RDU090333

A NEURO-FUZZY APPROACH FOR STATOR RESISTANCE ESTIMATION OF INDUCTION MOTOR

(PENDEKATAN NEURO-FUZZY UNTUK MERAMAL RINTANGAN STATOR PADA MOTOR INDUKSI)

Norazila Jaalam
Ahmed Mohamed Ahmed Haidar
Noor Lina Ramli
Nor Laili Ismail

RESEARCH VOTE NO:
090333

Fakulti Kejuruteraan Elektrik & Elektronik
Universiti Malaysia Pahang

2011

ABSTRACT

A NEURO-FUZZY APPROACH FOR STATOR RESISTANCE ESTIMATION OF INDUCTION MOTOR

(Keywords: Neuro-Fuzzy, Stator Resistance, Induction Motor)

During the operation of induction motor, stator resistance changes incessantly with the temperature of the working machine. This situation may cause an error in rotor resistance estimation of the same magnitude and will produce an error between the actual and estimated motor torque which can leads to motor breakdown in worst cases. Therefore, this project will propose an approach to estimate the changes of induction motor stator resistance using neuro-fuzzy. Then, it will be compared with conventional method like PI estimator to see the effectiveness. The behaviour of the induction machine will be analyzed when the stator resistance is changed. Based on the changes, a corrective procedure will be applied to ensure the stabilities of the induction motor. Generally, this project can be divided into three main parts, which are design of induction motor, design of neuro-fuzzy and PI estimator, and corrective procedure for the induction machine. The Newcastle Drives Simulation Library will be used to design the induction motor model and MATLAB SIMULINK will be used to design the stator current observer. The neuro-fuzzy estimator will be designed based on Sugeno Method Fuzzy Inference System.

Key Researchers:

Norazila binti Jaalam
Ahmed Mohamed Ahmed Haidar
Noor Lina Ramli
Nor Laili Ismail

E-mail : zila@ump.edu.my
Tel. No. : 012-6675421
Vote No. : RDU090333

ABSTRAK

PENDEKATAN NEURO-FUZZY UNTUK MENGANGGAR PERUBAHAN RINTANGAN STATOR PADA MOTOR INDUKSI

(Kata kunci: Neuro-Fuzzy, Rintangan Stator, Motor Induksi)

Ketika operasi motor induksi, rintangan stator berubah mengikut suhu mesin kerja. Perubahan ini boleh menyebabkan ralat dalam membuat anggaran pada rintangan motor yang sama magnitude dan seterusnya boleh menyebabkan ralat di antara nilai sebenar dengan anggaran tork motor yang boleh menjadi punca kepada kerosakan motor yang teruk sekiranya tidak di beri perhatian. Oleh itu, projek ini telah mencadangkan satu pendekatan bagi membuat anggaran perubahan rintangan stator dengan menggunakan pendekatan neuro-fuzzy. Kemudian, pendekatan ini akan dibandingkan dengan pendekatan yang sedia ada iaitu pendekatan PI untuk menilai kebolehannya. Perubahan yang berlaku pada rintangan stator akan di analisis dan berdasarkan analisis itu, langkah penambaikan dan pembetulan akan dilakukan untuk menjamin kestabilan sesebuah motor sewaktu ia beroperasi. Secara amnya, projek ini boleh dibahagikan kepada tiga bahagian penting iaitu mereka bentuk model motor induksi, mereka bentuk neuro-fuzzy dan PI, dan seterusnya melakukan kerja pembetulan pada rintangan stator. Newcastle Drives Simulation Library pula akan digunakan untuk mereka bentuk motor induksi manakala MATLAB SIMULINK akan digunakan untuk mereka bentuk pemerhati arus stator. Pendekatan neuro-fuzzy akan dilakukan berdasarkan Sugeno Method Fuzzy Inference System.

Penyelidik:

Norazila binti Jaalam
Ahmed Mohamed Ahmed Haidar
Noor Lina Ramli
Nor Laili Ismail

E-mail : zila@ump.edu.my
Tel. No. : 012-6675421
Vote No. : RDU090333

TABLE OF CONTENTS

CHAPTER 1

INTRODUCTION

1.0 Introduction

Nowadays, induction motors are extensively used for the most reliable electrical machines. This is due to its excellent characteristics which have high efficiency, high overload capability, cheap, robust and less prove to any failure at high speed. However, during the operation of induction motor, stator resistance changes incessantly with the temperature of the working machine. In induction motor, temperature escalation is generated by power loss inside the motor which the major causes come from the current flowing throughout the stator winding and the heat produced in the stator winding is proportional to the square of stator current magnitude and frequency [1]. In high-performance control of induction motor drives, the reliance of rotor and stator resistance on temperature may become a critical obstruction as a stator resistance error may cause an error in rotor resistance estimation of the same magnitude [2],[3]. Furthermore, a mismatch between the actual and estimated rotor fluxes will produce an error between the actual and estimated motor torque which in turn may leads to motor breakdown [4]. Therefore, the alteration of induction motor parameters and its consequence on the performance of induction motor drives have been long documented [1]-[16].

Figure 1 shows a simple block diagram of direct torque control of an induction machine.

