Fuzzy Logic Enhanced Speed Controller Of Sensorless Field Orientation Control Induction Motor Drive

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Abstract:

The goal of this paper is control and estimation speed of indirect field orientation control induction motor. The system is nonlinear and one therefore cannot directly use any linear system tools for estimation. However, the standard discrete Kalman filter (KF) has been used for state estimation. As such, the nonlinear model has been discredited and extended to be suitably applied for such filter. The entire state estimated system has been modeled using MATLAB/SIMULINK blocks. The state estimation algorithm and motor discretized model are coded inside special S- function of m-file type. Also, the error covariance matrices of measurement and process will be developed from the system model. PI controller is replaced by fuzzy logic controller. The common conclusion drawn from such study is that fuzzy logic controller has shown a superior performance.
Keywords: indirect field orientation indication motor, Kalman filtering, extended Kalman filtering

مسيطر سرعة ضبابي لمسوق المحرك الحثي ذو سيطرة توجيه المجال غير المباشر و خالي من متحسس السرعة

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الخلاصة :

الهدف من هذا البحث هو غاية السيطرة على سرعة المحركات الحثية ذو سيطرة المجال غير المباشرة. المنظومة هذه غير خطية ولذلك لايمكن استخدام المنظومات الخطية مباشرة للوصول للغاية المنشودة . ولذلك يستخدم مرشح كالمن (KF) النموذجي لتحقيق هذه الغاية .ولهذه الحالة تم تفصيل وتمديد النموذج اللاخطي ليكون ملائما لمثل هذا النوع من المرشحات .الحالة العامة للغاية المنشودة تم تمثيلها باستخدام مخططات (MATLAB/SIMULINK).

خوارزمية الحالة العامة وتفاصيل نموذج المحرك تم تحويلها لتناسب اعمل في تطبيق خاص   (S-function) في (m-file)، وكذلك متغيرات مصفوفة الخطأ في القياسات و الإجراءات والتي سوف تستنتج من نموذج المنظومة . تم أستخدام السيطرة المنطقية الضبابية() بدل المسيطر التناسبي التكاملي، حيث أثبتت النتائج من الدراسة أن أستخدام المسيطر الضبابي تتفوق على السيطرة بأستخدام المسيطر التناسبي التكاملي

1. Introduction

A fuzzy logic (FL) control system essentially embeds the experience and intuition of a human plant operator and sometimes those of a designer and/ or researcher of the plant. FL, on the other hand does not strictly need any mathematical model of the plant. It is based on plant operator experience and heuristics, and is very easy to apply. Fuzzy control is basically an adaptive and nonlinear controller , which gives robust performance for linear and nonlinear plant with parameter variation [2 ,12]

In controlling AC motor drives, speed transducers such as tacho-generator, resolvers, or digital encoders are used to obtain speed information. Using these speed sensors has some disadvantages [1]

- They are usually expensive
- The speed sensor and the corresponding wires will take up space.
- In defective and aggressive environments, the speed sensor might be the weakest part of the system .

Especially the last item degrades the systems reliability and reduces the advantage of an induction speed sensorless vector control method [1].

On the hand , avoiding sensor means use of additional algorithms and added computational complexity that requires high- speed processors for real time applications . as digital signal processors have become cheaper, and their performance greater , it has become possible to use them for controlling electrical drives as a cost effective solution.

Estimation of unmeasurable state variables is commonly called observation. A device (or a computer program) that estimates or observes the states is called a state – observer. An observer can be classified according to the type of representation used for the plant to be observed [3]

If the plant is deterministic, then the observer is a deterministic observer; otherwise it is a stochastic observer. The most commonly used observer is Luenberger and Kalman types.

The Luenberger observer (LO) is of the deterministic type, and the Kalman Filter (KF) is of the stochastic type. *The basic Kalman filter is only applicable to linear* Stochastic systems, and for non-linear systems the extended Kalman filter (EKF) can be used, which can provide estimates of the states of a system or of both the states and parameters [1].

The EKF is a recursive filter (based on the knowledge of statistics of both the state and noise created by measurement and system modeling), which can be applied to non-linear time varying stochastic systems EKF being insensitive to parameter changes and used for stochastic systems where measurement and modeling noises are taken into account.[1]

2. model of induction motor

The state space model for induction motor developed in stationary reference frame, is given below [4]

$\dot{x} = \mathbf{Ax} + \mathbf{Bu}$ **(1)**

$\mathbf{Y} = \mathbf{Cx}$ **(2)**

$$
p\begin{bmatrix} i_{ds}^s \\ i_{qs}^s \\ \lambda_{dr}^{`s} \\ \lambda_{qr}^{`s} \\ \omega_r \end{bmatrix} = \begin{bmatrix} -\dfrac{K_R}{k_L} & 0 & \dfrac{L_m \acute{r}_r}{L_r^{'2}K_L} & \dfrac{L_m\omega_r}{L_r^{'}K_L} & 0 \\ 0 & -\dfrac{k_R}{K_L} & \dfrac{L_m\omega_r}{L_r^{'}K_L} & \dfrac{L_m \acute{r}_r}{L_r^{'2}K_L} & 0 \\ \dfrac{L_m}{T_r} & 0 & -\dfrac{1}{T_r} & -\omega_r & 0 \\ 0 & \dfrac{L_m}{T_r} & \omega_r & -\dfrac{1}{T_r} & 0 \\ -K_{Te}\lambda_{qr}^{rs} & K_{Te}\lambda_{qr}^{rs} & 0 & 0 & 0 \end{bmatrix}
$$

Where **P = p/2** denoted the number of motor pole pairs.

$$
P = \begin{bmatrix} i_{ds}^s \\ i_{qs}^s \\ \lambda_{dr}^{`s} \\ \lambda_{qr}^{`s} \\ \omega_r \end{bmatrix} + \begin{bmatrix} \dfrac{1}{K_L} & 0 & 0 \\ 0 & \dfrac{1}{K_L} & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & -K_{TL} \end{bmatrix} \begin{bmatrix} V_{ds}^s \\ V_{qs}^s \\ T_L \end{bmatrix} \qquad \textbf{(3)}
$$

$$
\begin{bmatrix} i_{ds}^s \\ i_{qs}^s \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{i}_{ds}^s \\ \mathbf{i}_{qs}^s \\ \lambda_{dr}^{'s} \\ \lambda_{qr}^{'s} \\ \omega_r \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} V_{ds} \\ V_{qs} \\ T_L \end{bmatrix} \qquad \textbf{(4)}
$$

Where $\begin{bmatrix} i_{ds}^s \\ i_{qs}^s \end{bmatrix}$ d-axis & q-axis of stator current (A)

$$k_L = (\acute{L}_r L_s - L_m^2)/\acute{L}_r \qquad\qquad K_R = r_s + \acute{r}_r\left(\dfrac{L_m}{\acute{L}_r}\right)^2 , \quad K_{Te}=$$

$(3P^2L_m)/(2jL_r)$ and $K_{TL} = P/J$ .The parameters $\acute{L}_r$, L_s and L_m are rotor , stator and main inductance respectively **P** number of pole pairs . $T_r = \acute{L}_r/\acute{r}_r$ is the rotor time constant: **J** is the inertia constant of the motor: $\mathbf{T_L}$ is the external load: $\boldsymbol{\omega_r}$ is the rotor electrical speed in angular frequency.

The motor equation (2) is to be discredited for the digital implementation as: [5]

$$\mathbf{X_{k+1} = A_k x_k + B_k u_k} \qquad \textbf{(5)}$$

$$\mathbf{Y_k = C_k\,x_k} \qquad\qquad \textbf{(6)}$$

$\mathbf{A_k}$ and $\mathbf{B_k}$ are the discretized system and input matrices, respectively . They are

$$\mathbf{A_k = e^{AT} = I + AT + \dfrac{(AT)^2}{2!} + \dots\dots\dots \approx I + AT} \qquad \textbf{(7)}$$

$$\mathbf{B_k = \int_0^T e^{A\xi}Bd\xi = [\,e^{AT} - I]\,A^{-1}B = BT + \dfrac{ABT^2}{2!} + \dots}$$

$$\mathbf{\approx BT} \qquad\qquad \textbf{(8)}$$

$$\mathbf{C_k = C} \qquad\qquad \textbf{(9)}$$

Where T is the sampling time and **I** is an identity matrix.

