

PERFORMANCE EVALUATION OF A SENSORLESS INDUCTION MOTOR DRIVE USING A MRAS SPEED OBSERVER

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ABSTRACT: This paper presents Self-Tuning Fuzzy Logic Controller for sensorless vector controlled induction motor drives. When induction motor is continuously used long time, its electrical and mechanical parameters will change, which degrade the performance of PI controller considerably. This paper uses a Self-Tuning Fuzzy Logic Controller to improve the control performance. Here; the output gain of the controller is adjusted on-line by fuzzy rules according to the current trend of the controlled process. Tuning of the output gain has been given the highest priority because of its strong influence on the performance and stability of the system. For sensorless vector control, the rotor speed is estimated using Model Reference Adaptive System (MRAS). Simulations have been performed in the Matlab-Simulink. At the end of the paper some simulation results are provided to demonstrate the validity of proposed method.

KEYWORDS: Induction Motor, Self-Tuning Fuzzy Logic Controller (FLC), Scaling Factor (SF), Speed Sensorless Control, Field-Oriented Control, MRAS Estimator.

INTRODUCTION

Induction motors have been widely applied in industry because of the advantages of simple construction, ruggedness, reliability, low cost, and minimum maintenance ([Kouzi et al., 2004](#)). The use of vector controlled induction motor drives allows obtaining several advantages compared to the DC motor in terms of robustness, size, lack of brushes, and reducing cost and maintenance. Unfortunately the IFOC induction motor drive technique requires an accurate rotational speed sensor for good operation. But in most applications, speed sensor have several disadvantages, such as reduced reliability, susceptibility to noise, additional cost and weight, and increased complexity of the drive system. Therefore sensorless IFOC induction motor drive eliminates the need for speed sensor, overcoming these challenges. Over the past few years, there has been interest in the research community in developing high performance speed sensorless IFOC induction motor drive ([Agrebi Zorgani et al., 2010](#)). Among different rotor speed estimation techniques, model reference adaptive systems schemes are the most common strategies employed due to their relative simplicity and low computational effort ([Rashed and Stronach, 2004](#)). PI controller is widely used in the induction motor drive applications due to its simplicity in structure, superior robustness, and familiarity to most field

operators ([Han et al., 2003](#)). The key issue in designing PI controller for the induction motor drive is to settle the gains so that the controller works well in every condition. Unfortunately it is very difficult to suit a wide range of working conditions with only a set of fixed gains. A solution to this problem is addressed using Fuzzy Logic Controller FLC. However, a standard FLC of Mamdani is made up of parameters such as rules base, database, membership functions (MFs) and input, and output scaling factor (SF). Based on analogy with the human operator, the output SF should be considered a very important parameter of the FLC because its function is similar to that of the controller gain, and it is directly related to the stability of the control system. For the successful design of FLCs, there should be proper selection of the input and/or output (SFs) and/or the tuning of other controller parameters such as the determination of the shape and position of the membership functions FLCs with fixed parameters may be insufficient in controlling systems, and they cannot achieve ideal performance under severe perturbations of model parameters and operating conditions ([Merabet et al., 2011](#)). However, more sophisticated controllers are required, such as adaptive regulators, self-tuning regulators, which in presence of variations of plant parameters are able to modify their features in order to maintain the desired dynamic behavior of the system ([Miloud et al.](#)

2004). Different types of adaptive FLC's have been developed and proposed in the last years. In (Vuorimma, 1992) a simple algorithm for modifying triangular input membership functions has been used. Another approach to adaptation described in (Wu et al., 1992; He et al., 1993) has involved modification of the whole fuzzy rule base. In this paper we propose a simple but robust model independent self-tuning system, where the controller gain is adjusted continuously with the help of fuzzy rules. Here, our objective is to adapt only the output SF for given input SF's. Tuning of the output SF has been given the highest priority because of its strong influence on the performance and stability of the system. This paper is organized as follows. Section 2 shows the dynamic model of induction motor and principle of field-oriented controller; in section 3 the proposed Self-Tuning fuzzy controller is presented. In section 4 MRAS speed estimator configuration is given. In section 5, the performances of the proposed sensorless control are illustrated by simulation results. Finally section 6 draws the final conclusions