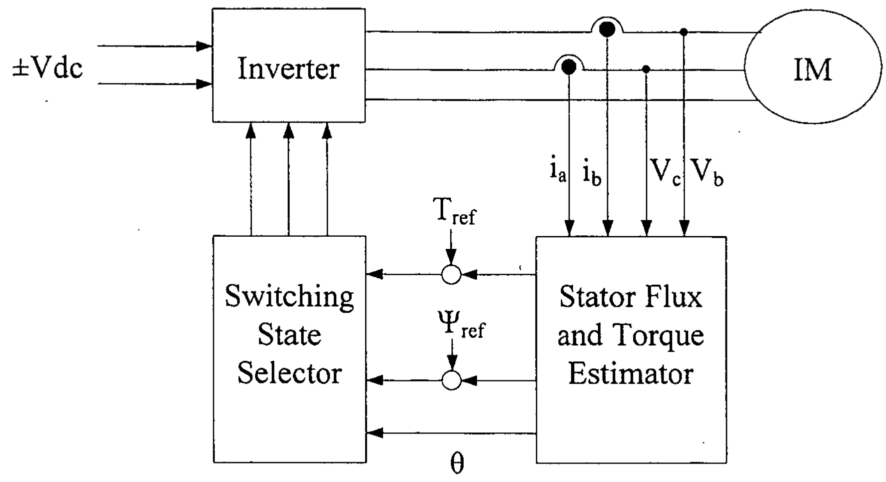

Fig. 1. Block diagram of direct torque control of induction machine.

In recent years, numerous methods have been proposed in order to estimate the changes in induction motor stator resistance. According to [6], an induction motor stator resistance estimation methods which included extended Kalman Filter, application of PI controller, Artificial Intelligence techniques (AI) and Model Reference Adaptive System (MRAS) are similar to those applied for rotor resistance estimation scheme.

It was found in [8], [9] that as conventional control theory experienced some boundaries caused by the nature of the controlled system such as time-invariance, linearity and etc, over the past decade, AI tools such as fuzzy logic, neural network and neuro-fuzzy have become more important and has extensively applied in process control, agriculture, identification, automation, military science, diagnostics, etc. According to Bose, who equalize AI as an emulation machine of human thinking process, neural network, fuzzy logic and neuro-fuzzy are expected to lead a new age in motion control, machine drive and power electronics area in the future [9].

Neural network, which tends to simulate the nervous system of a human brain is very powerful in control applications due to its learning capability [3], [9] while fuzzy logic, which can converts the linguistic control strategy of human experience and knowledge into an automatic control strategy [10], has transpire as important tool to typify and control a system which is unclear or ill-defined [9]. The combination of fuzzy set theory and neural networks with the advantages of both is known as neuro-fuzzy.

In this project, a neuro-fuzzy as induction motor stator resistance identifier will be considered based on Sugeno Method Fuzzy Inference System. This method which can mimic human decision making process has fast computation using fuzzy number operations and the most important, has self-learning, self-organizing and self-tuning capabilities.

1.1 General Problem Statements

During the operation of induction motor, stator resistance changes continuously with the temperature of the working machine. These changes can cause an error between the actual and estimated motor torque which can leads to motor breakdown in worst cases. Therefore, an approach to estimate these changes needs to be done to ensure the stabilization of working induction motor.

1.2 Objectives

The objectives of this project are:

1.2.1 to evaluate the effect of stator resistance using conventional method

1.2.2 to develop a new technique for detecting the variation of stator resistance

1.2.3 to develop a corrective procedures once the stator resistance changes is detected

1.3 Research Scopes

The scopes of the project are:

1.3.1 design an estimated induction motor model and stator current observer

1.3.2 design PI estimator and neuro-fuzzy estimator based on Sugeno Method Fuzzy Inference System

1.3:3 applied corrective procedures to stabilize the system

CHAPTER 2

LITERATURE REVIEW

2.0 Introduction

As mentioned in Chapter 1, numerous methods have been proposed in order to estimate the changes in induction motor stator resistance. Therefore, this chapter will reviews some of the methods used and it has been divided into two main sections. AI techniques will be first considered including fuzzy logic controller, artificial neural network and neuro-fuzzy. This will followed by the conventional methods including extended Kalman Filter, application of PI controller and MRAS respectively.

2.1 Artificial Intelligence Techniques

In this section, all methods which used fuzzy logic, neural network and neuro-fuzzy as induction motor stator resistance estimator will be reviewed.

2.1.1 Fuzzy Logic Controller

In [13], an application of fuzzy logic as a stator resistance (R_s) observer and ANN as a new observer for the rotor resistance (R_r) of indirect vector controlled induction motor has been proposed. Using fuzzy logic, the alteration of the R_s will be detected based on the error between the measured and estimated stator current [13]. The observed R_s then will be used to fix the R_r observer using neural networks [13].

Figure 2.1 illustrates the design of R_s identification using fuzzy estimator. By using fuzzy estimator, the error between the actual stator current $I_s(k)$ and estimated stator current $I_s{*}(k)$ are used to detect the variation of stator resistance ΔR_s. Meanwhile, the current error $e(k)$ and change in current error $\Delta e(k)$ are the inputs of the estimator and the ΔR_s is the output [13].

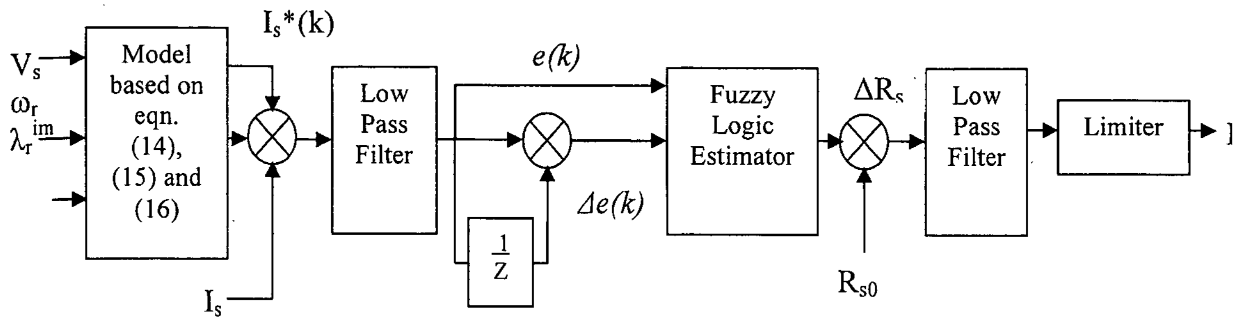

Fig. 2.1. Stator resistance identification using fuzzy logic estimator.