Where $X_5 = W_y$

$$A_k = \begin{bmatrix} a_{11} & 0 & a_{13} & a_{14}x_5 & 0 \\ 0 & a_{11} & -a_{14}x_5 & a_{13} & 0 \\ a_{33} & 0 & a_{33} & a_{34}x_5 & 0 \\ 0 & a_{31} & -a_{34}x_3 & a_{33} & 0 \\ -a_{15}x_4 & a_{15}x_3 & 0 & 0 & 1 \end{bmatrix} \quad (10)$$

$$B_d = \begin{bmatrix} b_{11} & 0 & 0 \\ 0 & b_{11} & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & b_{53} \end{bmatrix} \quad (11)$$

$$C_d = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \quad (12)$$

Where $\quad a_{11} = (1-T\frac{K_R}{K_L})$

$a_{13} = T\frac{L_m r'_r}{L'^2_r K_L}$, $\quad a_{14} = T\frac{L_m}{L'_r K_L}$

$a_{31} = T\frac{L_m}{T_r}$, $\quad a_{33} = 1-\frac{T}{T_r}$

$a_{34} = -T$, $\quad a_{15} = TK_{Te}$

$b_{11} = \frac{T}{K_L}$, $\quad b_{53} = -TK_{TL}$

3. Elements of Fuzzy Controller

A fuzzy controller basically comprises four basic principal components, i.e., a fuzzification inference, knowledge base, fuzzy inference engine and a defuzzification interface [6 , 9]. **Figure (1)** shows a block diagram of a fuzzy controller, which includes these Basic operations.
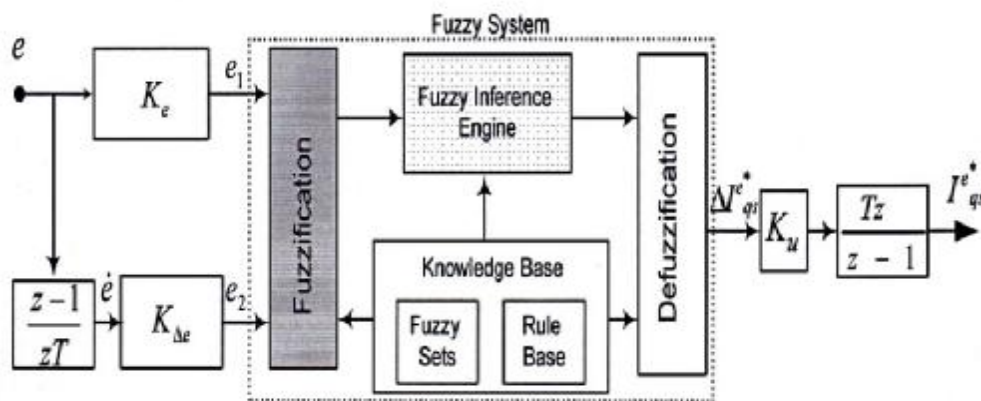

Fig.(1) fuzzy controller block diagram.

In **Figure (1**), a **PI** fuzzy controller is shown. The input of the controller is usually the error *e* and change of error *e·* The crisp output of the fuzzy controller is usually the control input (CI) I^{e*}_{qs} to. the IFOC induction motor. The gains *K* 's at the input are used for normalizing the corresponding universe of discourses, while those at the outputs will be used for tuning purposes. However by changing the gains K_e $K_{\Delta e}$, and K_u, the range of universe of discourse can either be increased (stretched) or decreased (compressed) [6, 9].

1) Fuzzification

The quantized input data are converted into suitable linguistic variables, which may be viewed as labels of fuzzy sets.

2) RuleBase:-

The general form of the linguistic rules is:- **If premise Then consequent.**
The premises (which are sometimes called antecedents) are associated with the fuzzy controller inputs. The consequents (sometimes called action) are associated with the fuzzy controller outputs. Each premise (or consequent) can be composed of the conjunction of several terms. Also the number of fuzzy' controller inputs and outputs places an upper limit on the number of elements in the premises and consequent.

3) Inference Engine:-

The inference or fuzzy processing is the heart of the FLC, it is the Specified process that transforms fuzzy inputs into a fuzzy output by dealing with fuzzy rules, as a result of which the response' corresponding to the inputs is produced. Mainly there are two different kinds of fuzzy rules according to the expression of the consequent [4,6]

- **Mamdani-type:** fuzzy rules consider a linguistic variable in the consequent:
  With (X_x,.,., X_n) and *(Y)* being the input and output linguistic variables, respectively, and (A_1,..., A_n) and *(B)* being linguistic variabels, each one of which having associated fuzzy set defining its meaning.

- **Takagi – sugino – King- type** :fuzzy rules are based on representing the consequent as a polynomial function inputs:
  If **x_1** is **A_1**, …….. **x_n** then:
  $Y = p_1 x_1 + ……… p_n x_n + p_o$
  With (x_1……….. x_n) and y being the input and output linguistic, respectively, and **p_0, p_1, p_2……….p_n** being real – value weight.

4) Defuzzification

Basically, defuzzification is a mapping from of a space of fuzzy control actions defined over an output universe of discourse into a space of nonfuzzy (crisp) control actions. The defuzzification strategy is aimed at producing a nonfuzzy control action that best represents the possibility distribution of an inferred fuzzy control action. Many strategies can be   used   for performing   the   defuzzification. Different   defuzzification   method   have   been Developed and applied :

Center of gravity/area-COG.

Center of sums.

Center of largest area.

First of maxima.

Middle of maxima and Height method.

The **COG** is the best well-known defuzzification method. It produces smoothly varying recommended actions, so it is favorable to use in control applications. This distinctive property encourages us to use COG defuzzification. The general expression for COG can be given by

$$\Delta\mathbf{I^{e}*}_{qs} = \frac{\sum_{i=1}^{R} Center \ \mu_u^i}{\sum_{i=1}^{R} \ \mu_u^i} \qquad (13)$$

Where R is the number of the active rules that apply for the given fuzzy inputs, $Center^1$ is the center of the ith output MF and μ_u^1 corresponds to the ith output MF. The result of the this process is the change of q-componente of stator current Δi_{qs}^e of fuzzy controller for IFOC IM.