1.1. Dynamic Model of Induction Motor

The mathematical model of induction machines supplied with voltage as a function of state variables is given by:

$$\begin{cases} \frac{d}{dt} I_{ds} = \frac{1}{\sigma L_s} \left[-R_r I_{ds} + \omega_s \sigma L_s I_{qs} + \frac{L_m R_r}{L_r} \psi_{dr} + \frac{L_m}{L_r} \omega_r \psi_{qr} + V_{ds} \right] \\ \frac{d}{dt} I_{qs} = \frac{1}{\sigma L_s} \left[-\omega_s \sigma L_s I_{ds} - R_r I_{qs} - \frac{L_m}{L_r} \omega_r \psi_{dr} + \frac{L_m R_r}{L_r} \psi_{qr} + V_{qs} \right] \\ \frac{d}{dt} \phi_{dr} = \frac{L_m R_r}{L_r} I_{ds} - \frac{R_r}{L_r} \psi_{dr} + \omega_g \psi_{qr} \\ \frac{d}{dt} \phi_{qr} = \frac{L_m R_r}{L_r} I_{qs} - \frac{R_r}{L_r} \psi_{qr} - \omega_g \psi_{dr} \\ \frac{d\omega_r}{dt} = \frac{p}{J} (T_{em} - T_l) - \frac{f}{J} \omega_r \end{cases} \quad (1)$$

Where

$$R_{st} = \left(R_s + R_r \frac{L_m^2}{L_r} \right); \quad \sigma = 1 - \frac{L_m^2}{L_s L_r};$$

$$\omega_g = \omega_s - \omega_r; \quad T_{em} = \frac{3}{2} p \frac{L_m}{L_r} (\psi_{dr} I_{qs} - \psi_{qr} I_{ds})$$

ω_s and ω_r are the electrical synchronous stator and rotor speed; σ is the linkage coefficient, and T_r is the rotor time constants.

1.2. Rotor Flux Orientation Strategy

There are two categories of vector control strategy. We are interested in this study to the

so-called IFOC. As shows in Eq. (1) that the expression of the electromagnetic torque in the dynamic regime presents a coupling between stator current and rotor flux (Messaoudi et al., 2008).

The main objective of the vector control of induction motors is, as in DC machines, to independently control the torque and the flux; this is done by using a d - q rotating reference frame synchronously with the rotor flux space vector. The d -axis is then aligned with the rotor flux space vector. Under this condition we get: $\psi_{dr} = \psi_r$ and $\psi_{qr} = 0$

The torque equation becomes analogous to the DC machine and can be described as follows:

$$T_e = \frac{3}{2} p \frac{L_m}{L_r} (\psi_r i_{qs}) \quad (2)$$

It is right to adjust the flux while acting on the stator current component i_{sd} and to adjust the torque while acting on the i_{sq} component.

Using the Eq (1) we get:

$$i_{sd} = p \frac{(1 + T_r s)}{L_m} \psi_r \bullet \quad (3)$$

$$i_{sq} = \frac{T_r}{L_m} \omega_{gl} \bullet \psi_r \bullet \quad (4)$$

We replace i_{sq} by its expression to obtain T_e as function of the reference slip speed $\omega_{gl} \bullet$

$$T_e = \frac{3}{2} p \frac{\psi_r \bullet^2}{R_r} \omega_{gl} \bullet \quad (5)$$

The stator voltage commands are:

$$v_{ds} \bullet = R_s i_{ds} - \sigma L_s \omega_s i_{qs} + \sigma L_s \frac{di_{ds}}{dt} + \frac{L_m}{L_r} \frac{d\psi_r}{dt} \quad (6)$$

$$v_{qs} \bullet = R_s i_{qs} + \sigma L_s \omega_s i_{ds} + \sigma L_s \frac{di_{qs}}{dt} + \frac{L_m}{L_r} \omega_s \psi_r$$

The rotor flux amplitude is obtained by solving Eq (3) and its spatial position is given by:

$$\theta_S = \int \omega_S \bullet dt = \int \left(p \cdot \Omega + \frac{L_m \cdot i_{sq}}{T_R \cdot \psi_r \bullet} \right) \bullet dt \quad (7)$$

1.3. The Proposed Self-Tuning Fuzzy Controller

In literature fuzzy logic algorithms with adaptive characteristics can be found under various names: self-tuning, self-organizing, self-learning, adaptive and expert algorithms or fuzzy logic algorithms with a varying rule base. Our proposed FLC is tuned by modifying the output SF of an existing FLC so we describe it as a self-tuning FLC (Miloud et al., 2004).

The block diagram of the proposed self-tuning FLC is shown in figure 2. The output SF (gain) of the controller is modified by a self-tuning mechanism, which is shown by the dotted boundary.