The findings of this study revealed that the R_r was insensitive to R_s alteration and it was clearly shown that R_r of induction motor can be estimated using ANN supported by a fuzzy logic based R_s observer [13].

Another approach using fuzzy logic controller and PI control as an estimation method for the alteration in stator resistance during the operational conditions of the machine is presented in [5]. In order to detect the alteration in stator resistance, machine stator current vector was observed and an analogous change will be made in the stator resistance if there is a change detected [5].

Figure 2.2 shows a direct torque control (DTC) with fuzzy resistance estimator. The stator current error *e(k)* and change in stator current error *Δe(k)* are the two inputs of the estimator. The experimental and simulation results proved that both estimators are capable to estimate the alteration in stator resistance and it was found that the fuzzy estimator have a better performance than the PI estimator [5]. The performance of DTC at low speed is also improved.

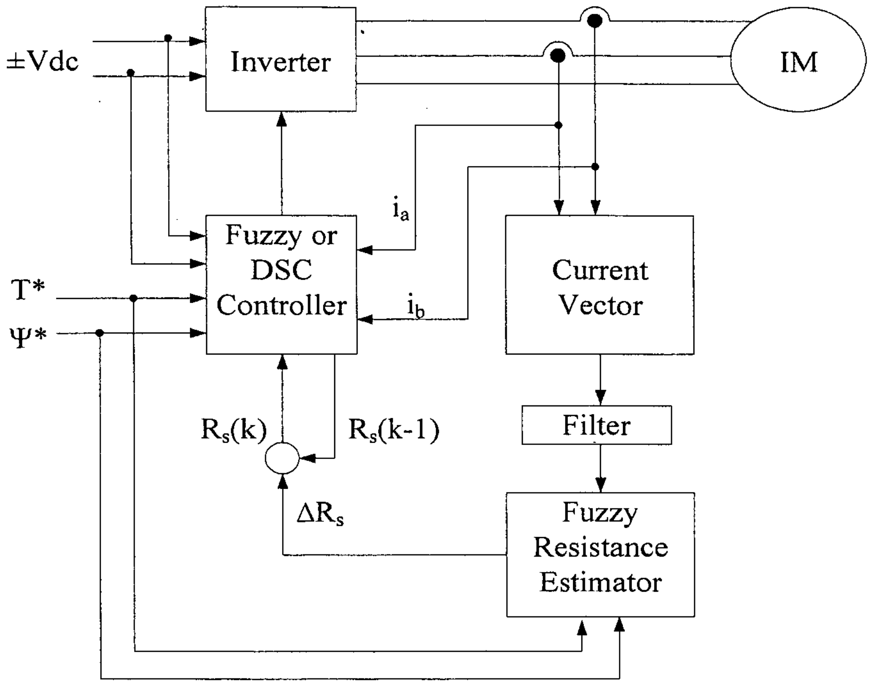

Fig. 2.2. Fuzzy logic-based resistance estimator.

As DTC has been widely used in industrial applications [14], Zidani, Diallo, Benbouzid, and Nait-Sait have proposed fuzzy logic based stator resistance identification scheme for DTC of induction motor which is based on the error of filtered and estimated flux [15]. The inputs for the scheme are the phase errors and stator flux magnitude while the output is the change in stator resistance, ΔR_s which is generated by using defuzzification and fuzzy inference [15]. The proposed identification scheme has successfully improved the performance of DTC in high torque application at low speed.

Other proposal, which is presented in [16], used a quasi-fuzzy method to estimate stator resistance of induction motor. In this method, stator resistance is derived from stator-winding temperature approximation through an estimated dynamic thermal model of the machine as a function of frequency and stator current [16]. As this method shows an excellent performance both at dynamic and static conditions when it was calibrated with a thermistor network, it was believed that this estimator shows possibly one of the best applications of fuzzy logic [16].

2.1.2 Artificial Neural Network (ANN)

In [11], the paper discussed on how to tune the stator resistance of induction motor using universal approximation, neural network. For the simulation purposes, back propagation algorithm and parallel recursive prediction error were used to train the neural network [11]. Figure 2.3 depicts the neural network structure to identify the variation of the stator resistance.

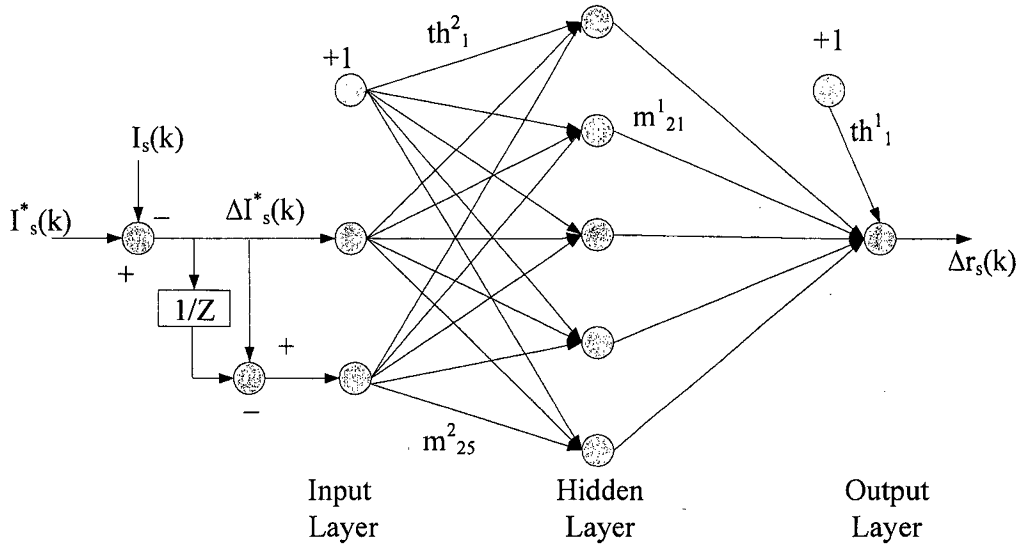

Fig. 2.3. The neural network structure.

