(F_{ds}\, i_{qs} - F_{qs}\, i_{ds}\right) \quad 2.11$$

$$T_e - T_L = J\left(\frac{P}{2}\right)\frac{d\omega_r}{dt} \quad 2.12$$

Where

d: direct axis,

q: quadrature axis,

s: stator variable,

r: rotor variable,

F_{ij}: is the flux linkage (i=q or d and j=s or r)

V_{qs}, V_{ds}: q and d-axis stator voltages,

V_{qr}, V_{dr}: q and d-axis rotor voltages,

F_{mq}, F_{md}: q and d axis magnetizing flux linkages,

R_r: Rotor resistance,

R_s: Stator resistance,

X_{ls}: Stator leakage reactance(ω_e, L_{ls}),

X_{lr} : Rotor leakage reactance(ω_e, L_{lr}),

$$x^*_{ml} : \frac{1}{\left(\frac{1}{x_m}+\frac{1}{x_{ls}}+\frac{1}{x_{lr}}\right)},$$

i_{qs} , i_{ds}: q and d-axis stator currents,

i_{qr}, i_{dr}: q and d-axis rotor currents,

p: number of poles,

J: moment of inertia,

T_e: electrical output torque,

T_L: load torque,

ω_e :stator angular electrical frequency,

ω_b: motor angular electrical base frequency, and

ω_r: rotor angular electrical speed.

For a squirrel cage induction machine V_{qr} and V_{dr} in equations (3) and (4) are set to zero. An induction machine model can be represented with five differential equations as seen above.

To solve these equations, they have to be rearranged in the state-space form,

$$X = Ax + B$$

Where $X = [F_{qs}\ F_{ds}\ F_{qr}\ F_{dr}\ \omega_r]^T$ is the state vector.

$$F_{ij} = \psi_{ij} * \omega_b, \quad 2.13$$

Where "F_{ij}" is the flux linkage and ψ_{ij} is the flux.

In this case, state space form can be achieved by inserting (2.5)and(2.6) in (2.1-2.4) and collecting the similar terms together so that each state derivative is a function of only other state variables and model inputs.

2.4 MOTOR PARAMETERS

Machine Rating	2.2KW
Switching Frequency	10KHZ
Rotor resistance	R_r = 1.34
Stator resistance	R_s = 1.77
Base frequency	f_b = 100
Stator inductance	l_{ls} = 5.25/(2*pi*f_b)
Rotor inductance	l_{lr}= 4.57/(2*pi*f_b)
Magnetizing inductance	l_m=139/(2*pi*f_b)
Number of poles	P = 4
Moment of inertia	j = 0.025

$l_r = l_{lr} + l_m$

$t_r = \frac{l_r}{r_r}$

Base speed	ω_b = 2*pi*f_b
Stator impedance	$X_{ls} = \omega_b * l_{ls}$
Rotor impedance	$X_{lr} = \omega_b * l_{lr}$
Magnetizing impedance	$X_m = \omega_b * l_m$

V_{dc}= 300V

2.5 MODELING EQUATIONS IN STATE SPACE

$$\frac{dF_{qs}}{dt} = \omega_b \left[v_{qs} - \frac{\omega_e}{\omega_b} F_{ds} + \frac{R_s}{x_{ls}} \left(\frac{x^*_{ml}}{x_{lr}} F_{qr} + \left(\frac{x^*_{ml}}{x_{ls}} - 1 \right) F_{qs} \right) \right] \quad 2.14$$

$$\frac{dF_{ds}}{dt} = \omega_b \left[v_{ds} - \frac{\omega_e}{\omega_b} F_{qs} + \frac{R_s}{x_{ls}} \left(\frac{x^*_{ml}}{x_{lr}} F_{dr} + \left(\frac{x^*_{ml}}{x_{ls}} - 1 \right) F_{ds} \right) \right] \quad 2.15$$

$$\frac{dF_{qr}}{dt} = \omega_b \left[-\frac{(\omega_e - \omega_r)}{\omega_e} F_{dr} + \frac{R_r}{x_{lr}} \left(\frac{x^*_{ml}}{x_{ls}} F_{qs} + \left(\frac{x^*_{ml}}{x_{lr}} - 1 \right) F_{qr} \right) \right] \quad 2.16$$