In order to design a self-tuning fuzzy logic controller, the following steps must be performed:

- 1) Development of a suitable rule set;
- 2) Selection of input/output variables and their quantization in fuzzy sets;
- 3) Definition of membership functions to be associated to the input/output variables;
- 4) Selection of the inference method;
- 5) Selection of the defuzzification technique.

1.4. Membership Functions

All membership functions (MF's) for: 1) controller inputs, i.e., error (e) and change of error (Δe) and 2) incremental change in controller output (ΔT_e^*), are defined on the common interval [-1,1]; whereas the MF's for the gain updating factor (α) is defined on [0,1]. We use trapezoidal and symmetric triangles as shown in Figure 2. These input membership functions are used to transfer crisp inputs into fuzzy sets.

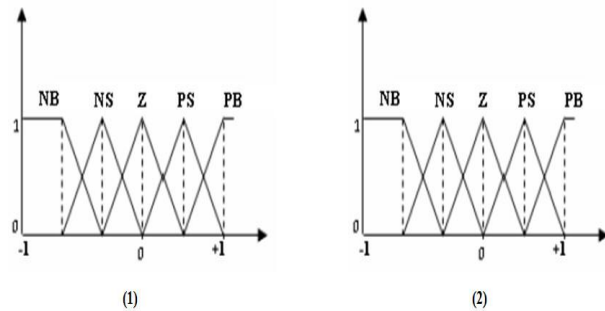


Figure 1: Membership functions of (1) e, Δe and (2) ΔT_e .

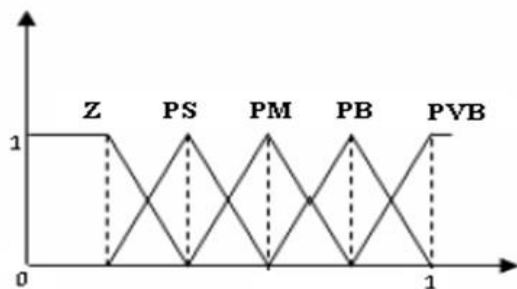


Figure 2: Membership functions of gain updating factor α .

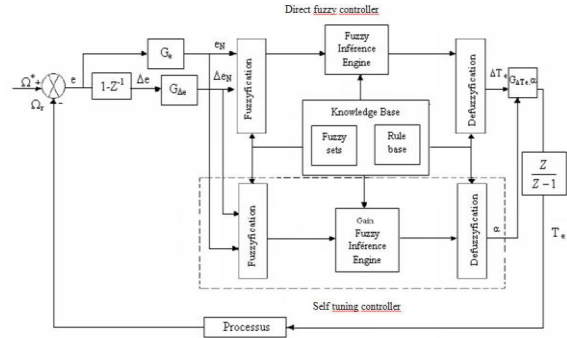


Figure 3: Structure of the Self-Tuning Fuzzy Logic Control Scheme.

The values of the actual inputs e and Δe are mapped onto [-1,1] by the input SF's G_e and $G_{\Delta e}$, respectively.

On the other hand, the actual output of the self-tuning FLC is obtained by using the effective SF ($\alpha.G\Delta T_e^*$) as shown in Figure 3. Selection of suitable values for G_e , $G_{\Delta e}$ and $G\Delta T_e^*$ are made based on the knowledge about the process to be controlled and sometimes through trial and error to achieve the best possible control performance.

We propose to compute α on-line using a model independent fuzzy rule base defined in terms of e and Δe . The relationships between the SF's and the input and output variables of the self-tuning FLC are as follows:

$$e_N = G_e \cdot e \tag{8}$$

$$\Delta e_N = G_{\Delta e} \cdot \Delta e \tag{9}$$

$$T_e^* = \Delta T_e^* \cdot \alpha \cdot G\Delta T_e^* \tag{10}$$

The value of $G\Delta T_e^*$ is constant for a particular type of conventional FLC. But the gain of our self-tuning FLC does not remain fixed while the controller is in operation; rather it is modified in each sampling time by the gain updating factor α , depending on the trend of the controlled process output. The reason behind this on-line gain variation is to make the controller respond according to the desired performance specifications

1.5. The Rule Bases

The expert experience has been incorporated into a knowledge base with 25 rules (5x5). Then, the inference engine based on the input fuzzy sets, uses appropriate IF-THEN rules in the knowledge base to imply the final output fuzzy sets.