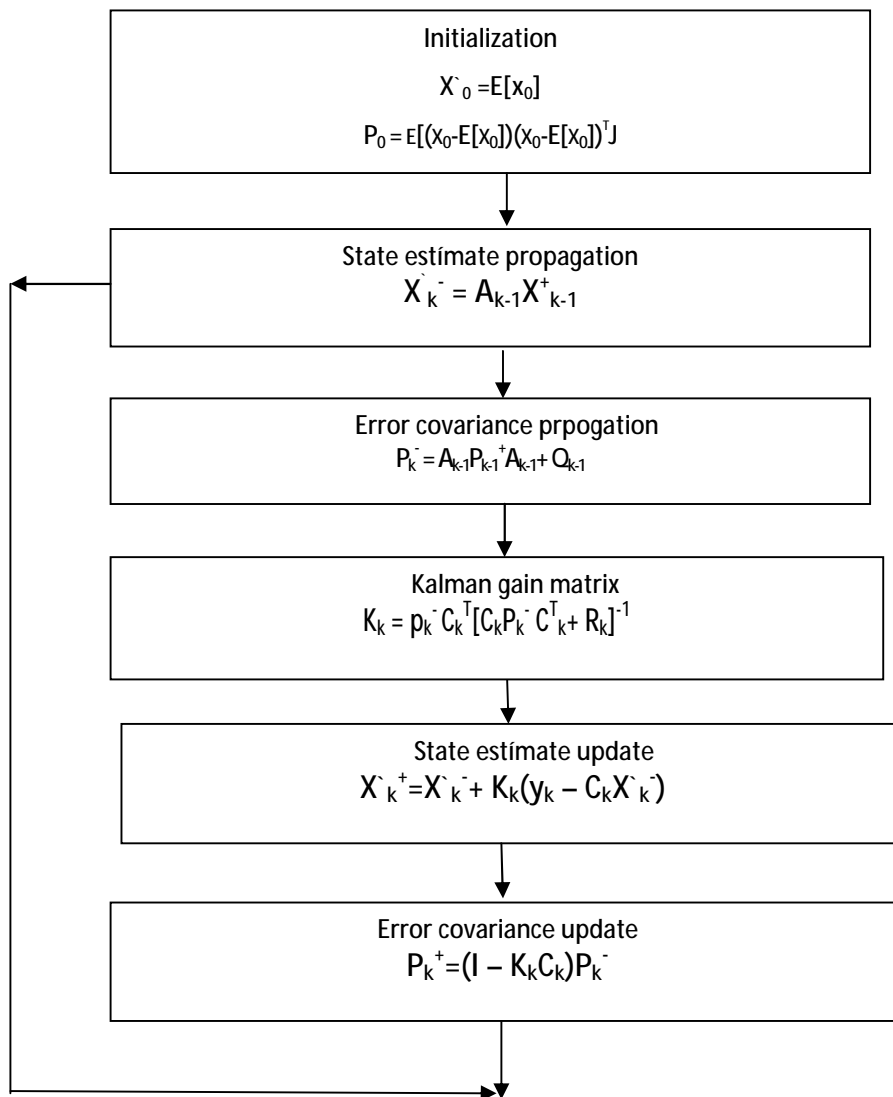## 4. The Kalman filter theory and algorithm

The aim in all estimation problems is to have an estimator that gives an accurate estímate of the true state even though one cannot directly measure it. Two obvious requirements, should be attained: [10.11]

- First, the average value of our state estímate is to be equal to the average value of the true state. That is, the estímate has not to be biased one way or another. Mathematically, one would say that the expected value of the estímate should be equal to the expected valué of the state.

- Second, the requirement a state estimate that varies from the true state as little as possible. That is, not only do we want the average of the state estimate to be equal to the average of the true state, but also want an estimator that results in the smallest possible variation of the state estímate. Mathematically, an estimator with the smallest possible error variance is sought

It so happens that the Kalman filter is the estimator that satisfies these two criteria. But the Kalman filter solution does not apply unless certain assumptions about the noise that affects the system under study must be satisfied:

1. It is firstly to assume that the average valué of both w_k and v_k are zero.
2. One has to further assume that no correlation exists between w_k and v_k. That is, at any time k, w_k and v_k are independent random variables.

One may summarize the recursive state estimation of the discrete Kalman filter as shown, in **Figure.(2)**. In the figure, the superscripts "-1", *"T"* "+" and "-" indícate matrix inversión, matrix transposition, posteriori and priori of variable respectively[13]. The K matrix is called the Kalman gain and the P matrix is called the estimation error covariance. The flowchart includes the initialization of state $\mathbf{x_0}$ in the absence of any observed data at *k=0,* and the initial valué of the a posteriori covariance matrix $\boldsymbol{P_0}$.

Fig. (2) Recursive algorithm of Discrete Kalman filter

The timing diagram of the various quantities involved in the discrete optimal filter equations is shown in **Figure.(3).** The figure shows that after we process the measurement at time *(k-1)*, we have an estimate of x_{k+i} (denoted x_{kA}) and the covariance[7, 8] of that estímate (denoted P_{k-1}^+). When time *k* arrives, before we process the measurement at time *k* we compute an estímate of x_k (denoted x_k) and the covariance of that estímate (denoted P_k^-). Then the measurement is processed at time *k* to refine our estímate of x_k. The resulting estimate of x_k is denoted x_k and its covariance is denoted P_k^+ .[9]
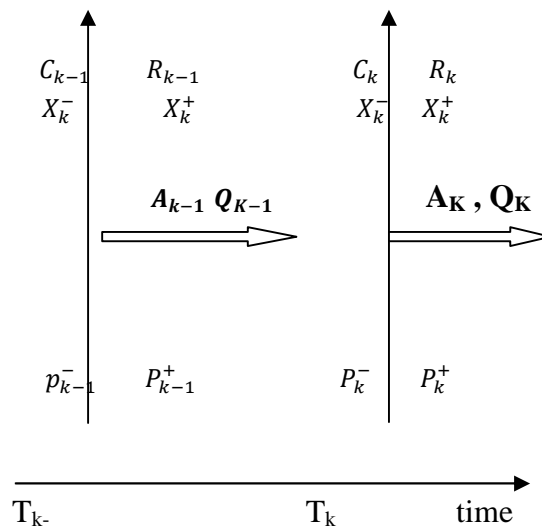
Fig. (3) Timeline showing a priori and a posteriori state estimates and estimation- error covariance

By substituting error covariance update equation into propagation equation, and the state estímate propagation equation into update equation, the algorithm of **Figure.(2)** will be summarized as

$$\mathbf{K_k} = \mathbf{P_k}\ C_K^T\ [\ \mathbf{C_k P_k}\ C_K^T\ {}_+\mathbf{R_k}\ ]^{\ -1} \qquad (14)$$

$$X_k = A_{k-1}\ X_k\ +\mathbf{K_k}(\mathbf{y_k} -\ C_k\ X_k) \qquad (15)$$

$$\mathbf{P_k} = \mathbf{A_{k-1}}\ (\ (1-\mathbf{K_k C_k})\mathbf{P_k})\mathbf{A_{k-1}} +\mathbf{Q_{k-1}} \qquad (16)$$

5. Extendevcd Kalman Filter (EKF)

To estimate the rotor speed, it nonlinear model is formed with the states consisting of the parameter to be estimated and the original states. Equation (2) is the free-noise discretized versión of IM model. The new model is formed after corruption with state and. Measurement noises to give [14 , 15]

$$X_{k+1} = f\ (x,u,k) + w_k$$
$$y_k = C_d \quad X_k + v_k \qquad (17)$$

Where

$$X_k = [\ (\ i_{ds}^s \quad i_{qs}^s \quad \lambda_{dr}^s \quad \lambda_{qr}^s \ \textbf{G}\Im\textbf{r}\ ]_k^{+}$$

is the combined state and parameter matrix, $f(x,U,k)$ is the nonlinear state function, which is given by

$$f(x,u,k) = A_k x_k + B_d u_k = \begin{bmatrix} a_{11}x_1 + a_{13}x_3 + a_{14}x_4x_5 + b_{11}u_1 \\ a_{11}x_2 - a_{14}x_5x_3 + a_{13}x_4 + b_{11}u_2 \\ a_{31}x_1 + a_{33}x_3 + a_{34}x_4x_5 \\ a_{31}x_2 - a_{34}x_3x_5 + a_{33}x_4 \\ -a_{15}x_4x_1 + a_{15}x_2x_3 + x_5 + b_{53}T_L \end{bmatrix}_K = \begin{bmatrix} f_1 \\ f_2 \\ f_3 \\ f_4 \\ f_5 \end{bmatrix} (18)$$

