# Sensorless Speed field-oriented Control of Induction Motor Tacking Core Loss into Account

Aissa KHELDOUN, Djalal Eddine KHODJA, Larbi REFOUFI
Signals & Systems Laboratory, Institute of Electrical and Electronic Engineering,
University of Boumerdes
Avenue of Independence 35000, Boumerdès, Algeria
Tel/fax: +213 24 81 83 33, Email: aissakheldoun@gmail.com

*Abstract* – In field-oriented controlled induction motor drives, the instantaneous rotor speed is measured using whether sensors or estimators. Since the basic Kalman filter is a state observer, its use in vector controlled schemes has received much attention. However, these schemes are based on the assumption that the existence of iron loss in the induction motor may be neglected. The paper shows the effect of iron loss on the extended Kalman filter performance that is designed on the basis of the classical *dq* model. Original simulation results are carried out to demonstrate this effect as well as the effectiveness of the suggested approach to minimise the speed estimation error without modifying the EKF's algorithm.

*Key words* – Field-oriented control, Speed estimation, Extended Kalman filter, core loss

## 1. Introduction

The problem of speed estimation in induction motor drives has received over the last two decades a great attention. Indeed, elimination of speed sensor results in more robust, lower and more noise immunity drives. For these features, many sensorless schemes have been extensively studied and can be broadly classified as: Open loop estimators; Magnetic – saliency based methods ; Model Reference Adaptive Schemes; Observers based approaches and Extended kalman filters.

Many examples of open speed estimators are given in Guanghui W. [1]. They are based on the measure of current or voltage or both of them which are very sensitive to parameter variations. Many schemes using saliency have been elaborated to estimate the rotor velocity and that are divided into two large groups. The first group is based on the geometrical effect and the second on the saturation effect. As an example of geometrical methods, the reader can refers to Peter Vas's book [2]. In another hand, methods using saliency based on saturation effects can be found in Janson's *et al.* [3]

Model Reference Adaptive Scheme (MRAS) is proposed in [4] where one of the flux estimator acts as a reference model and the other acts as the adaptive estimator. The estimation is based on the comparison between the output of the two estimators and the output errors are used to drive a suitable adaptation mechanism that generates the estimated speed. Adaptive observers based approaches [5] can have preferred performances using the derived adaptive laws with relatively simple computation time. However their robustness to parameter uncertainties and noises is never guaranteed [6]. Extended Kalman filters have been proposed in [7, 8, 9]. They can be used both under steady state and transient conditions of the induction motor. However, its computational burden is relatively heavy, for this raison if the core loss must be considered, the computational time will be very large since the number of differential equations will increase, and consequently, its implementation will be very complicated.

In this paper, the effect of the core loss is shown through simulation framework for indirect control scheme. It will be shown also that even when the modified indirect filed oriented controller, introduced by Levi *et al.* [10] is used to enhance the decoupling performances, the estimation speed error still not eliminated. A mechanism to reduce this estimation error is suggested without modifying the EKF's algorithm or at least retune the covariance matrices.

## 2. Speed estimation using EKF

In order to estimate the rotor speed of the induction motor, the state vector must be extended to include $\Omega_r$, thus $x^T\left[x_1\, x_2\, x_3\, x_4\, x_5\right]=\left[i_{\alpha s}\, i_{\beta s}\, \varphi_{\alpha r}\, \varphi_{\beta r}\, \Omega_r\right]$. This results in a non-linear state space model and therefore the Kalman filter is said to be an Extended Kalman Filter (EKF).

The continuous model of the induction motor is given by the following:

$$\begin{aligned} \dot{x} &= f(x,u,t)+w(t) \\ y &= h(x)+v(t) \end{aligned} \quad (1)$$

where:

$$f(x)=\begin{bmatrix} -\gamma.x_1+\frac{K_l}{T_r}.x_3+p.K_l.x_4.x_5+\frac{1}{\sigma l_s}.u_{\alpha s} \\ -\gamma.x_2+\frac{K_l}{T_r}.x_4-p.K_l.x_3.x_5+\frac{1}{\sigma l_s}.u_{\beta s} \\ \frac{l_m}{T_r}.x_1-\frac{1}{T_r}.x_3-p.x_4.x_5 \\ \frac{l_m}{T_r}.x_2-\frac{1}{T_r}.x_4+p.x_3.x_5 \\ 0 \end{bmatrix},$$

with

$$\gamma=\frac{R_s}{\sigma l_s}+\frac{l_m^{\ 2}.R_r}{\sigma l_s l_r^{\ 2}},\ K_l=\frac{l_m}{\sigma l_s l_r},\ T_r=\frac{l_r}{R_r},\ \sigma=1-\frac{l_m^{\ 2}}{l_s l_r},$$

and

$$h(x)=\left[i_{\alpha s}\ i_{\beta s}\right]^T$$

It can be noticed from (1) that the time-varying function *f(x, u, t)* depends on the added state variable $\Omega_r$. Discreet space model is required for implementation of EKF algorithm.