The implied fuzzy set is transformed to a crisp output by the center of gravity defuzzification technique as given by the formula (11), where z_i is the numerical output at the i th number of rules and $\mu(z_i)$ corresponds to the value of fuzzy membership function at the i th number of rules.

The summation is from one to n, where n is the number of rules that apply for the given fuzzy inputs (Miloud et al., 2004).

$$z_0 = \frac{\sum_{i=1}^n z_i \cdot \mu(z_i)}{\sum_{i=1}^n \mu(z_i)} \quad (11)$$

The crisp output ΔT_e^* is multiplied by the gain factor $\alpha \cdot \Delta T_e^*$ and then integrated to give:

$$T_e(k) = T_e(k-1) + \Delta T_e^* \cdot \alpha \cdot \Delta T_e^* \quad (12)$$

This torque component command is used as an input to the I.F.O.C. block of figure 6.

Table 1: Fuzzy rules for the computation of ΔT_e

e Δe	NB	NS	Z	PS	PB
NB	NB	NB	NS	NS	Z
NS	NB	NS	NS	Z	PS
Z	NS	NS	Z	PS	PS
PS	NS	Z	PS	PS	PB
PB	Z	PS	PS	PB	PB

Table 2: Fuzzy rules for the computation of α

e Δe	NB	NS	Z	PS	PB
NB	PVB	PVB	PM	PM	Z
NS	PB	PS	PS	Z	PM
Z	PM	PS	Z	PS	PM
PS	PM	Z	PS	PS	PVB
PB	Z	PM	PM	PB	PVB

NB : Negative Big
NS : Negative Small
Z : Zero
PS : Positive Small
PM : Positive Medium
PB : Positive Big
PVB : Positive Very Big

1.6. Principle of Model Reference Adaptive System (MRAS)-Based Speed Estimation

The rotor flux MRAS speed estimator shown in figure 4 consists mainly of a reference model, an adaptive model and an adaptation scheme which generates the estimated speed. The reference model, usually expressed by the voltage model, represents the stator equation. It generates the reference value of the rotor flux components in the stationary reference frame from the monitored stator voltage and current components (Ramesh and Krishnan, 2010). The reference rotor flux components obtained from the reference model are given by (Shauder, 1992):

$$p \Psi_{r\alpha}^s = \frac{L_r}{L_m} (v_{s\alpha} - R_s i_{s\alpha} - \sigma L_s p i_{s\alpha}) \quad (13)$$

$$p \Psi_{r\beta}^s = \frac{L_r}{L_m} (v_{s\beta} - R_s i_{s\beta} - \sigma L_s p i_{s\beta})$$

The adaptive model, usually represented by the current model, describes the rotor equation where the rotor flux components are expressed in terms of stator current components and the rotor speed. The rotor flux components obtained from the adaptive model are given by (Shauder, 1992):

$$p \Psi_{r\alpha}^{\wedge} = \frac{L_m}{T_r} i_{s\alpha} - \frac{1}{T_r} \Psi_{r\alpha}^{\wedge} - \omega_r \Psi_{r\beta}^{\wedge} \quad (14)$$

$$p \Psi_{r\beta}^{\wedge} = \frac{L_m}{T_r} i_{s\beta} - \frac{1}{T_r} \Psi_{r\beta}^{\wedge} + \omega_r \Psi_{r\alpha}^{\wedge}$$

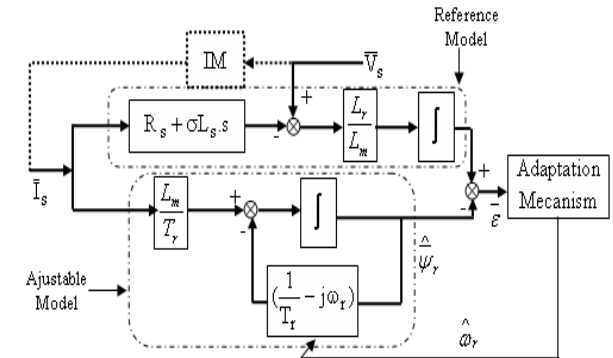


Figure 4: MRAS adaptive scheme to estimate rotor speed of induction motor.