To use nonlinear model of **IM** with standard **KF**, the model must be linearized about current operating point, giving a linear perturba model represented by Jacobian m **F(x , u , k)**

$$F\ (x,u,k) = \frac{\partial f(x,u,k)}{\partial x}\ ]_{x\ (k)\ +\ u(k)} \quad = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \frac{\partial f_1}{\partial x_3} & \frac{\partial f_1}{\partial x_4} & \frac{\partial f_1}{\partial x_5} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \frac{\partial f_2}{\partial x_3} & \frac{\partial f_2}{\partial x_4} & \frac{\partial f_2}{\partial x_5} \\ \frac{\partial f_3}{\partial x_1} & \frac{\partial f_3}{\partial x_2} & \frac{\partial f_3}{\partial x_3} & \frac{\partial f_3}{\partial x_4} & \frac{\partial f_3}{\partial x_5} \\ \frac{\partial f_4}{\partial x_1} & \frac{\partial f_4}{\partial x_2} & \frac{\partial f_4}{\partial x_3} & \frac{\partial f_4}{\partial x_4} & \frac{\partial f_4}{\partial x_5} \\ \frac{\partial f_5}{\partial x_1} & \frac{\partial f_5}{\partial x_2} & \frac{\partial f_5}{\partial x_3} & \frac{\partial f_5}{\partial x_4} & \frac{\partial f_5}{\partial x_5} \end{bmatrix}$$

$$= \begin{bmatrix} a_{11} & 0 & a_{13} & a_{14}x_5 & a_{14}x_4 \\ 0 & a_{11} & -a_{14}x_5 & a_{13} & -a_{14}x_3 \\ a_{31} & 0 & a_{33} & a_{34}x_5 & a_{34}x_4 \\ 0 & a_{31} & -a_{34}x_5 & a_{33} & -a_{34}x_3 \\ -a_{15}x_4 & a_{15}x_3 & a_{15}x_2 & -a_{15}x_1 & 1 \end{bmatrix}_K$$

6. Simulated Results

SIMULINK is an extension to MATLAB and allows graphical block diagram modeling and simulation of dynamic systems. It is easier to develop state estimator using this package, as many componentes of the system are already included in the SIMULINK block diagram library. [16]

The discretized model of the motor and the state estimation algorithm has been entered into a S-function-type of m-file. An m-file is a MATLAB program that allows algorithms or equations to be entered in a programming language. An S-function block, from the SIMULINK nonlinear library, links this m-file into a graphical block for use within the overall state estimation system.

The liguistic rule shown in **Table (1)** are used in the **F.L.** controller, the number (3) corresponds to positive large and (2) indicates positive médiums etc.

Table (1) FL controller rule base

Rule base		E_{e2}^i						
	U^m	-3	-2	-1	0	1	2	3
	-3	3	3	3	2	2	2	1
	-2	3	3	2	2	2	0	-3
	-1	3	2	2	2	1	-1	-3
E_{e1}^i	0	3	2	1	0	-1	-2	-3
	1	3	1	-1	-2	-2	-2	-3
	2	3	0	-2	-2	-2	-3	-3
	3	-1	-2	-2	-2	-3	-3	-3

1. **The step responses Performance of fuzzy**:-

The step responses for **PI** and **FL** controllers are tuned to reach 120 rad/s in about 0.68 sec. With no overshoot. For both Controllers, these settings are kept constant for the following tests as a basis for comparison as show in **Figure (4) And Figure (5).**
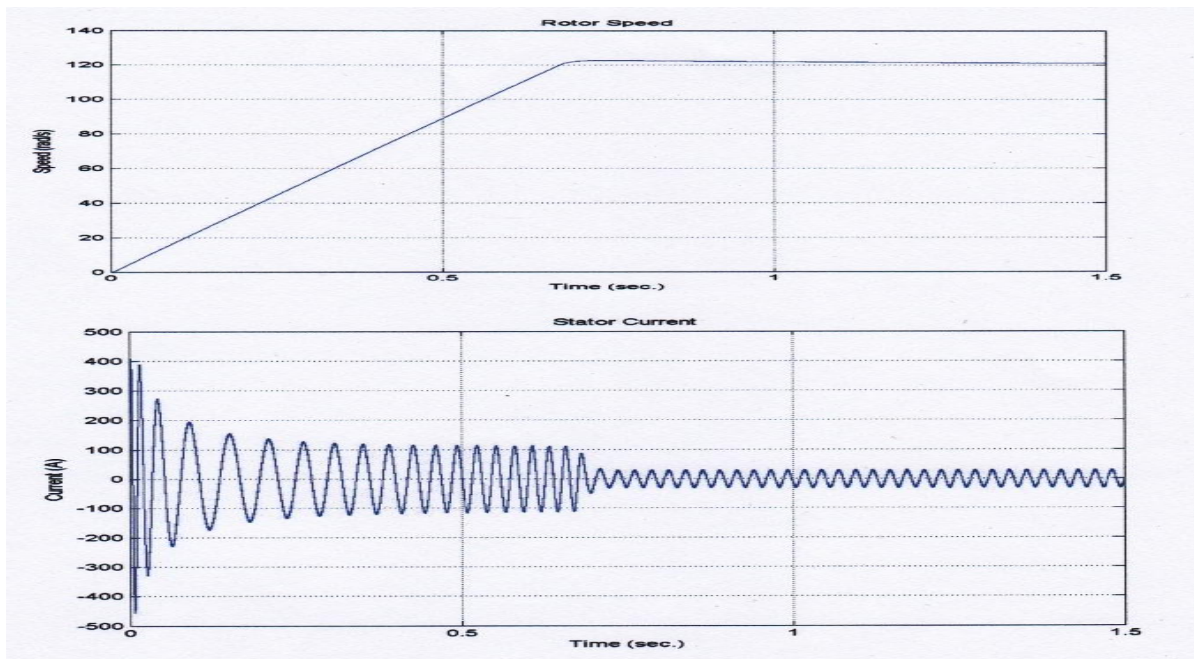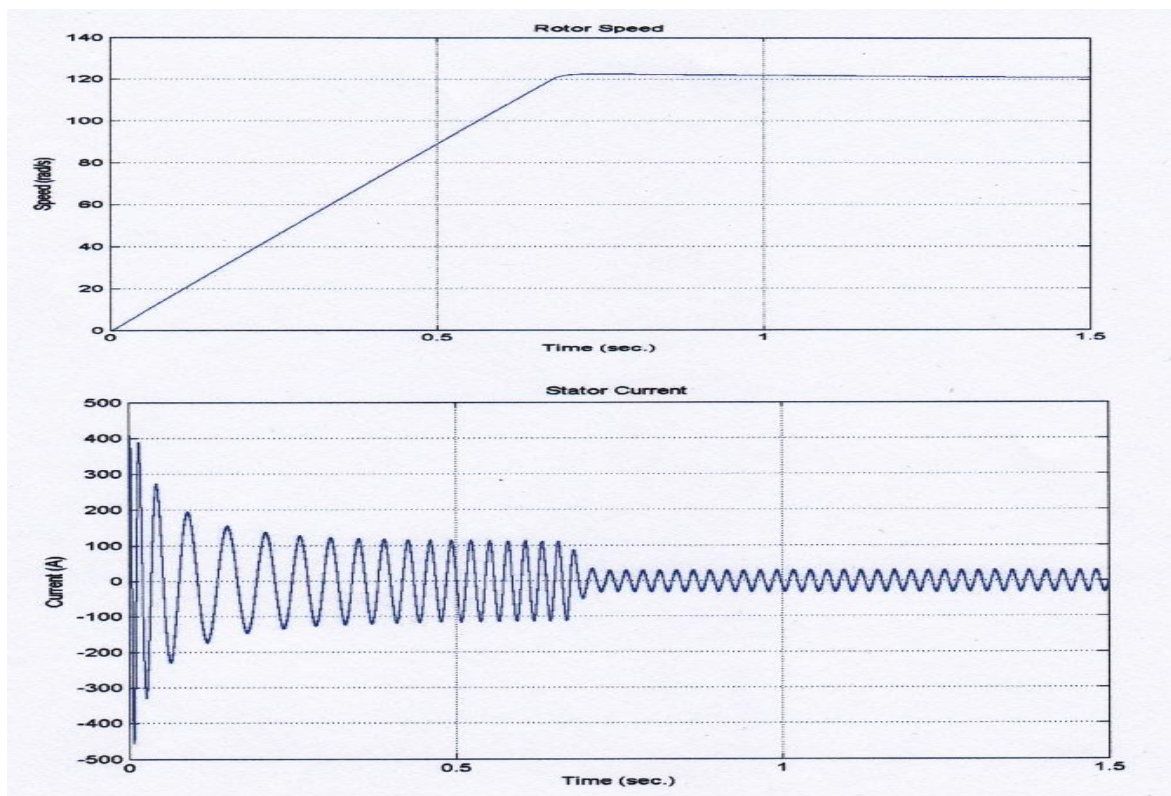
Fig. (4)step speed response of PI