$$\frac{dF_{dr}}{dt} = \omega_b \left[\frac{(\omega_e - \omega_r)}{\omega_e} F_{qr} + \frac{R_r}{x_{lr}} \left(\frac{x^*_{ml}}{x_{ls}} F_{ds} + \left(\frac{x^*_{ml}}{x_{lr}} - 1 \right) F_{dr} \right) \right] \quad 2.17$$

$$\frac{d\omega_r}{dt} = \left(\frac{P}{2J}\right)(T_e - T_L) \quad 2.18$$

2.5 CONTROL STRATEGIES OF INDUCTION MACHINE

The control and estimation of ac drives in general are considerably more complex than those of dc drives, and this complexity increases substantially if high performances are demanded. The main reasons for this complexity are the need of variable-frequency, harmonically optimum converter power supplies, the complex dynamics of ac machines, machine parameter variations, and the difficulties of processing feedback signals in the presence of harmonics.

To limit the above problems, different types control strategies are introduced in recent years. Induction motor has 3 control strategies.

- Volts/Hz control of Induction motor
- Vector control or Field Oriented Control(FOC)
- Direct Torque Control(DTC)

In these, vector control is used as a control strategy because in this the induction motor can be controlled like a separately excited motor, brought a renaissance in the high performance control of ac drives. Because of dc machine like performance, vector control is known as decoupling, orthogonal, or Trans vector control.

2.7 VECTOR CONTROL CONCEPT

The various control strategies for the control of the inverter fed induction motor have provided good steady-state but poor dynamic response. From the traces of the dynamic responses, the cause of such poor dynamic response is found to be that the air gap flux linkages deviate from their set values. The deviation is not only in magnitude but also in phase. The variations in the flux linkages have to be controlled by the magnitude and frequency of the stator and rotor phase currents and their instantaneous phases.

The oscillations in the air gap flux linkages result in oscillations in electromagnetic torque and, if left unchecked, reflect as speed oscillations. This is undesirable in many high-performance applications.

Separately excited dc drives are simpler in control because they independently control flux, which, when maintained constant contributes to an independent control of torque. This is made possible with separate control of field and armature currents which, in turn, control the field flux and torque independently.

The dc motor control requires only the control of the field or armature current magnitudes, providing simplicity not possible with ac machine control. By contrast, ac induction motor drives require a coordinated control of stator current magnitudes, frequencies, and their phases, making it a complex control. The requirement of phase, frequency, and magnitude control of the currents and hence of the flux phasor is made possible by inverter control. The control is achieved in field coordinates hence it is called “field oriented control” or “vector control”.

2.7.1 PRINCIPLE OF VECTOR CONTROL

The fundamental principle vector control of the vector controlled induction machine can be explained with the d-q model which is as shown in Fig. 2.2.

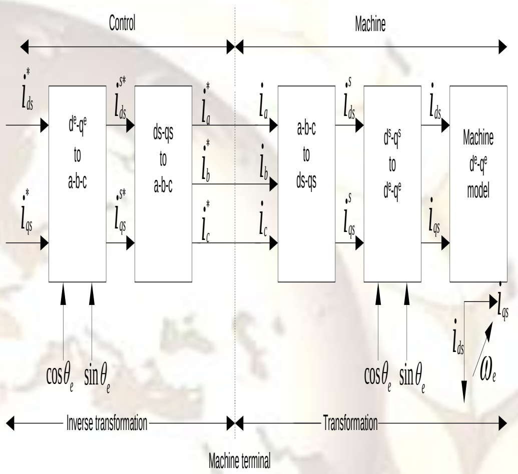

Fig 2.3 Vector Control Implementation Principle with Machine d^e–q^e Model

In diagram the machine models represented in a synchronously rotating reference frame. The inverter is omitted, assuming that it has unity current gain i.e. it generates current i_a, i_b, i_c by the corresponding command currents i^*_a, i^*_b, i^*_c from the controller. The machine terminal phase currents i_a, i_b, i_c are converted into i^s_{qs}, i^s_{ds} components by 3-phase to 2-phase transformation. These are then rotating frame by the unit vector components $\cos\theta_e$ and $\sin\theta_e$ before applying them to the d^e - q^e machine model.