If we suppose that the speed velocity $\Omega_r$ is driven by a noise with the same characteristics as mentioned previously, the estimation process by EKF of $\Omega_r$ is given after linearization of (1) in two steps too:

a) Prediction

$$\hat{x}(k)=f_d(x(k),u(k))$$
$$P(k)=\left.\frac{\partial f_d}{\partial x}\right|_{x=\hat{x}}.P(k).\left.\frac{\partial f_d}{\partial x}\right|_{x=\hat{x}}^T+Q \tag{2}$$

b) Correction

$$K(k+1)=P(k).\left.\frac{\partial h_d}{\partial x}\right|_{x=\hat{x}}^T.\left[\left.\frac{\partial h_d}{\partial x}\right|_{x=\hat{x}}P(k).\left.\frac{\partial h_d}{\partial x}\right|_{x=\hat{x}}^T+R\right]^{-1}$$
$$\hat{x}(k+1)=\hat{x}(k)+K(k+1).\left[Y_m-\left.\frac{\partial h_d}{\partial x}\right|_{x=\hat{x}}.\hat{x}(k)\right] \tag{3}$$
$$P(k+1)=P(k)-K(k+1).\left.\frac{\partial h_d}{\partial x}\right|_{x=\hat{x}}.P(k)$$

Where $\left.\frac{\partial f_d}{\partial x}\right|_{x=\hat{x}}$ is the Jacobean matrix (4) and $\left.\frac{\partial h_d}{\partial x}\right|_{x=\hat{x}}$ is the measurement one (5).

This algorithm has been simulated with an indirect vector controlled-squirrel cage induction motor whose parameters are given in table.1.

The motor is fed by a current controlled PWM inverter, therefore an external noise signal, required by the EKF, is needless since the output voltage and current contain high frequency harmonics.

$$\left.\frac{\partial f_d}{\partial x}\right|_{x=\hat{x}}=\begin{bmatrix} 1-T_e.\gamma & 0 & T_e.\frac{K_l}{T_r} & p.T_e.K_l.x_5 & p.T_e.K_l x_4 \\ 0 & 1-T_e.\gamma & -p.T_e.K_l.x_5 & T_e.\frac{K_l}{T_r} & -pT_eK_l.x_3 \\ T_e.\frac{l_m}{T_r} & 0 & 1-T_e.\frac{1}{T_r} & -p.T_e.x_5 & -p.T_e.x_4 \\ 0 & T_e.\frac{l_m}{T_r} & p.T_e.x_5 & 1-T_e.\frac{1}{T_r} & p.T_e.x_3 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{4}$$

$$\left.\frac{\partial h_d(x(k+1))}{\partial x}\right|_{x=\hat{x}}=\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \tag{5}$$

**Table 1 induction motor parameters**

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| $R_s$ | 4.85 Ω | $P_n$ | 1.5 |
| $R_r$ | 3.805 Ω | 2xp | 2x2 |
| $R_{fe}$ | 500 Ω | $V_n$ | 220/380 V |
| $L_m$ | 0.258 H | $I_n$ | 3.64/6.31 A |
| $L_s$ | 0.274 H | $N_n$ | 1420 RPM |
| $L_r$ | 0.274 H | F | 50 Hz |
| J | 0.031 Kg.m$^2$ | $T_L$ | 10 N.m |
| B | 0.008 Nm.s/rd | | |

Covariance matrices are adequately adjusted so that better speed estimation is obtained.

$P_0 = [p1\ \ p1\ \ p2\ \ p2\ \ p3]$, where $p1= 10^{-3}$, $p2=10^{-2}$, $p3=28$;

$Q = [q1\ \ q1\ \ q2\ \ q2\ \ q3]$, where $q1= 10^{-4}$, $q2=10^{-3}$, $q3=10^{-1}$;

$R = [r\ \ \ r]$, where $r = 1$.

The desired speed given to PI speed controller is in Fig.1(a). The output that's reference torque will determine the torque producing current component $i_{qs}^*$ whereas the flux reference is maintained at its rated value and generates the direct current component $i_{ds}^*$. The decoupling is guaranteed by maintaining the slip frequency to that generated by the indirect filed oriented controller.