Fig .(5) step speed response of the FL-based induction motor drive

2. Speed Tracking Performance of fuzzy

Figures (6) and (7) show the speed tracking performance, under no load condition, of both FL and PI controllers; as the PI and FC gains are being freezed with their settings in the previous step response. The slope of the trapezoidal command speed is $(\omega_{bm}/2)$ (rad/s). Initially, both controllers have difficulty in following the command because of the current limit and the time needed to build up the flux once the flux is established.

As seen from **Figure (6),** the PI controller fails to track the ramp with zero steady-error over the tracking cycle; as a small valué of steady state valué of error remains along the tracking response. To improve the speed tracking performance, the gains of the PI controller have to be retuned, such as increasing the integration gain K_i. However, overshoot and oscillation are usually associated with the increase of K_i. Therefore, there is a serious conflict in the speed performance. **Figure (7)** shows that after a short period of starting time (about 0.2 sec), the FL controller shows very good speed tracking performance, indicated by the almost perfect overlap of the command speed with the actual speed. A gain, the speed performance in the transient period can be improved by a good initial setting of FL input
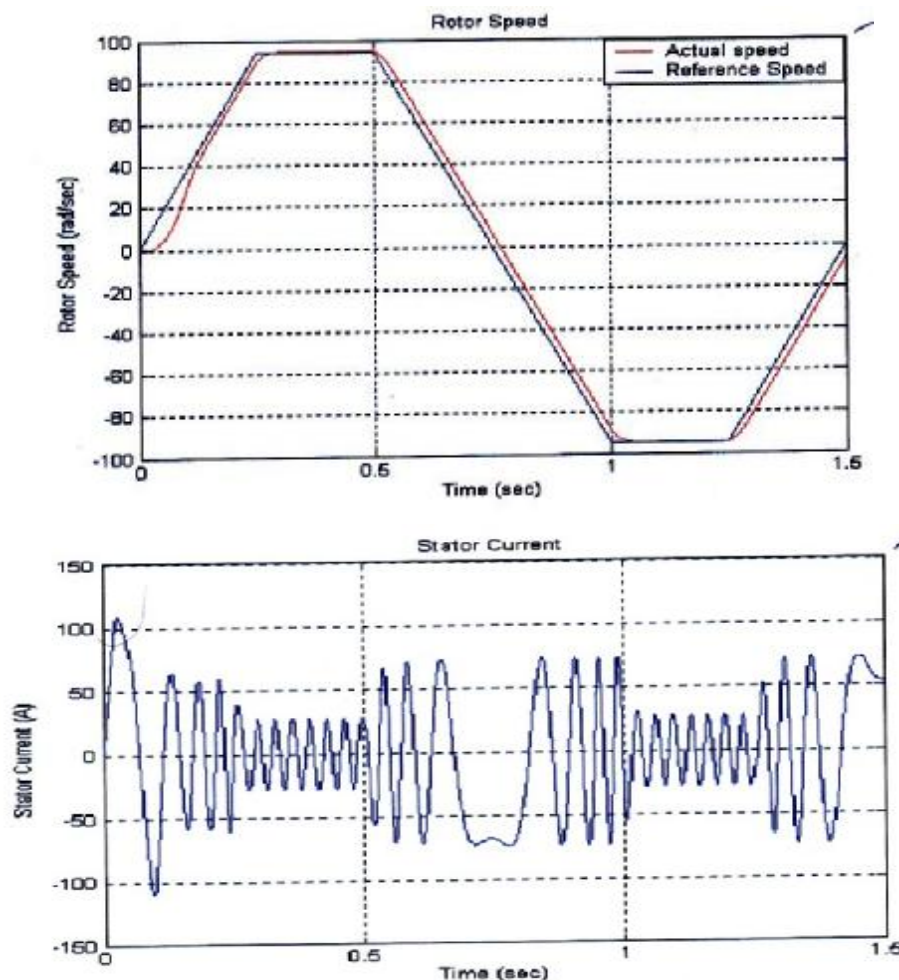

Fig. (6) speed tracking performance of the PI – based induction motor
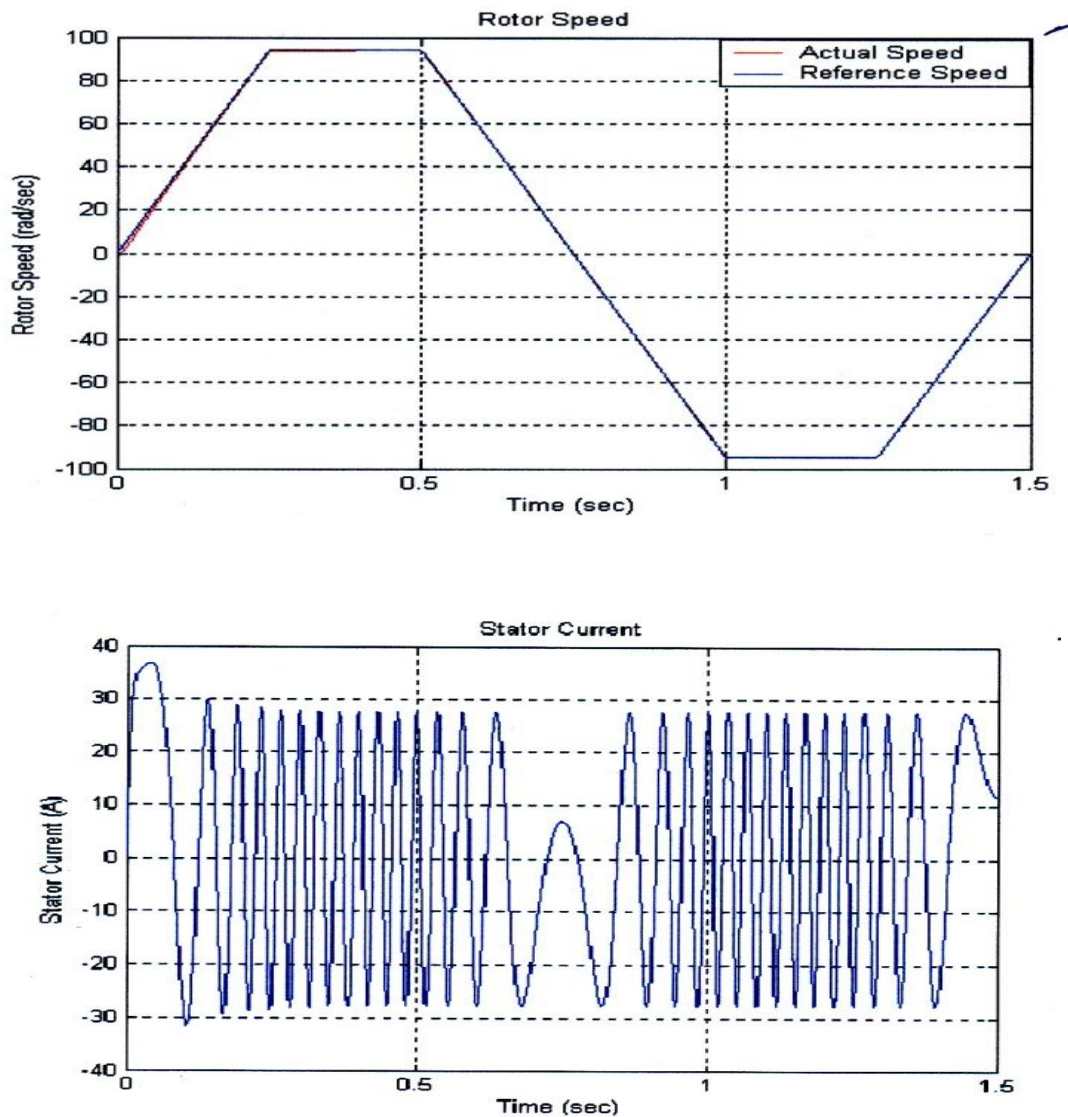
Fig .(7) speed tracking performance of the FL – based induction motor drive

3. Detuning Effects

The rotor's resistance is doubled while the motor is unloaded. Consequently, the flux and torque current commands are no longer decoupled. As expected, the field orientation-detuning problem causes the greatest degradation in performance.