To explain the principle of vector control, an assumption is made that the position of the rotor flux linkage phasor, λ_r, is known. λ_r is at θ_f from a stationary reference, θ_f is referred to as field angle, and the three stator currents can be transformed into q and d axes currents in the synchronous reference frames by using the transformation

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$$\begin{bmatrix} i_{qs}^e \\ i_{ds}^e \end{bmatrix} = \frac{2}{3} \begin{bmatrix} \sin\theta_f & \sin\left(\theta_f - \frac{2\pi}{3}\right) & \sin\left(\theta_f + \frac{2\pi}{3}\right) \\ \cos\theta_f & \cos\left(\theta_f - \frac{2\pi}{3}\right) & \cos\left(\theta_f + \frac{2\pi}{3}\right) \end{bmatrix} \begin{bmatrix} i_{as} \\ i_{bs} \\ i_{cs} \end{bmatrix}$$

2.19

The stator current phasor, i_s, is derived as

$$i_s = \sqrt{\left(i_{qs}^e\right)^2 + (i_{ds}^e)^2}$$

2.20

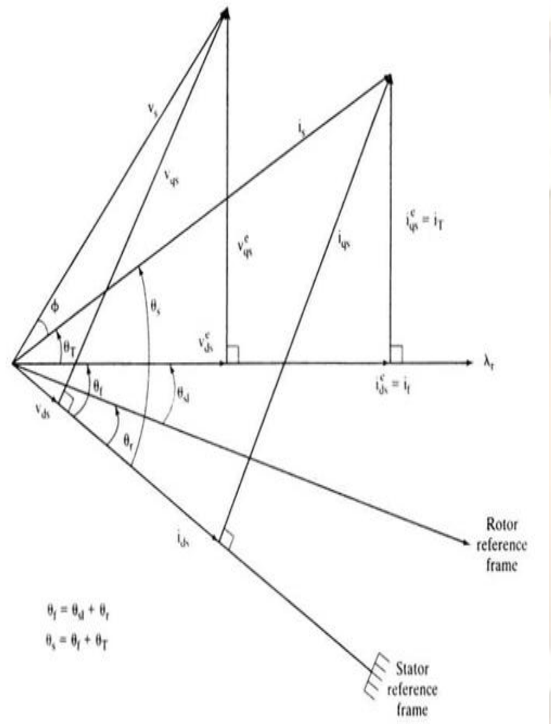

Fig 2.4 Phasor diagram of the Vector Controller

And the stator phasor angle is

$$\theta_s = \tan^{-1}\left\{\frac{i_{qs}^e}{i_{ds}^e}\right\}$$

2.21

Where i_{qs}^e and i_{ds}^e are the q and d axes currents in the synchronous reference frames that are obtained by projecting the stator current phasor on the q and d axes, respectively.

The current phasor i_s produces the rotor flux λ_r and the torque T_e. The component of current producing the rotor flux phasor has to be in phase with λ_r. Therefore, resolving the stator current phasor along λ_r reveals that the component i_f is the field producing component, as shown in Fig 2.4. The perpendicular component i_T is the torque producing component.

$$\lambda_r \propto i_f \qquad 2.22$$

$$T_e \propto \lambda_r\, i_T \propto i_f\, i_T \qquad 2.23$$

i_f and i_T have only dc components in steady state, because the relative speed with respect to that of the rotor field is zero; the rotor flux linkages phasor has a speed equal to the sum of the rotor and slip speeds, which is equal to the synchronous speed.

The field angle can be written as

$$\theta_f = \theta_r + \theta_{sl} \qquad 2.24$$

Where θ_r the rotor is position and θ_{sl} is the slip angle. In terms of the speeds and time, the field angle is written as

$$\theta_f = \int(\omega_r + \omega_{sl})dt = \int \omega_s dt \qquad 2.25$$

The controller makes two stages of inverse transformation both at the control currents i_{ds}^* to i_{qs}^* corresponds to the machine model i_{ds} and i_{qs} respectively. The unit vector assures correct alignment of i_{ds} current with the flux vector (ψ_r) and i_{qs} perpendicular to it.

The transformation and inverse transformation including the inverter ideally do not incorporate any dynamics and therefore, the response to $i_{ds}$and i_{qs} is instantaneous. The orientation of $i_{ds}$with rotor flux (Ψ_r) air gap flux (Ψ_m) or stator flux (Ψ_s) is possible in the vector control. Rotor flux orientation gives natural decoupling control where as air gap or stator flux orientation gives coupling effect, which has to be compensated by a decoupling compensator current.