By considering the thresholds connected to each neuron as weights to be adapted with the training algorithm, the current error *e(k)* and change in current error *Δe(k)* are the two inputs of the neural network [11]. The neural network which was trained on-line is presented in three different configurations and it was found that the largest neural network gave better results compared to others. This research has also shown that ANN was very effective in tuning the stator resistance of induction motor due to the use of erroneously estimated resistance [11].

Neural network was combined with fuzzy logic to estimate the stator resistance of induction motor in [12]. It was presented that fuzzy-neural network (FNN) can optimize fuzzy rule and membership function using its self-organizing learning [12]. By using double input and single output model, this method has proved that FNN has better characteristics in measuring stator resistance and the performance of direct torque control system is efficiently improved at low speed [12].

2.1.3 Neuro-fuzzy

Direct torque control (DTC) is a relatively novel induction motor control method, that is relatively easy to implement and that enables high performance to be achieved. It was stated in [17] that a conventional DTC technique has some drawbacks such as large torque ripple in the low speed region according to the change of motor parameters. The sensitivity of the DTC to temperature variations, leading to stator resistance changes, is eliminated by online estimation of stator resistance [17]. This paper describes an adaptive neuro-fuzzy method of stator resistance estimation of induction motor. An estimator is designed through adaptive Neuro-fuzzy Inference Systems (ANFIS) for stator resistance estimation with reference to the temperature.

2.2 Conventional methods

2.2.1 Extended Kalman Filter

In [4], a ninth-order nonlinear algorithm has been designed by Marino, Peresada, and Tomei for online estimation of stator resistance. It was reported that the design which based on stator voltages, stator currents and rotor speed measurements has improved the performance of induction motor and its efficiency.

2.2.2 Application of Estimator

Other method, which discussed in [3], [5] used proportional integral (PI) to estimate the stator resistance of induction motor. The estimator will detect the changes in stator resistance by observing the estimated and actual current of the machine. A corresponding adjustment will be created in the stator resistance if there is a change identified [5]. The experimental and simulation results clearly indicated that the PI estimator was capable to estimate and correct the changes in stator resistance of induction motor.

2.2.3 Model Reference Adaptive Scheme

In 2003, Vasic, Vukosavic and Levi have proposed a parallel MRAS estimator that enables instantaneous estimation of induction motor rotor speed and stator resistance. It is reported that the structure of the estimator is derived by applying hyperstability theory and the second degree of freedom with the error of estimated rotor flux is used for parallel stator resistance estimation. It is shown in [18] that the stator resistance estimation is independent of the setting of the rotor time constant while speed estimation is independent of the inverter dead-time.

BEMF detector is used in [7] to identify the stator resistance for AC drive systems. Using this approach, the BEMF detector was configured with model reference adaptive controller (MRAC) and the output of the detector was employed to update the stator resistance value in MRAC. This technique has shown that the BEMF detector has excellent dynamic and transient characteristics and it is well-suited with most control strategies [7].

CHAPTER 3

INDUCTION MACHINE MODEL

3.0 Introduction

As mentioned in Chapter I, the stator resistance will change respectively to the changes in temperature. Therefore, for the purpose of analysis, two machine models have been constructed to observe the effect of the changes and this chapter will discuss the methods used in constructing both induction machine models. Basically, this chapter can be divided into two main sections. Both sections discuss on induction motor design where the methods used are divided into Newcastle University Drives Simulation Library and MATLAB SIMULINK. The first method is used to model an actual induction machine while the latter is to model an estimated induction machine which later will be called stator current observer.

3.1 Induction Machine Model using Newcastle University Drives Simulation Library

In this project, as there is no real machine involved, one machine model has been constructed using Newcastle University Drives Simulation Library to act as an actual machine. Referring to Figure 3.1, there are seven sub-libraries which can be accessed from the DRIVES block located in the main SIMULINK window.

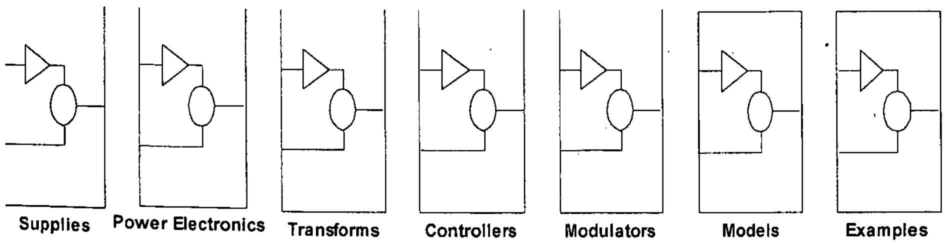

Fig. 3.1. Newcastle University Drives Simulation Library

The first six sub-libraries contain simulation blocks which can be used to develop and simulate several of drives while the seventh sub-library contains the simulations constructed using a choice of blocks from the other sub-libraries. For this project, only one sub-library block is used which is known as 'Examples'. It consists of four main blocks, as shown below.