The speed response performance with PI controller much degrades when the rotor resistance increased to two times the rated value (0.228).It is evident frorn **Figure(8)** that the response is oscillatory. This is because the decoupling is lost the system becomes coupled. On the other hand, FC has the potentials to compénsate the parameter variation, as shown in **Figure. (9).**
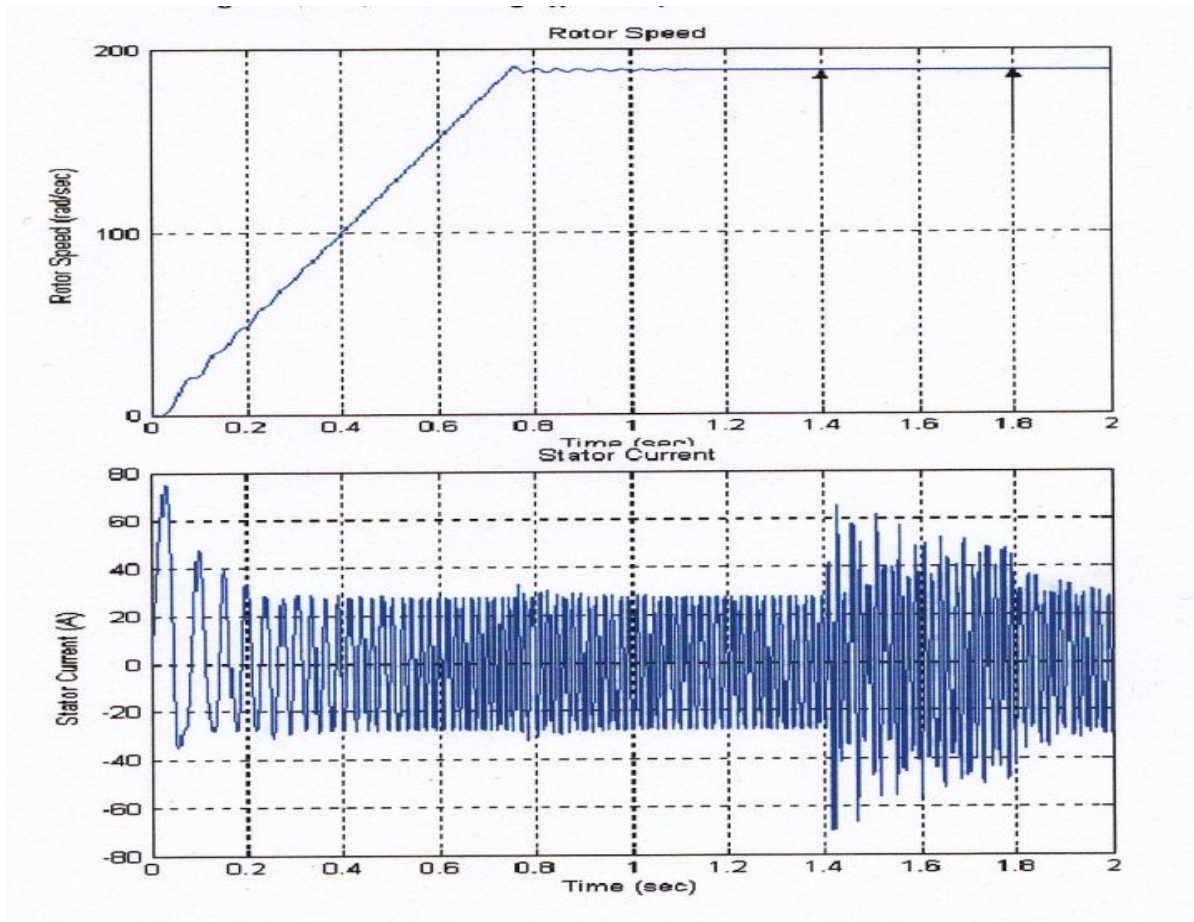
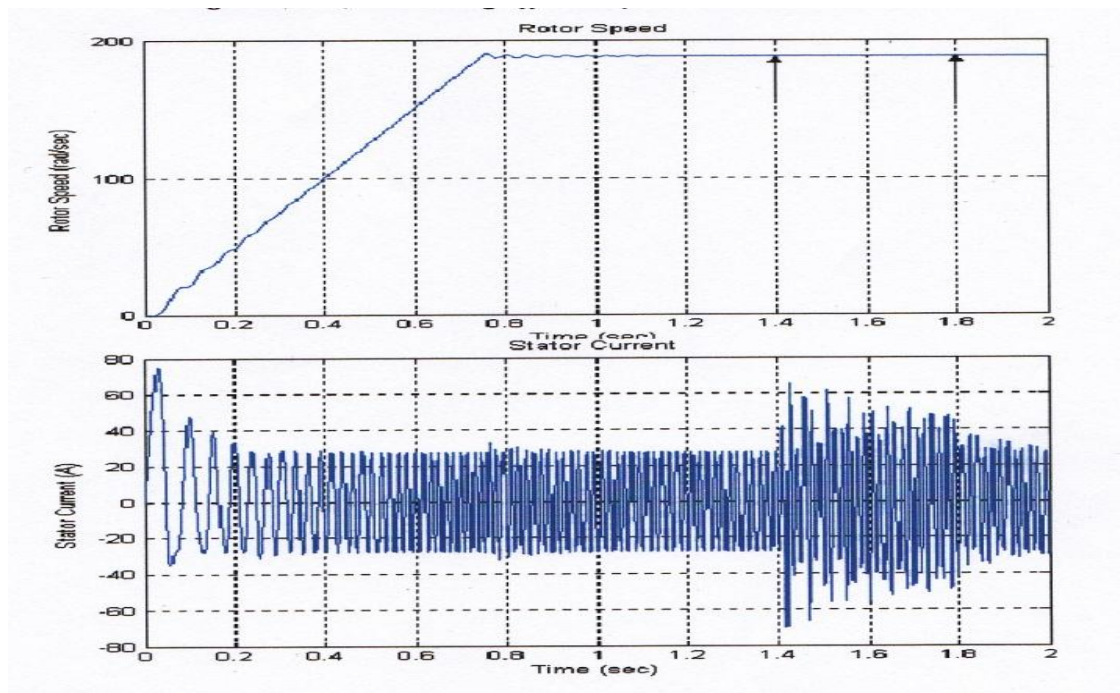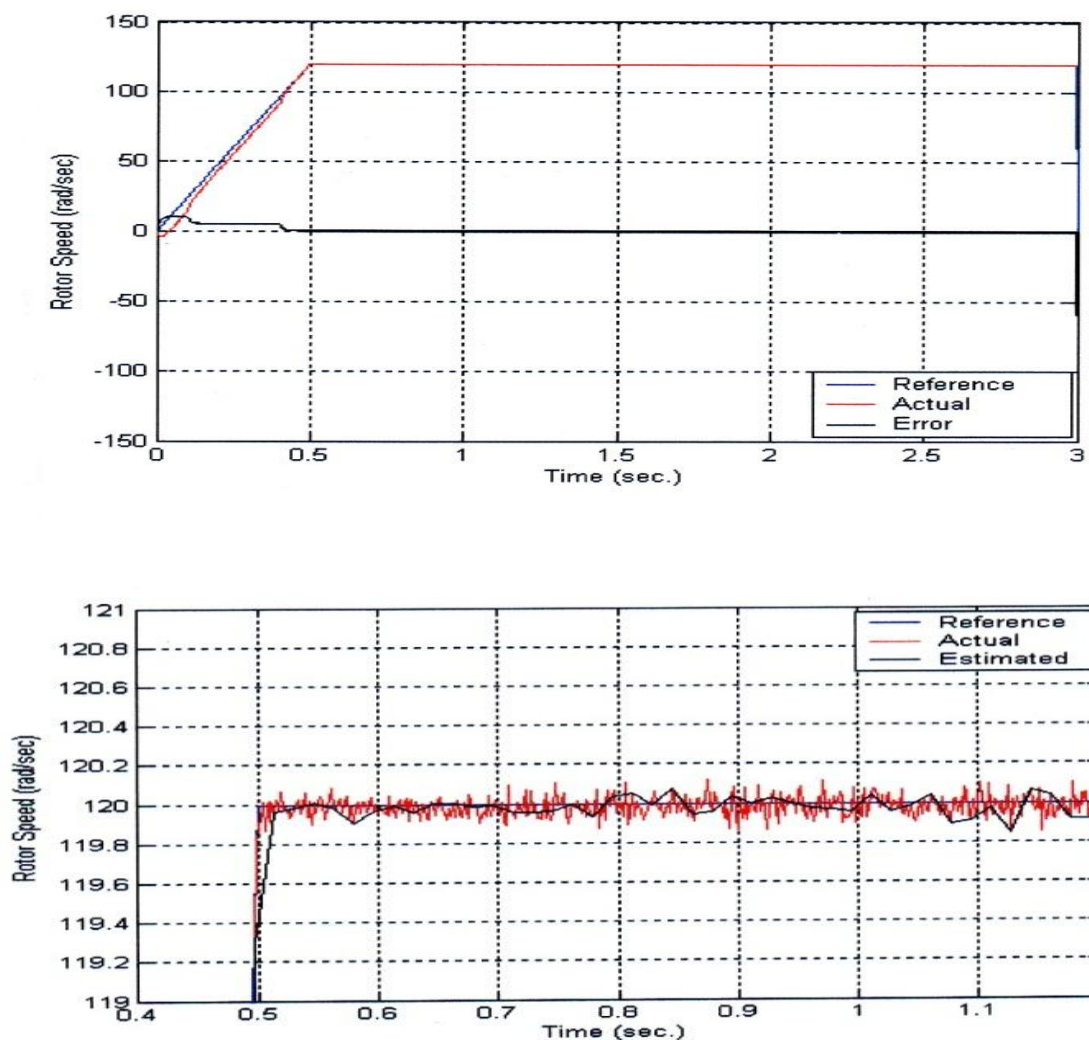**Fig .(8) Detuning effect of PI induction motor**