2.8 TYPES OF FIELD ORIENTATED CONTROL (FOC) METHODS

In the induction motor torque control is performed by the quadrature component of the stator current space phasor i_{qs}, whereas in the DC motor, it is performed by armature current i_a. The field control is performed by the direct component of the stator current space phasor i_{ds}, whereas in the DC motor, it is performed by the field current i_f , in the separately excited winding. One should note that in the control portion of the drive for the induction motor, all the variables are in the rotor flux reference frame, which is rotating synchronously with the rotor flux linkage space phasor. Therefore, all the variables are dc quantities as explained earlier. Thus, a vector controlled induction motor drive system is similar to a DC motor drive system.

Further, the vector controlled induction motor drive system will give dynamic performances similar to that of DC motor drive system.

For vector control operation of the induction motor, the arbitrary reference frame must be aligned along the rotor flux linkage space phasor at every instant. It is therefore essential that the position of the rotor flux linkage space phasor "ρ", be accurately known at every instant. This knowledge of rotor flux linkage space phasor position can be acquired either by measuring the flux directly or by estimating the flux from terminal variables i.e. by indirect means. This leads to two possible control techniques of induction motor.

- Direct field oriented control
- Indirect field oriented control

2.8.1 DIRECT FIELD ORIENTED CONTROL (DFOC)

In this mode of control the flux measurement can be made using either the hall sensors or the stator search (sense) coils. If the stator coils are used, then the voltage sensed from the coils will have to be integrated to obtain the air gap flux linkages. The measured air flux linkage components are used to calculate the required (rotor, stator or air gap) flux linkage space phasor magnitude and position "ρ". The value of ρ thus computed is used to align the arbitrary axis along the flux linkage space phasor to achieve decoupled control of the torque and flux producing components of the stator current and space phasor.

The flux sensing devices are placed in the air gap of the machine, which will determine the air gap flux space phasor. Any other flux space phasor can be calculated as it has an algebraic relationship with the air gap flux space phasor. The air gap flux sensed by either hall-effect devices or stator search coils suffer from the disadvantage that a specially constructed induction motor is required. Further, hall sensors are very sensitive to temperature and mechanical vibrations and the flux signal is distorted by large slot harmonics that cannot be filtered effectively because their frequency varies with motor speed.

In the case of stator Search (sense) coils, they are placed in the wedges close to the stator slots to sense the rate of change of air flux. The induced voltage in the search coil is proportional to the rate of change of flux. This induced voltage has to be integrated to obtain the air gap flux. At low speeds below about 1HZ, the induced voltage will be significantly low which would give rise to in accurate flux sensing due to presence of comparable amplitudes of noise and disturbances in a practical system. As an alternative, indirect flux estimation techniques are preferred as explained in the next sub-section.

III NSVPWM BASED INDIRECT VECTOR CONTROL OF INDUCTION MOTOR DRIVE

3.1 INTRODUCTION

The conventional Space Vector Pulse Width Modulation (SVPWM) for indirect vector controlled induction motor drive has some limitations to obtain the desired performance of the system. The neural network methodology is introduced to give better performance.

A neural network is a powerful data-modeling tool that is able to capture and represent complex input/output relationships. The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform "intelligent" tasks similar to those performed by the human brain. Neural networks resemble the human brain in the following two ways:

- A neural network acquires knowledge through learning.
- A neural network's knowledge is stored within inter-neuron connection strengths known as synaptic weights.

Artificial Neural Networks are being counted as the wave of the future in computing. ANN has several types of methods are introduced in recent researches. Here in this project adapted Kohonen's Neural Network. The following section explains the description of neural based Space Vector Pulse Width Modulation using Kohonen's Competitive net.

3.2 KOHONEN'S NEURAL NETWORK

The Kohonen neural network differs considerably from the feed forward back propagation neural network. The Kohonen neural network differs both in how it is trained and how it recalls a pattern. The Kohonen neural network does not use any sort of activation function. Further, the Kohonen neural network does not use any sort of a bias weight. Output from the Kohonen neural network does not consist of the output of several neurons. When a pattern is presented to a Kohonen network one of the output neurons is selected as a "winner". This "winning" neuron is the output from the Kohonen network. Often these "winning" neurons represent

groups in the data that is presented to the Kohonen network. The most significant difference between the Kohonen neural network and the feed forward back propagation neural network is that the Kohonen network trained in an unsupervised mode. This means that the Kohonen network is presented with data, but the correct output that corresponds to that data is not specified. Using the Kohonen network this data can be classified into groups.