Figure1(b) shows the real motor speed and its estimated response. The rotor speed starts from halt to reach 140 rad/s with ramp change. After 1 second, the motor changes smoothly the direction to get -140 rad/s. It can be noticed from results shown in Fig.1(b) and (c) that the extended Kalman filter is able to perfectly reproduce the real speed; therefore it can be considered as powerful tool for sensorless speed drives.

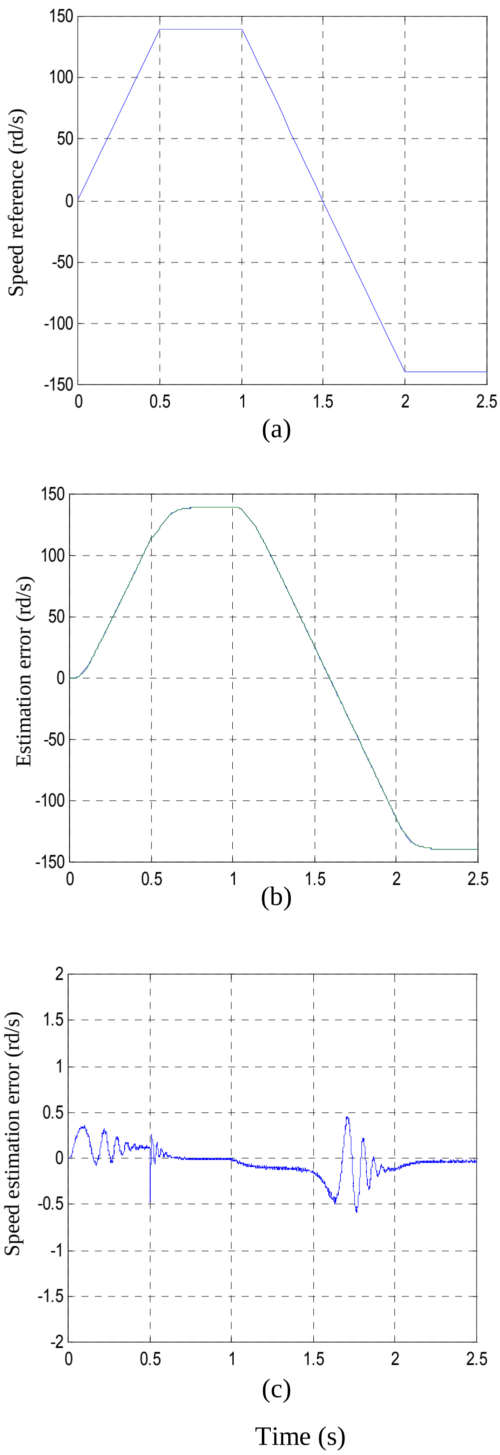



Fig. 1 Rotor speed estimation by EKF

## 3. Core loss effect on speed estimation

### 3.1 Modelling of induction motor with core loss

The core loss consists of eddy current loss $P_{core}{}^{e}$ and hysteresis loss $P_{core}{}^{h}$, and they are given by $P_{core}{}^{e} = k_e.w^2.\varphi_m{}^2$ and $P_{core}{}^{h} = k_h.w.\varphi_m{}^2$, where $k_e$, $k_h$ denote the coefficient of eddy current loss and hysteresis loss respectively [11, 12]. Both are proportional to the square of the magnetizing flux level $\varphi_m$. Note that in an induction motor, the angular frequency of the stator and rotor currents are different, *i.e.* the angular frequency of stator is $w_e$ and that of rotor is $w_{sl}= w- w_r$. From that we can conclude that core loss in rotor part can be ignored. Thus the total core loss can be approximated as follows:

$$\begin{aligned} P_{core} &= (k_e w^2 + k_h w\ ).\varphi_m^2 \\ &\approx \frac{w^2.\varphi_m^2}{1/k_e} \\ &= \frac{w^2.\varphi_m^2}{R_{fe}} \end{aligned} \tag{6}$$

Where $\varphi_m$ is the air gap flux. Since $w\varphi_m$ represents the air gap voltage, $1/k_e$ has the dimension of resistance. Letting $R_{fe} =1/k_e$, we obtain the equivalent circuit of the induction motor with core loss [12], as shown in fig.2.