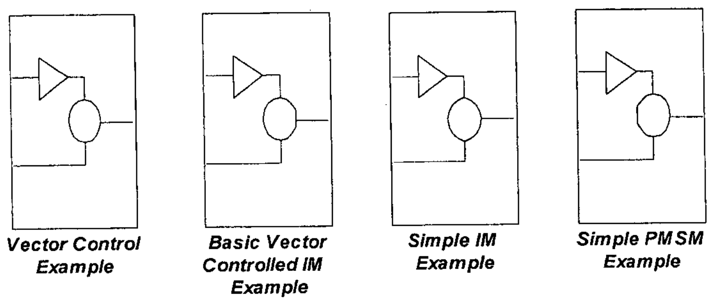

Fig. 3.2. 'Examples' sub-library.

As the project aims to investigate the changes in stator resistance of induction motor, the 'Simple IM' block is used and Figure 3.3 illustrates the SIMULINK model of this induction motor which used four main blocks.

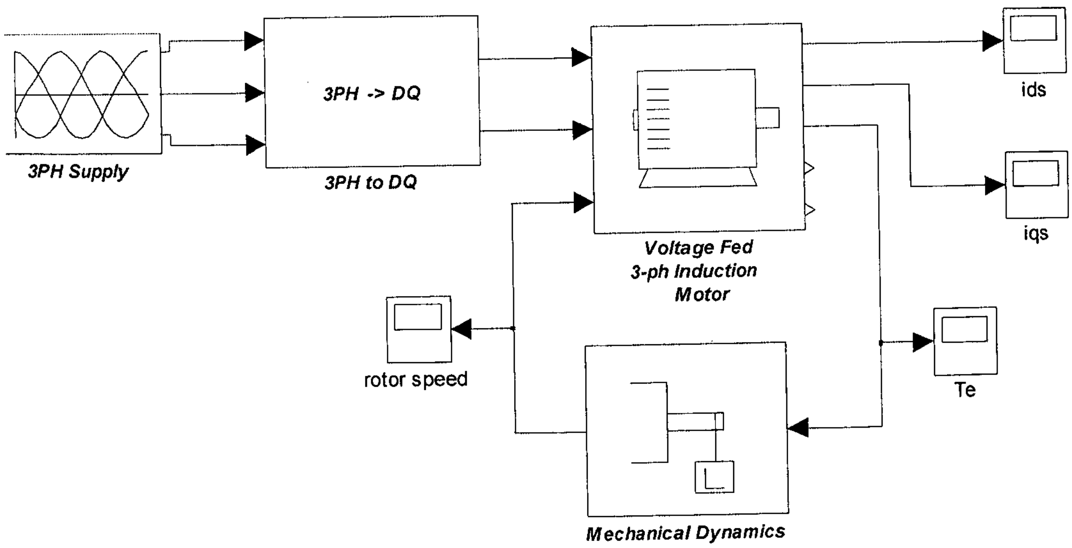

Fig. 3.3. Induction machine model using Newcastle University Drives Simulation Library.

Referring to Figure 3.3, the first block is a three phase supply block. This block has no input and three outputs which can be defined as 'A' phase voltage, 'B' phase voltage and 'C' phase voltage. The magnitude of the voltage and the frequency can be changed using the source block parameters.

The second block is a three phase to DQ transform block which has three inputs and two outputs. The inputs are phase 'A' value, phase 'B' value, and phase 'C' value while the outputs are D-axis value and Q-axis value. The three phases to DQ block is used to transform a three phase values to their identical DQ axis values. Note that, the DQ modelling will always be used in induction motor to make ease in calculation.

The next block is a voltage fed three phase induction motor. This block has three inputs and five outputs. The inputs are D-axis stator voltage, Q-axis stator voltage and rotor speed while the outputs are D-axis stator current, Q-axis stator current, electromagnetic torque, D-axis rotor current and Q-axis rotor current. All the DQ modelling is conducted in stator reference frame.

Lastly, the mechanical dynamics block is used to provide a load to the induction machine model. This block has only one input which is an electromagnetic torque and also one output which is a rotor speed. The equations for both electromagnetic torque and rotor speed are given by:

$$T_e = \frac{3}{2} L_m \left(i_{qs} i_{dr} - i_{ds} i_{qr} \right) \tag{3.1}$$

$$\omega_r = \int \frac{1}{J} \left[Te - Tld - \mathrm{sgn}(\omega_r) \left(B\omega_r + H(\omega_r)^2 + K(\omega_r)^3 \right) \right] \tag{3.2}$$

Table 1 gives the parameter's value used in this induction machine model.

Parameter	**Value**
Stator resistance, R_s	1.2Ω
Rotor resistance, R_r	1.8Ω
Stator inductance, L_s	0.156H
Rotor inductance, L_r	0.156H
Magnetizing inductance, L_m	0.143H
Voltage	311.13V
Frequency	50Hz
Rated speed	1440rpm
Rated Power	4000W
Number pole pairs	2
Inertia, J	$0.024kgm^2$

Table 1. Induction machine parameters.

3.1.1 Without Load Induction Machine Model

The induction machine model is first tested without load to make sure that all blocks are well functioned. Figure 3.4 indicates the rotor speed of the induction motor without load. It is found that the rotor speed, ω_r is equal to 157.1 rads/sec which actually can be calculated using (3.3).

$$\omega_r = \frac{2\pi f}{polepair} \tag{3.3}$$

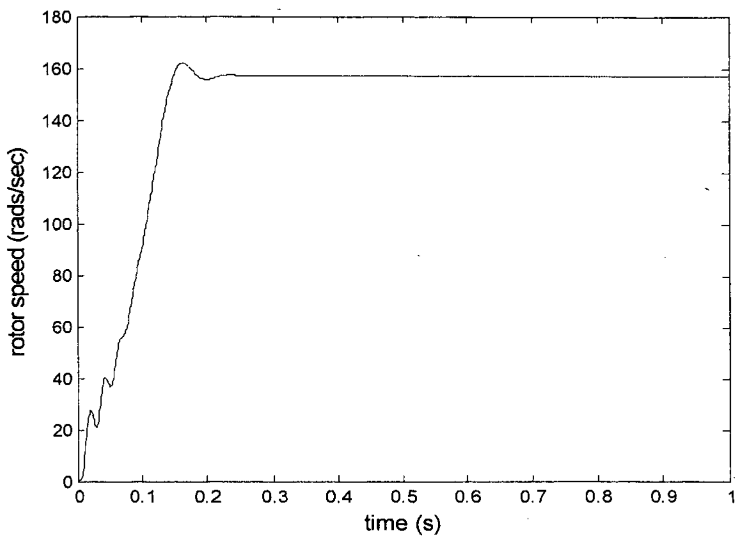

Fig. 3.4. Induction machine rotor speed.