It is also important to understand the limitations of the Kohonen neural network. Kohonen neural networks are used because they are a relatively simple network to construct that can be trained very rapidly.

3.2.1 STRUCTURE OF THE KOHONEN NEURAL NETWORK

The Kohonen neural network works differently than the feed forward neural network. The Kohonen neural network contains only an input and output layer of neurons. There is no hidden layer in a Kohonen neural network. The input to a Kohonen neural network is given to the neural network using the input neurons. These input neurons are each given the floating point numbers that make up the input pattern to the network. A Kohonen neural network requires that these inputs be normalized to the range between -1 and 1. Presenting an input pattern to the network will cause a reaction from the output neurons.

The output of a Kohonen neural network is very different from the output of a feed forward neural network. In a Kohonen neural network only one of the output neurons actually produces a value. Additionally, this single value is either true or false. When the pattern is presented to the Kohonen neural network, one single output neuron is chosen as the output neuron. Therefore, the output from the Kohonen neural network is usually the index of the neuron (i.e. Neuron #5) that fired. The structure of a typical Kohonen neural network is shown in Fig5.1.

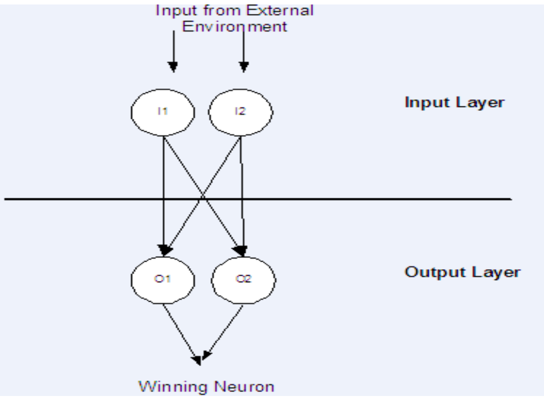

Fig 3.1 Kohonen Neural Network

3.2.2 KOHONEN NETWORK LEARNING

There several steps involved in this training process. Overall the process for training a Kohonen neural network involves stepping through several epochs until the error of the Kohonen neural network is below acceptable level. The training process for the Kohonen neural network is competitive. For each training set one neuron will "win". This winning neuron will have its weight adjusted so that it will react even more strongly to the input the next time. As different neurons win for different patterns, their ability to recognize that particular pattern will be increased.

Kohonen’s neural network is trained by repeating epochs until one of two things happens. If they calculated error is below acceptable level business at block will complete the training process. On the other hand, if the error rate has all only changed by a very marginal amount this individual cycle will be aborted with tile any additional epochs taking place. If it is determined that the cycle is to be aborted the weights will be initialized random values and a new training cycle began. This training cycle will continue the previous training cycle and that it will analyze epochs on to solve get the two is either abandoned or produces a set of weights that produces an acceptable error level. The most important part in the network's training cycles is the individual epochs.

The learning rate is a constant that will be used by the learning algorithm. The learning rate must be a positive number less than 1. Typically the learning rate is a number such as 0.4 or 0.5. Generally setting the learning rate to a larger value will cause the training to progress faster. Though setting the learning rate to too large a number could cause the network to never converge. This is because the oscillations of the weight vectors will be too great for the classification patterns to ever emerge.

3.3 NSVPWM FOR INDIRECT VECTOR CONTROL (IVCIM) DRIVE

In a voltage source inverter the space vector modulation technique requires the use of the adjacent switching vectors to the reference voltage vector and the pulse times of these vectors. For this purpose, the sector where the reference voltage vector is positioned must be determined. This sector number is then used to calculate the position θ of the reference voltage vector with respect to the closest clockwise switching vector (Fig 3.2). The pulse time can then be determined by using the trigonometric function *Sin* (θ) and *Sin* (60 −θ) as in (5.5) and (5.6).