The error between the states of the two models given by Eq. (15) is used to drive a suitable adaptation mechanism that generates the

$$\varepsilon = \Psi_r^{\wedge} - \Psi_r^{\wedge} \quad (15)$$

And

$$\dot{\varepsilon} = \left(-\frac{1}{T_r} + j \hat{\omega}_r\right) \varepsilon + j(\omega_r - \hat{\omega}_r) \Psi_r^{\wedge} \quad (16)$$

Eq. (16) can be written in state error model representation as:

$$\dot{\varepsilon} = [A] \varepsilon - [W] \quad (17)$$

With:

$$[A] = \begin{bmatrix} -\frac{1}{T_r} & -\omega_r \\ \omega_r & \frac{1}{T_r} \end{bmatrix}, \quad W = (\omega_r - \hat{\omega}_r) \hat{\psi}_r$$

Where $[W]$ is the feedback block. The term of $[W]$ is the input and $[\varepsilon]$ is the output of the linear forward block.

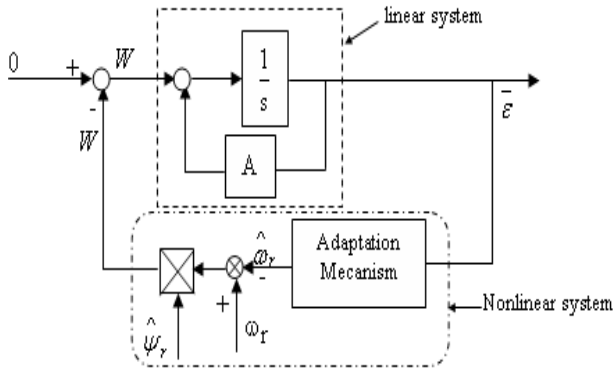


Figure 5: control structure by MRAS.

The asymptotic behavior of the adaptation mechanism is achieved by the simplified condition $\lim_{t \rightarrow \infty} [\varepsilon(\infty)]^T = 0$, for any initialization. The system is hyperstable if the transfer matrix in the forward path of the MRAS is strictly positive real and that the non-linear block in the feedback path satisfies Popov's criterion (12)

$$\int_0^{t_1} [\varepsilon]^T [W] dt \geq -\gamma^2 \quad t_1 \geq 0 \quad (18)$$

γ : Positive real constant

Schauder proposes the following adaptation law:

$$\hat{\omega}_r = Q_2(\varepsilon) + \int_0^t Q_1(\varepsilon) d\tau \quad (19)$$

Using the expression of $\hat{\omega}_r$ given by Eq. (19) and replacing ε and W by their value in Eq. (18), we get:

$$\int_0^t [\varepsilon]^T [\hat{\psi}_r] \left[\omega_r - Q_2(\varepsilon\varepsilon) - \int_0^t Q_1(\varepsilon\varepsilon) dt \right] dt \geq -\gamma^2 \quad (20)$$

The solution of this equation is given by the following relationship:

$$\int_0^t K \left(\frac{df(t)}{dt} \right) f(t) dt \geq -\frac{1}{2} K f^2(0), \quad K > 0 \quad (21)$$

Using the expression (21) to resolve all of Popov (20), we obtain the following system:

$$\begin{cases} Q_1 = K_i (\varepsilon_\beta \hat{\psi}_{ar} - \varepsilon_\alpha \hat{\psi}_{br}) \\ Q_2 = K_p (\varepsilon_\beta \hat{\psi}_{ar} - \varepsilon_\alpha \hat{\psi}_{br}) \end{cases} \quad (22)$$

By replacing (22) in (19), the estimated value of $\hat{\omega}_r$ is given by the following adaptation law:

$$\hat{\omega}_r = K_p (\varepsilon_\beta \hat{\psi}_{ar} - \varepsilon_\alpha \hat{\psi}_{br}) + K_i \int_0^t (\varepsilon_\beta \hat{\psi}_{ar} - \varepsilon_\alpha \hat{\psi}_{br}) dt \quad (23)$$

The Self-Tuning Fuzzy Logic speed Controller of indirect field oriented induction motor equipped with MRAS estimator proposed in this paper is shown in figure 6. The input of the Self-Tuning Fuzzy Logic Controller is the speed error and its change. Then, the electromagnetic torque reference is generated at the output of the Self-Tuning Fuzzy Logic Controller.

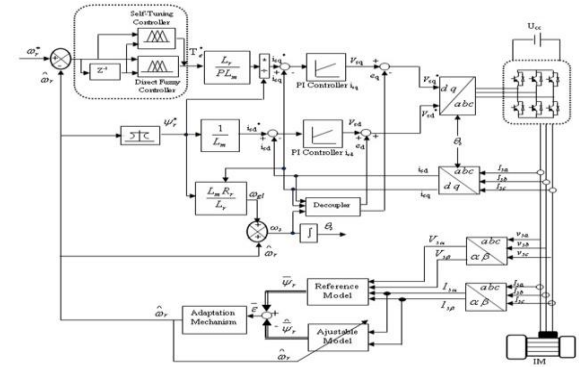


Figure 6: Block diagram of the proposed sensorless vector controlled induction motor drive.