Note that, the basic principles of induction machine operation are described by Faraday's Law. If the rotor is at standstill and the stator winding is energised, the stator-produced rotating field will move with respect to the rotor. At this moment, the rotor is rotating at synchronous speed. Therefore, there will be no relative motion between the rotor and air-gap flux and consequently, no torque is produced as there is no current induced. Figure 3.5 shows the induction motor torque which proves that at no load, the torque is equal to zero.

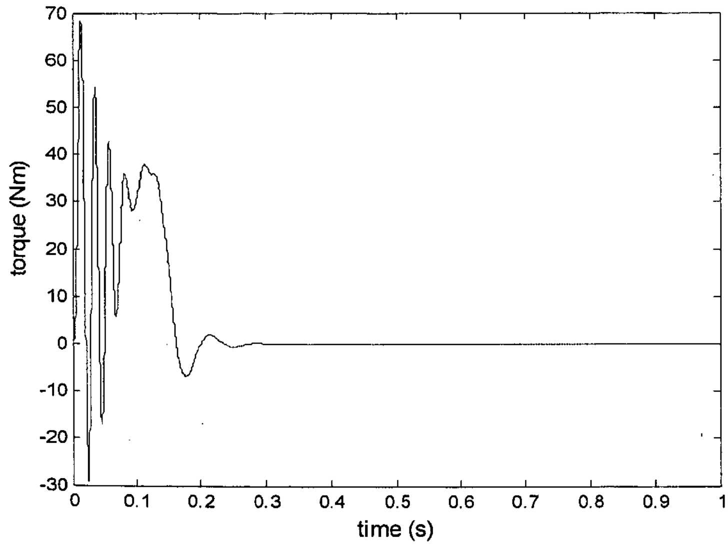

Fig. 3.5. Induction machine torque at no load.

Similarly, Figure 3.6 shows no changes in stator current when the induction machine is tested without load. Even though there is no load applied, it can be observed that there is a magnetizing current which equal to 6.4A. The current is DC as the amplitude of actual stator current is represented as:

$$I_s = \sqrt{i_{ds}^s + i_{qs}^s} \tag{3.4}$$

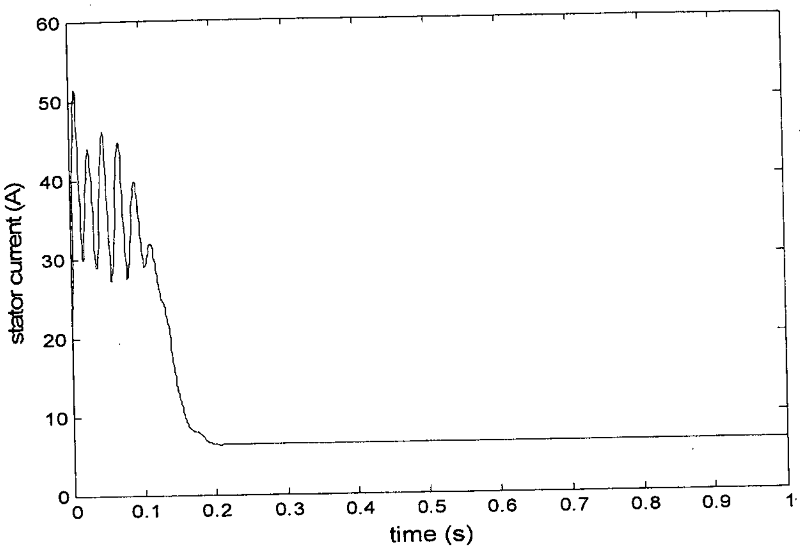

Fig. 3.6. Induction machine stator current.

3.1.2 With Load Induction Machine Model

When a mechanical load is applied in induction machine, the motor will begin to slow down and the revolving field will cut the rotor bars at a higher rate. As a result, an induced voltage and current in the bars will increase progressively to produce a torque. The rotor speed needs to be different with the synchronous speed as well to produce a torque. The difference between these two speeds is known as slip and this slip is practically proportional to the torque. The slip can be defined as:

$$s = \frac{n_s - n_r}{n_s} \tag{3.5}$$

where s is the slip, n_s is the synchronous speed (usually defined in rev/min) and n_r is the rotor speed.

In order to observe the system response over a load disturbance, the induction machine load is set to 80% of the rated torque with 0.4 step time. The rated torque can be calculated as:

$$T_{rated} = \frac{P_{rated}}{\omega_{rated}} = \frac{P_{rated}}{N_{rated}\, x \frac{2\pi}{60}} = \frac{4000W}{1440rpm\, x \frac{2\pi}{60}} = 26.52Nm$$

Therefore, the load torque is:

$$T_{load} = 80\%\, x\, 26.52Nm = 21.22Nm$$

As mentioned before, the results shown in Figure 3.7, 3.8, and 3.9 explain that when the load is applied, the rotor speed is decreased while the stator current is increased to produce a torque.