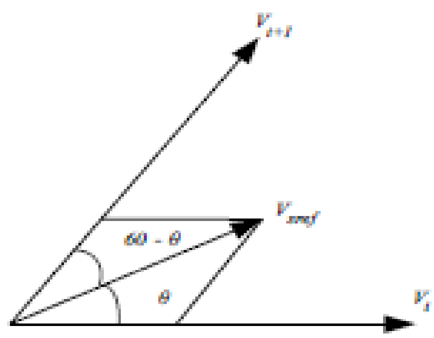

Fig 3.2 Two winner neurons of the competitive layer closest to V_{sref}

However, it is also possible to determine the two non-zero switching vectors which are adjacent to the reference voltage vector by computing the *cosine* of angles between the reference voltage vector and six switching vector and then by finding those two angles whose *cosine* values are the largest.

Mathematically this can be obtained by computing the real parts of the products of the reference voltage space vector and the six non-zero switching vectors and selecting the two largest values. These are proportional to *Cos* (θ) and *Cos* (60−θ) respectively, Where θ and (60−θ) are the angles between the reference voltage vector and the adjacent switching vectors.

It is also possible to use an ANN based on Kohonen's competitive layers. It has two winner neurons and the outputs of the winner neurons are set to their net inputs. If normalized values of the input vectors are used, then the six outputs (six net values (n_1,n_2 ,.....,n_6) will be proportional to the *cosine* of the angle between the reference voltage vector and one of the six switching vectors.

The two largest net values are then selected. These are n_i and n_{i+1}, proportional to *Cos* (θ) and *Cos* (60 −θ). Since the space vector modulation is a deterministic problem and all classes are known in advance, there is no need to train the competitive layer.

$$\text{Net} = V_{sref} \,.\, W = |V_{sref}|\,|W|\,\cos\theta \qquad 5.1$$

Since the input vector and the weight vector [6] are normalized, the instars net input gives the *cosine* of the angles between the input vector and the weight vectors that represent the classes. The largest in star net input wins the competition and the input vector is then classified in that class. The winner of the competition is the closest vector to the reference vector.

The six net values can be written in a matrix form for all neurons as:

$$\begin{bmatrix} n_1 \\ n_2 \\ n_3 \\ n_4 \\ n_5 \\ n_6 \end{bmatrix} = \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ -\frac{1}{2} & \frac{1}{2} & -1 \\ -\frac{1}{2} & 1 & -\frac{1}{2} \\ -1 & \frac{1}{2} & \frac{1}{2} \\ -\frac{1}{2} & -\frac{1}{2} & 1 \\ \frac{1}{2} & -1 & \frac{1}{2} \end{bmatrix} \begin{bmatrix} V_{Aref} \\ V_{Bref} \\ V_{Cref} \end{bmatrix}$$

5.2

Where

$$\overline{W} = \begin{bmatrix} 1 & \frac{1}{2} & -\frac{1}{2} & -1 & -\frac{1}{2} & \frac{1}{2} \\ -\frac{1}{2} & \frac{1}{2} & 1 & \frac{1}{2} & -\frac{1}{2} & -1 \\ \frac{1}{2} & -1 & -\frac{1}{2} & \frac{1}{2} & 1 & \frac{1}{2} \end{bmatrix} ; \quad \overline{V_{ref}} = \begin{bmatrix} V_{Aref} \\ V_{Bref} \\ V_{Cref} \end{bmatrix}$$

Assuming V_{sref} is applied to the competitive layer and n_i and $n_{i+1}$are the neurons who win the competition. Then from (5.1) we have

$$\begin{bmatrix} n_i \\ n_{i+1} \end{bmatrix} = |\overline{V}_{sref}| \begin{bmatrix} \cos\theta \\ \cos(60-\theta) \end{bmatrix} \qquad 5.3$$

Also

$$\begin{bmatrix} \cos\theta \\ \cos(60-\theta) \end{bmatrix} = \frac{2}{\sqrt{3}} \begin{bmatrix} \frac{1}{2} & 1 \\ 1 & \frac{1}{2} \end{bmatrix} \begin{bmatrix} \sin\theta \\ \sin(60-\theta) \end{bmatrix} \qquad 5.4$$

Substituting (5.4) in (5.3) we get

$$\frac{2}{3}\frac{T_s}{V_{dc}} \begin{bmatrix} -1 & 2 \\ 2 & -1 \end{bmatrix} \begin{bmatrix} n_i \\ n_{i+1} \end{bmatrix} = \frac{2}{\sqrt{3}}\frac{|\overline{V}_{sref}|}{V_{dc}} \begin{bmatrix} \sin(60-\theta) \\ \sin\theta \end{bmatrix} T_s \qquad 5.5$$

Equation (3.5) is the on duration of the consecutive adjacent switching state vector V_i and V_{i+1}, which is same as (4.12) and (4.13).Therefore we have

$$\begin{bmatrix} T_i \\ T_{i+1} \end{bmatrix} = \frac{2}{3}\frac{T_s}{V_{dc}} \begin{bmatrix} -1 & 2 \\ 2 & -1 \end{bmatrix} \begin{bmatrix} n_i \\ n_{i+1} \end{bmatrix} \qquad 5.6$$

The implementation of this method is depicted in fig5.3 first n_k for k=1………6 are calculated.