SIMULATION RESULTS AND DISCUSSION

In order to evaluate and validate the effectiveness of our proposed control design presented in the previous sections, a simulation program has been developed by using Matlab/Simulink, the self-tuning fuzzy speed control of indirect field oriented induction motor equipped with MRAS estimator shows in figure 6. The system parameters of the induction motor tested in this study are given in the appendix.

Figure 7 shows the simulation results for the performance of the proposed system under ± 8 N.m Load Torque disturbance using the MRAS estimator based on rotor flux, his disturbance can be seen at $t = 1$ s and $t = 2$ s. The estimated speed tracks the real speed with no steady-state error, the torque and stator phase current are very good dynamic. Quadratic rotor flux ψ_{qr} are stabilises to almost zero, ψ_{dr} are stabilises to its rated value. The obtained results are successful, and they validate the proposed scheme. Figures

8 and 9 show the good performance of the sensorless vector Control, when the IM is operated at different reference speeds. It shows

that the estimated speed tracks the actual speed reasonably.

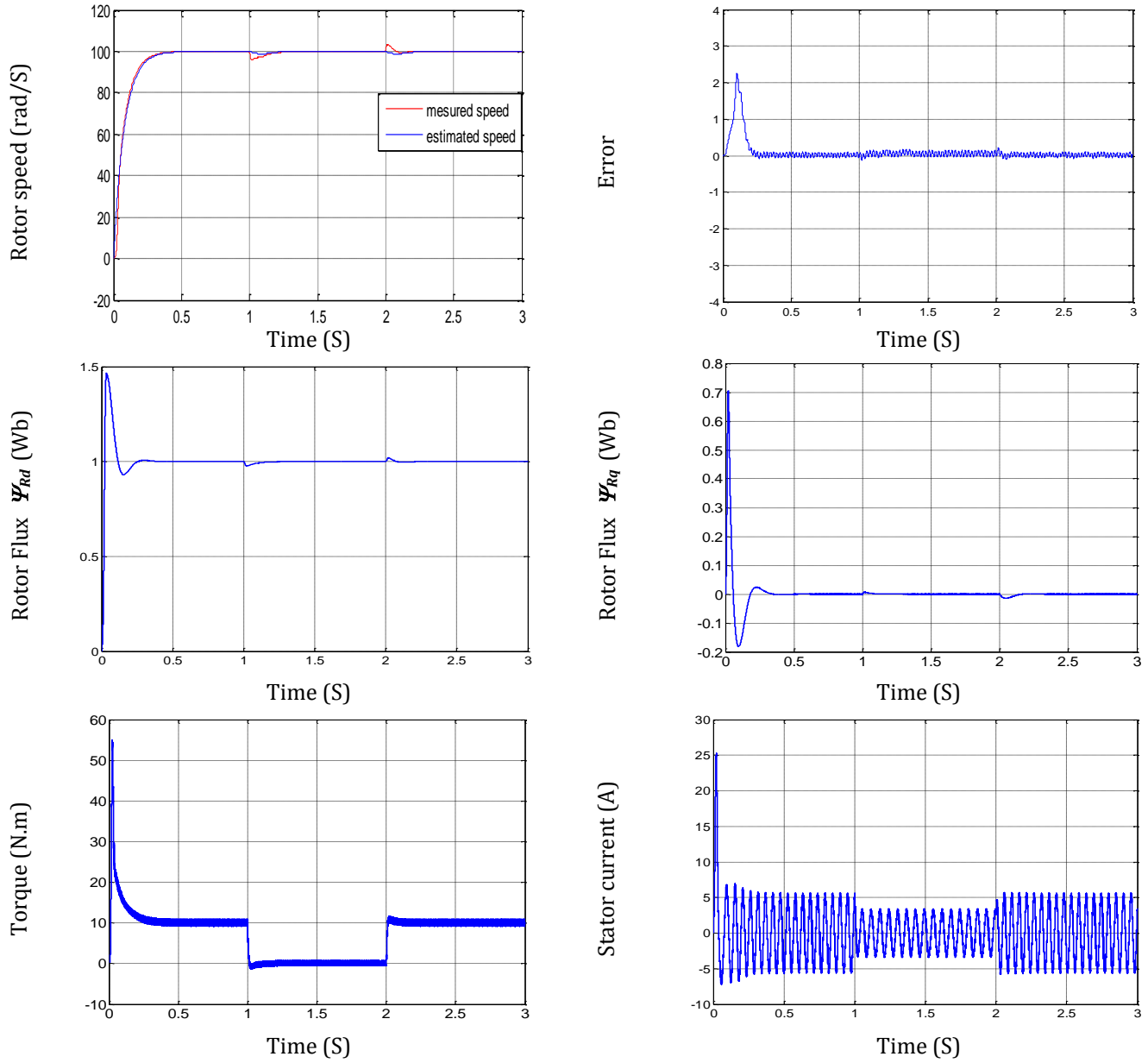
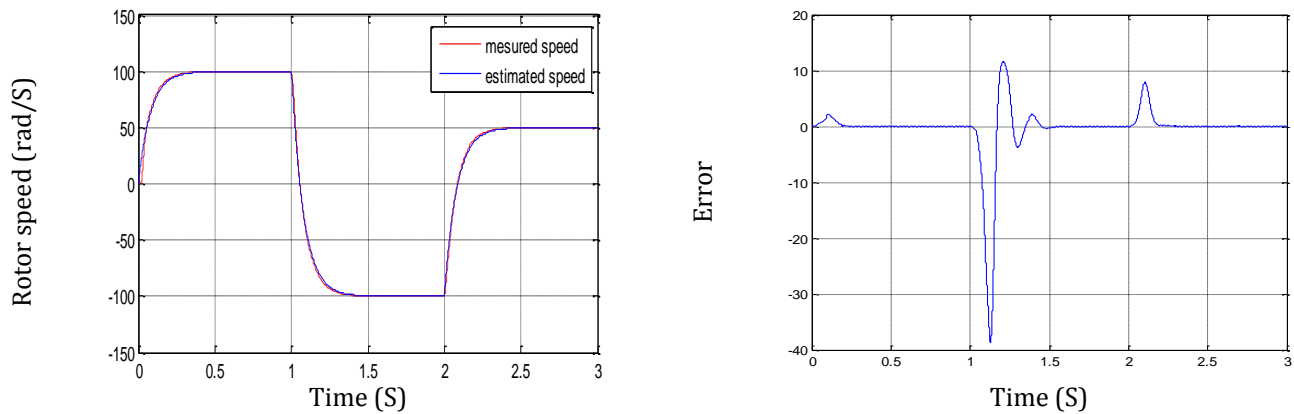