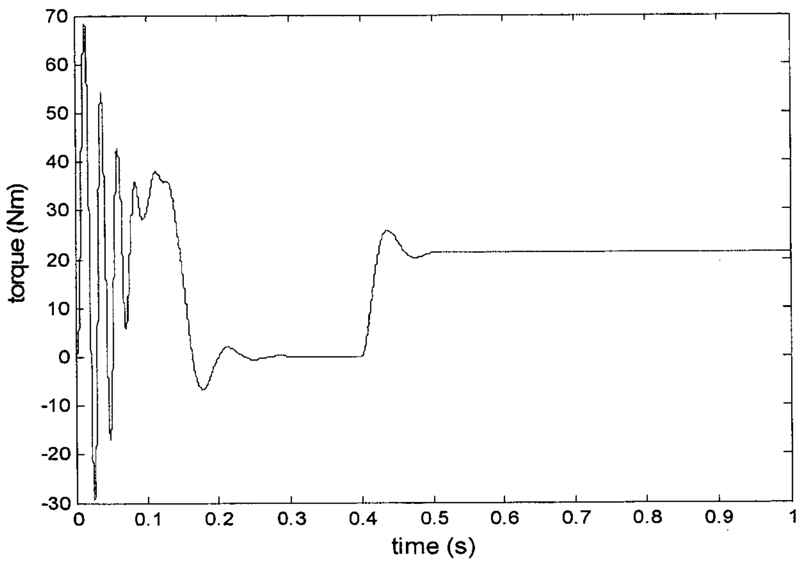

Fig. 3.7. Induction motor torque.

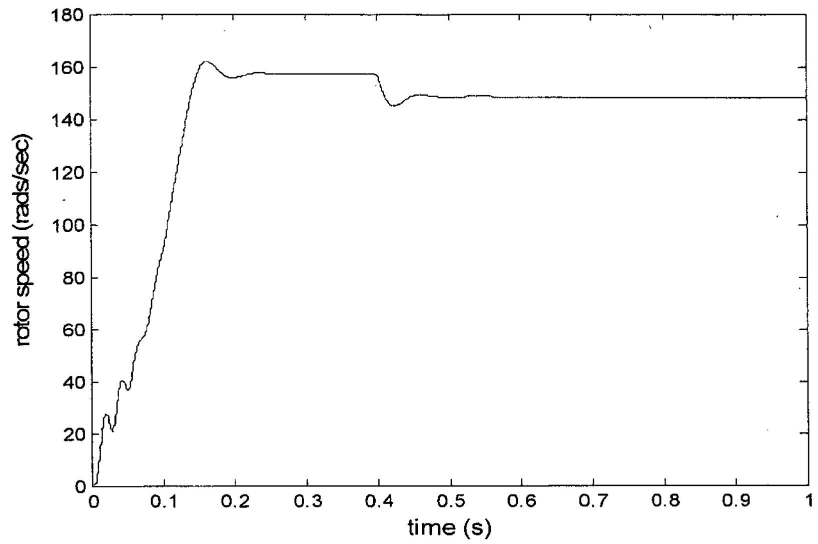

Fig. 3.8. Induction motor rotor speed.

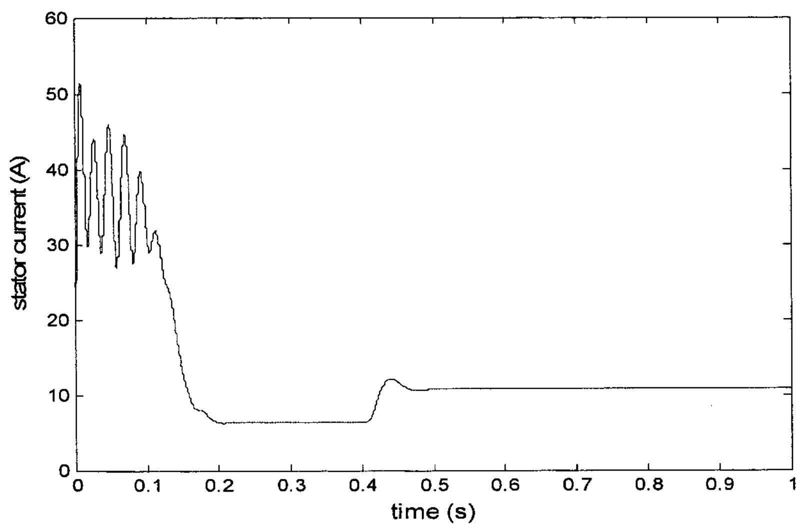

Fig.. 3.9. Induction motor stator current.

3.2 Stator Current Observer

In this section, the stator current observer is constructed using MATLAB SIMULINK in order to study the effect of estimated stator current compared to the actual stator current when an estimated stator resistance is changed. The design process for this stator current observer begins with the derivation of stator current which is shown in Appendix 1. The same parameter given in Table 1 is used for this stator current observer.

Figure 3.10 illustrates the SIMULINK model for both machines to give the overview on how this section will work.