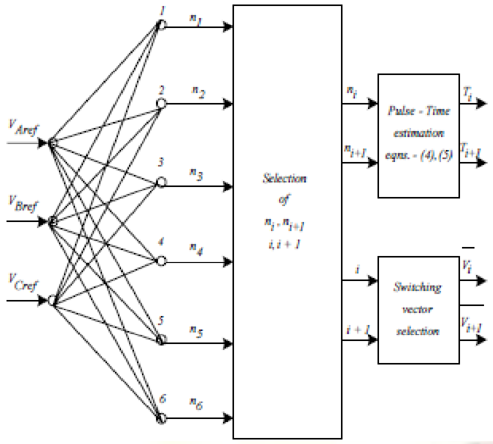

Fig 3.3 Kohonen's Competitive Layer based Implementation of the Space Vector Modulation Technique for VSI

Two largest n_i, n_{i+1} and their corresponding indexes (i.e. *i* and *i+1*) are selected by Kohonen's competitive network. The on duration (T_i and T_{i+1}) of the two adjacent space vectors are computed. The Space Vector V_i and V_{i+1} are selected according to the value of *i* and *i+1*. When adjacent vectors and on times are determined the procedure for defining the sequence for implementing the chosen combination is identical to that used in conventional space vector modulation as depicted in Fig. 3.4.

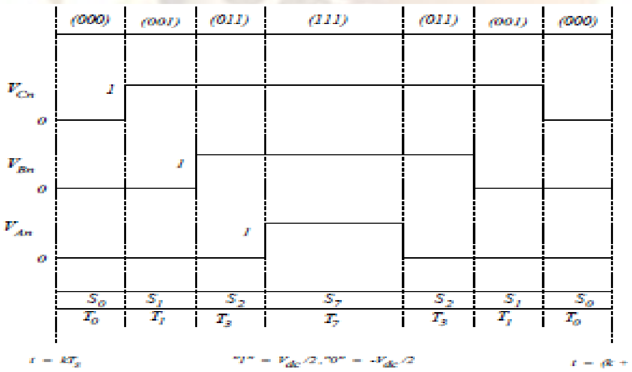

Fig.3.4. Pulse patterns generated by space vector modulation in sector1

3.4 BLOCK DIAGRAM REPRESENTATION OF NSVPWM FOR (IVCIM) DRIVE

Indirect vector controlled drive has enhance the performance using neural network. The proposed scheme is implementing by replacing the conventional SVPWM with Neural based SVPWM. According to the Neural Network theory the Kohonen Competitive layer is adapted. The Fig 3.5 shows the block diagram representation of NSVPWM based indirect vector control for induction motor drive.

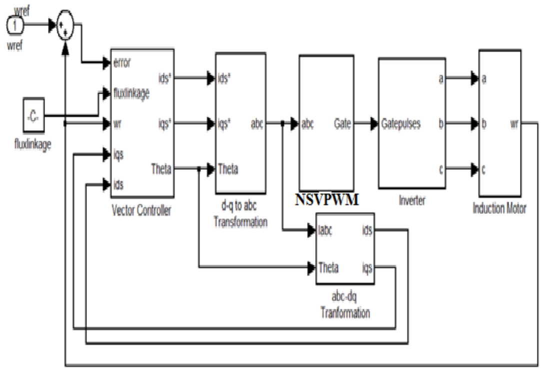

Fig 3.5 Block diagram representation of NSVPWM based (IVCIM) drive

Figure captions appear below the figure, are flush left, and are in lower case letters. When referring to a figure in the body of the text, the abbreviation "Fig." is used. Figures should be numbered in the order they appear in the text.Table captions appear centered above the table in upper and lower case letters. When referring to a table in the text, no abbreviation is used and "Table" is capitalized.