Fig .(9) Detuning effect of FL induction motor

4. The step Speed Responses of fuzzy and EKF:-

In the case of **Figure (10)** simulation, state covariance is decreased; the algorithm begins to behave such that the state space model gives more accurate estimates compared to measure valúes so it assigns less importance to the measurements. This causes a decrease in Kalman gain, which reduces the correction speed of the currents. In the extra time used for current correction the algorithm finds opportunity to decrease the steady-state error. This is clear in **Figure (10),** where the speed errors are plotted on the same graph of reference and actual speed. One can see that the speed error finally reaches zero at appropriate setting of covariance matrices. The filter showed high performance in terms of noise rejection and the improvement of motor opearation.

Fig .(10) (a) (b)
(step speed response of the FL-based induction motor drive)
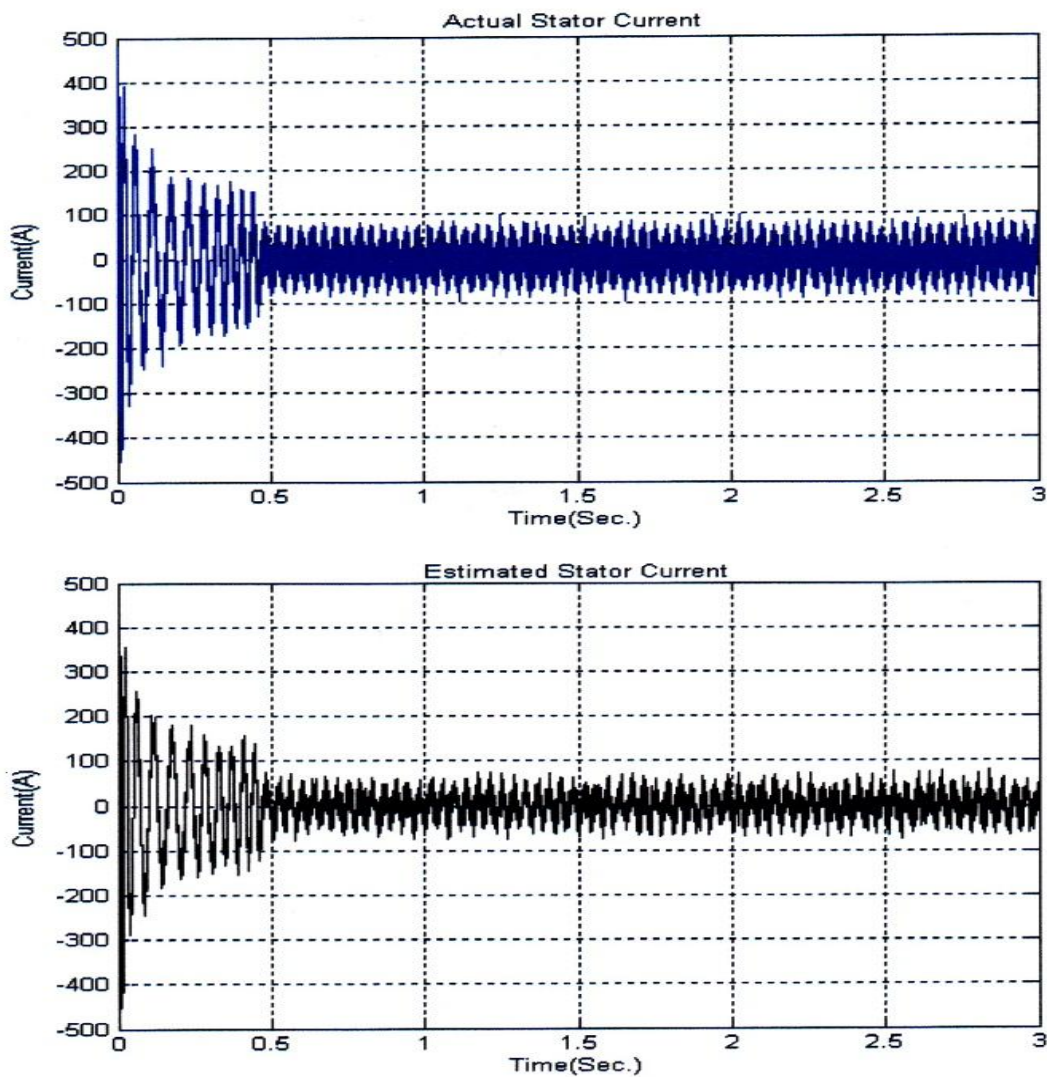
Fig .(10) (c) (d)
step speed response of the FL-based induction motor drive

5. Speed Tracking Performance of fuzzy and EKF

In **Figure (11),** speed reversal at no-load is given with reference speed. The speed sequence is given as follows:

Time_ref= [0, 0.5, 1, 1.5, 2, 2.5, 3];

 Speed_ref= [0 120 120 O -120 -120 O];

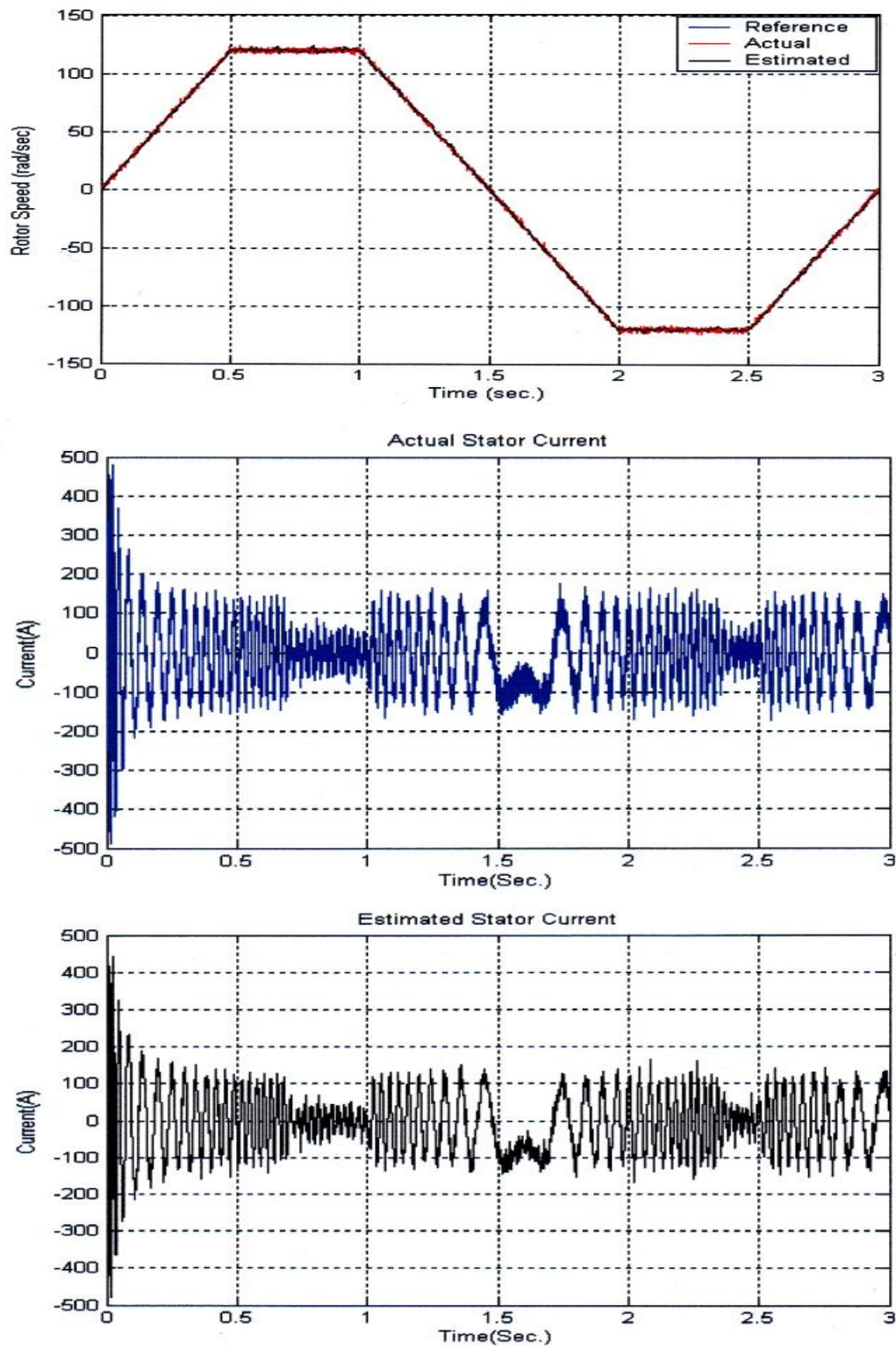 The actual speed, estimated speed and the reference speed are plotted together.

Fig .(11) speed tracking performance of the FL – based induction motor drive

Conclusion:

1- In step response situation, both FL and PI controller share the same designing procedure; as the response time constant can be controlled by retuning of their constructing gains. Since The IM system, as previously mentioned, is of nonlinear nature, and there is no systematic procedure to design these controllers for the required response. Therefore, in some settings of its gains, PI controller might be superior to FL counterpart.

2- FL controller shows an excelente tracking performance as compared to PI controller. As it is clear from the related figures, there is a perfect overlap between the actual and reference speed. Yet, tracking performance of PI controller can be improved by retuning of its gains (proportional and integral gains), but excessive increase might lead to instability problems.

3- The EKF showed high performance in terms of noise rejection and the improvement of motor operation.

4- The EKF shows high tracking performance for both high and low speed estimations and close to reference speed.

References

1- B. Akin, "State Estimations Techniques for Speed Sensorless Field Oriented Control of Induction Machine", Master's thesis, The Middle East technical university, 2003.

2- K. M. Passino And S. Yurkovich, "Fuzzy Control", Dep. Elect. Eng., The Ohio State University, 1998.

3- B. K. Bose, "Modern Power Electronics and AC Drive," University of Tennessee, Knoxville, Prentice Hall, 2002.

4- C -Mun Ong, "Dynamic Simulation of Electric Machinery Using Matlab/Simulink", Purdue University, Prentice Hall PTR, 1998

5- G. F. Franklin etal, "Digital Control of Dynamic Systems," Addison-Wegly Longman,Inc., 1998.

6- B. Heber, L. Xu and Y. Tang, "Fuzzy Logic Enhanced Speed Control of an Indirect Field Oriented Induction Machine Drive" IEEE Trans. Power Electronics, Vol. 12, No. 5, pp. 772-778, 1997

7- L. Reznik, "Fuzzy Controllers" Victoria University of Technology, Australia, 1997.

8- **F.F. Cheng and S.N. Yeh, "Application of Fuzzy Logic in the Speed Control of AC Servo Systems and an Intelligent Inverter" IEEE Trans. Energy Conversión, Vol 8, No. 2, pp. 312-318, June 1993.**

9- **Y. Tang And L. Xu, "Fuzzy Logic Application for Intelligent Control of a Variable Speed Drive" IEEE Transactions on Energy Conversión, Vol.9, No.4, December 1994.**

10- **A. Gelb etal, "Applied Optimal Estimations," Cambridge, Mass, 1974.**

11- **R. G. Brown, "Introduction to Random Signal Analysis and Kalman Filter," Johon Wiley and Sons, Inc., 1983.**

12- **D. Simon, "Kalman Filtering and Neural Networks," Johon Wiley and Sons, Inc., 2001.**

13- **G. Wejch and Gary Bishop, "An Introduction to the Kalman Filter," ACM, Inc., 2001.**

14- **D. Simón , "Kalman Filtering,"72 Embedded Systems Programming, JUNE 2001.**

15- **D. Simón, "Using Nonlinear Kalman Filtering to Estímate Signáis," 2003.**

16- **"Short Tutorial on Matlab," Tomas Co., 2004**

Appendix

The parameters three-phase induction motor are listed in Table

Rated power	*37.4 Kw*
Rated voltage	*460 V*
Base frequency (f)	*50 Hz*
Base Torque(Tb)	*197.88 Nm*
Number of poles (P)	*4*
Stater leakage inductence (L_{ls})	*0.8mH*
Rotor leakage inductance (L_{lr})	*0.8mH*
Magnetizing inductance (L_m)	*34.7m H*
Rotor resistance (r_r)	*0.228 ohm*
Stator resistance (r_s)	*0.087 ohm*
Rated speed (n)	*1725 rpm*