Figure 7: Performance of the proposed system under ± 8 N.m Load Torque disturbance.



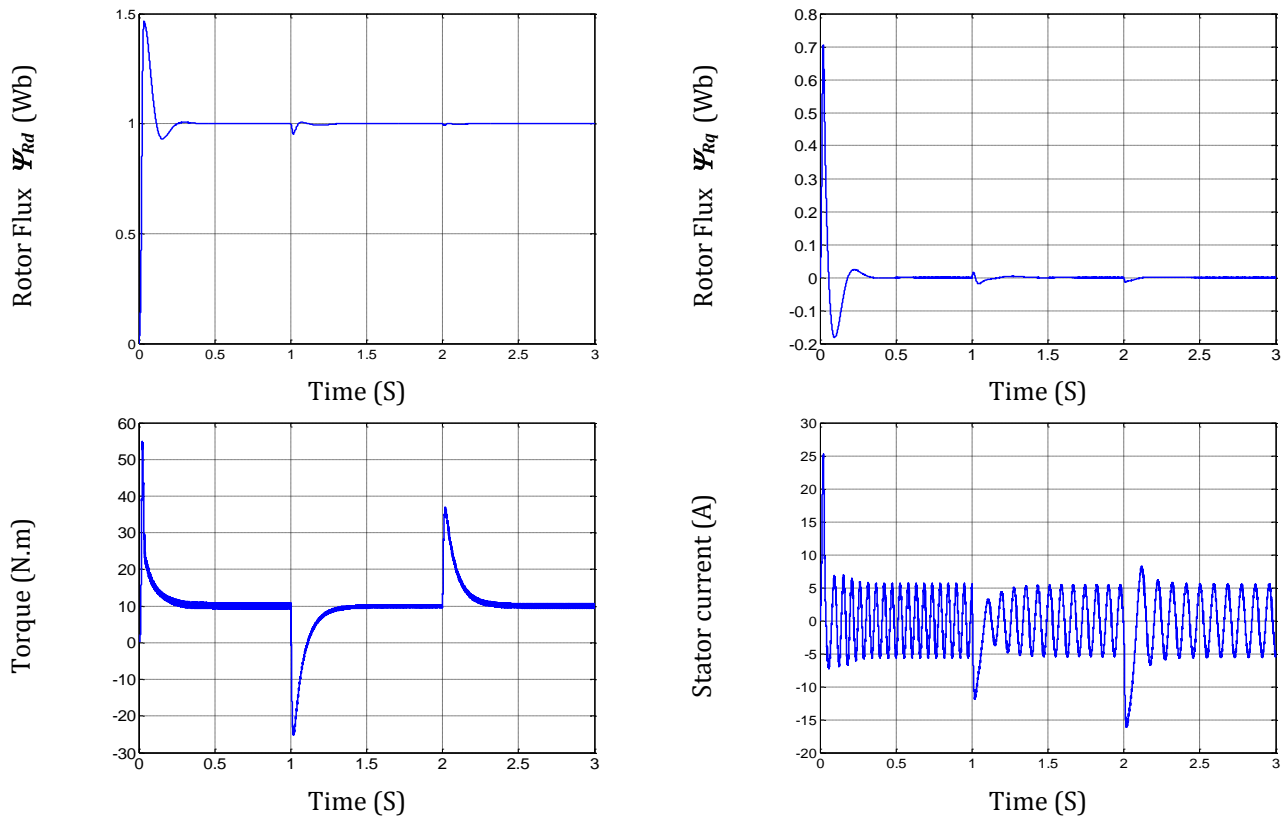


Figure 8: Performance of the proposed sensorless vector controlled induction motor drive using a Self-Tuning fuzzy Logic speed controller.

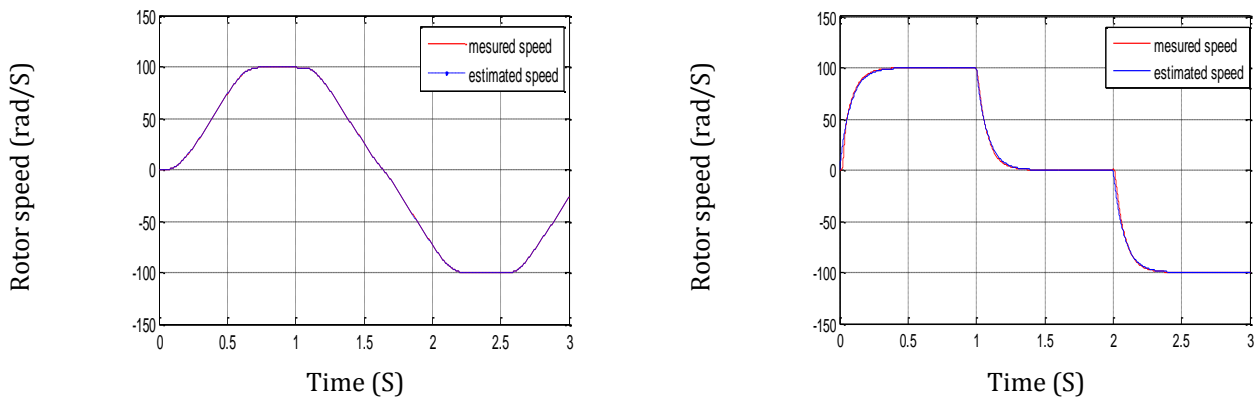


Figure 9: Speed Tracking Performance.

CONCLUSION

This paper has proposed a self-tuning fuzzy logic controller for sensorless vector-controlled induction motor drive, the rotor speed is estimated using MRAS method. The proposed controller is simple in structure but robust. The simulation results show that the proposed approach realises a good dynamic. The motor reaches the reference speed rapidly, trapezoidal commands under no load are tracked with zero steady state error, a good rejection of load disturbance.

APPENDIX

Induction Motor Parameters

50 Hz, 1.5 Kw, 1420 rpm, 380 V, 3.7A	
Rotor resistance	$R_r = 3.805 \Omega$
Stator resistance	$R_s = 4.85 \Omega$
Rotor inductance	$L_r = 274 \text{ mH}$
Stator inductance	$L_s = 274 \text{ mH}$
Moment of inertia	$J = 0.031 \text{ kg.m}^2$
Friction coefficient:	$F=0.00114\text{kg.m}^2/\text{s}$

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