The speed response is reached to the reference speed gradually as compared to the conventional SVPWM. From the Fig 3.9 it is observed that the speed response of the NSVPWM is improved as compared to the SVPWM at load condition.

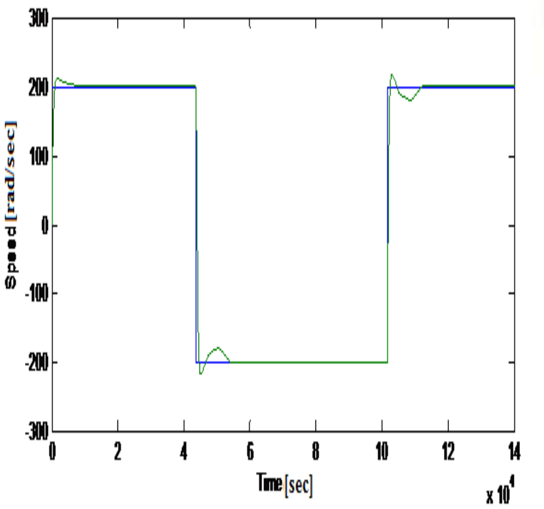

Fig 3.10 Speed response of IVCIM using NSVPWM

At initial conditions of the load i.e. at t=0 the magnitudes of the currents are shown, when load applied the variations in the currents are shown in Fig 3.10. The response of the SVPWM has been improved as compared to the NSVPWM.

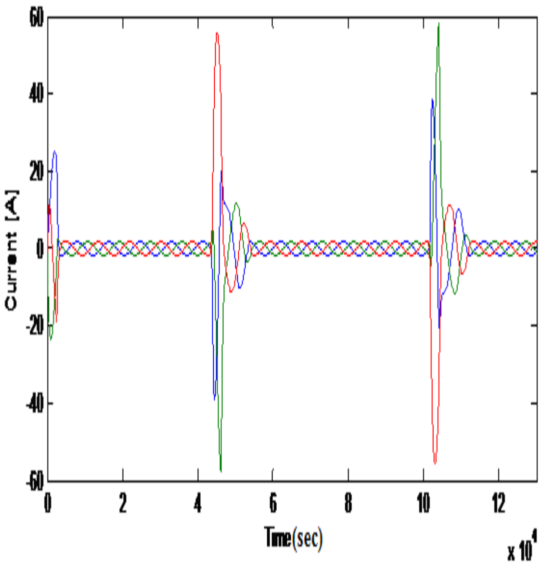

Fig 3.11 Stator Currents of IVCIM using NSVPWM

The step command of the load torque is applied to the induction motor; the output torque of the motor is improved as compared to the SVPWM. The improved torque response is shown in Fig 5.11.

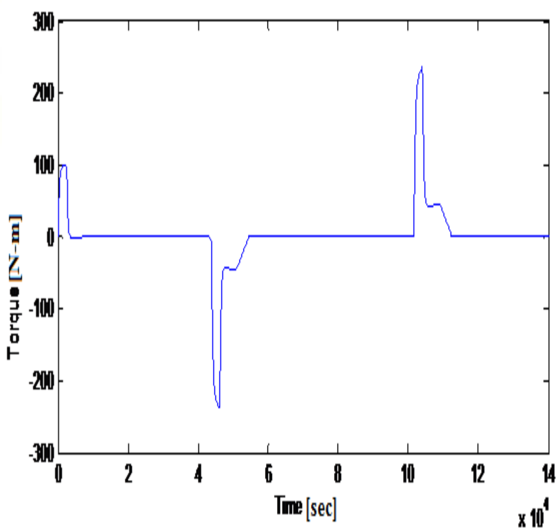

Fig 3.12 Electromagnetic Torque response of IVCIM using NSVPWM

I. CONCLUSION

In the present work, indirect vector control (IVC) technique is employed to a 3-Φ induction motor and complete model has been designed in MATLAB/SIMULINK package. The work carried out in this project is aimed and focused to implement Neural based IVCIM drive. The simulation has been carried out for different operating conditions. In developing of drive, the switching pulses are generated by using SVPWM and NSVPWM. Use of ANN based technique avoids the direct computation of non-linear function as in conventional space vector modulation implementation. The ANN based SVPWM can give higher switching frequency which is not possible by conventional SVPWM. The performance of the NSVPWM based IVCIM drive is better than SVPWM based IVCIM drive.

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