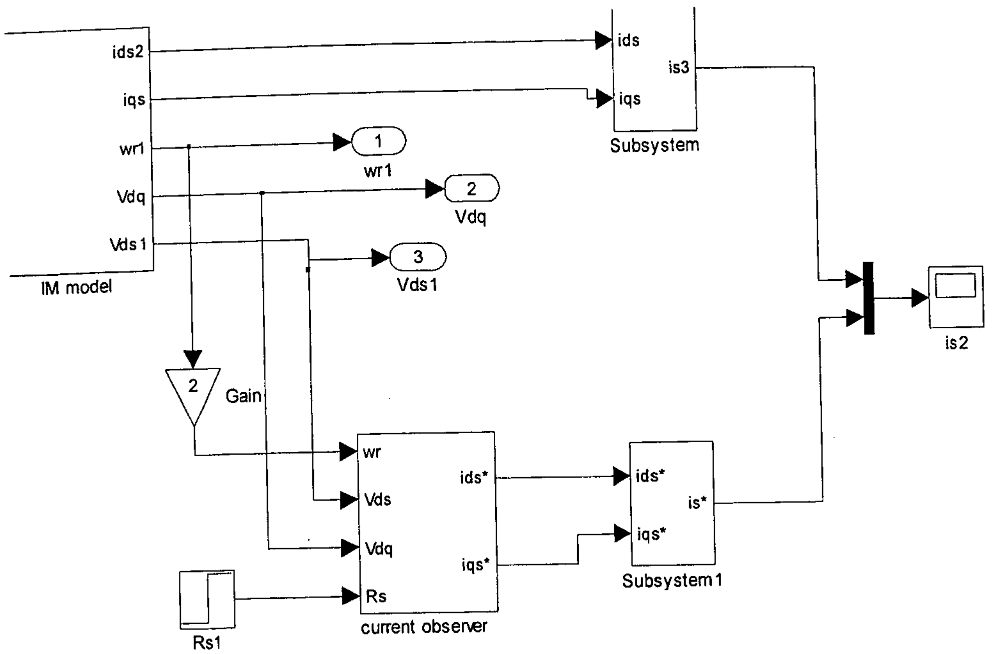

Figure 3.10. SIMULINK model for both machines to compare the stator current output.

3.2.1 *d*-axis and *q*-axis Stator Flux Linkages in Stator Reference Frame

To obtain the stator current, the stator flux linkages must be obtained first. From Appendix 1, the equations for the d-axis and q-axis stator flux linkages in stator reference frame are given by:

$$\frac{d\lambda_{dr}^{s\ \ im}}{dt} = -\frac{1}{T_r}\lambda_{dr}^{s\ \ im} - \omega_r\lambda_{qr}^{s\ \ im} + \frac{L_m}{T_r}i_{ds}^{s\ *} \tag{3.5}$$

$$\frac{d\lambda_{qr}^{s\ \ im}}{dt} = \omega_r\lambda_{dr}^{s\ \ im} - \frac{1}{T_r}\lambda_{qr}^{s\ \ im} + \frac{L_m}{T_r}i_{qs}^{s\ *} \tag{3.6}$$

The stator flux linkages for both axes are then were implemented using MATLAB SIMULINK as shown in Figure 3.11 and 3.12.

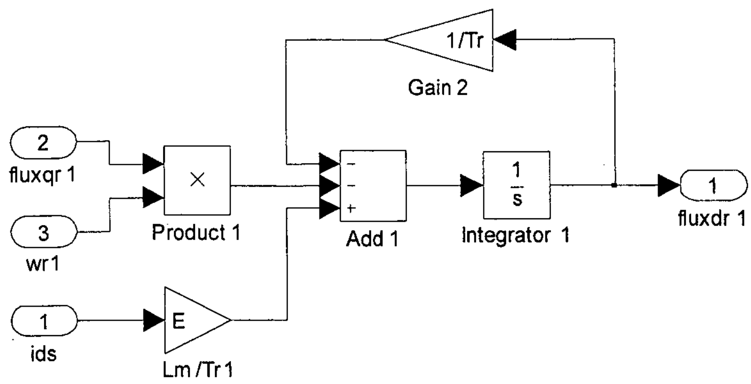

Fig. 3.11. d-axis stator flux linkages in stator reference frame.

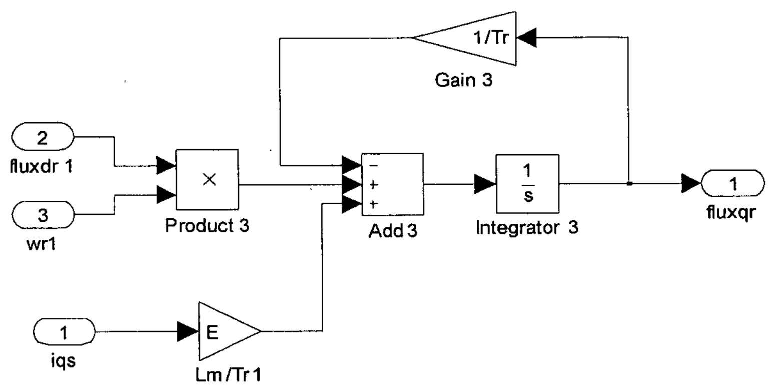

Fig. 3.12. q-axis stator flux linkages in stator reference frame.

3.2.2 d-axis and q-axis Stator Current in Stator Reference Frame

Subsequently, from Appendix 1, the equations for d-axis and q-axis stator current in stator reference frame are stated as:

$$\frac{di_{ds}^{s\ *}}{dt} = \frac{1}{\sigma L_s}\left[\frac{L_m}{L_r T_r}\lambda_{dr}^{s\ im} + \frac{L_m}{L_r}\omega_r \lambda_{qr}^{s\ im} - \frac{L_m^{\ 2}}{L_r T_r} i_{ds}^{s\ *} + v_{ds}^{s} - R_s i_{ds}^{s\ *}\right] \tag{3.7}$$

$$\frac{di_{qs}^{s\ *}}{dt} = \frac{1}{\sigma L_s}\left[\frac{L_m}{L_r T_r}\lambda_{qr}^{s\ im} - \frac{L_m}{L_r}\omega_r \lambda_{dr}^{s\ im} - \frac{L_m^{\ 2}}{L_r T_r} i_{qs}^{s\ *} + v_{qs}^{s} - R_s i_{qs}^{s\ *}\right] \tag{3.8}$$

These stator current are then were implemented using MATLAB SIMULINK as indicates in Figure 3.13 and 3.14.