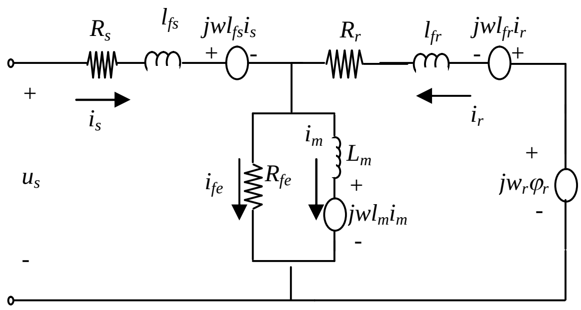



Fig. 2 Equivalent circuit of IM in rotating reference frame with core loss

It's easy now, to deduce from the equivalent circuit the new bi-phase model. We can notice that the behaviour of the induction motor, when the core loss is considered, may be described by seven differential equations:

$$\begin{aligned} u_{ds} &= R_s.i_{ds} + l_{fs}.\frac{di_{ds}}{dt} - w.l_{fs}.i_{qs} + R_{fe}.(i_{ds} + i_{dr} - i_{dm}) \\ u_{dq} &= R_s.i_{qs} + l_{fs}.\frac{di_{qs}}{dt} + w.l_{fs}.i_{ds} + R_{fe}.(i_{qs} + i_{qr} - i_{qm}) \\ 0 &= R_r.i_{dr} + l_{fr}.\frac{di_{dr}}{dt} - w.l_{fr}.i_{qr} + R_{fe}.(i_{ds} + i_{dr} - i_{dm}) + w_r\varphi_{qr} \\ 0 &= R_r.i_{qr} + l_{fr}.\frac{di_{qr}}{dt} + w.l_{fs}.i_{ds} + R_{fe}.(i_{qs} + i_{qr} - i_{qm}) - w_r\varphi_{dr} \\ \frac{d\varphi_{dm}}{dt} &= R_{fe}.(i_{ds} + i_{dr} - i_{dm}) + w.\varphi_{qm} \\ \frac{d\varphi_{qm}}{dt} &= R_{fe}.(i_{qs} + i_{qr} - i_{qm}) - w.\varphi_{dm} \end{aligned} \tag{7}$$

Where:

$$\begin{aligned} \varphi_{dr} &= l_{fr}i_{dr} + \varphi_{dm} = l_{fr}i_{dr} + L_m i_{dm} \\ \varphi_{qr} &= l_{fr}i_{qr} + \varphi_{qm} = l_{fr}i_{qr} + L_m i_{qm} \end{aligned} \tag{8}$$

Changing the state vector to $x^T = [i_{\alpha s}\ \ i_{\beta s}\ \ i_{\alpha r}\ \ i_{\beta r}\ \ i_{\alpha m}\ \ i_{\beta m}\ \ \Omega_r]^T$ and express the

ISBN: 978-960-474-262-2

equations in the stationary reference frame ($w$=0), equations (7) can be written as follows:

$$
\begin{aligned}
\frac{di_{\alpha s}}{dt} &= -\frac{R_s + R_{fe}}{l_{fs}} i_{\alpha s} - \frac{R_{fe}}{l_{fs}}.i_{\alpha r} + \frac{R_{fe}}{l_{fs}} i_{\alpha m} + \frac{1}{l_{fs}} u_{\alpha s} \\
\frac{di_{\beta s}}{dt} &= -\frac{R_s + R_{fe}}{l_{fs}} i_{\beta s} - \frac{R_{fe}}{l_{fs}}.i_{\beta r} + \frac{R_{fe}}{l_{fs}} i_{\beta m} + \frac{1}{l_{fs}} u_{\beta s} \\
\frac{di_{\alpha r}}{dt} &= -\frac{R_r + R_{fe}}{l_{fr}} i_{\alpha r} - \frac{R_{fe}}{l_{fr}}.i_{\alpha s} + \frac{R_{fe}}{l_{fr}} i_{\alpha m} - p.\Omega_r.i_{\beta r} - p.\Omega_r.i_{\beta m} \\
\frac{di_{\beta r}}{dt} &= -\frac{R_r + R_{fe}}{l_{fr}} i_{\beta r} - \frac{R_{fe}}{l_{fr}}.i_{\beta s} + \frac{R_{fe}}{l_{fr}} i_{\beta m} + p.\Omega_r.i_{\alpha r} + p.\Omega_r.i_{\alpha m} \\
\frac{di_{\alpha m}}{dt} &= \frac{R_{fe}}{l_m} i_{\alpha s} + \frac{R_{fe}}{l_{ms}}.i_{\alpha r} - \frac{R_{fe}}{l_m} i_{\alpha m} \\
\frac{di_{\beta m}}{dt} &= \frac{R_{fe}}{l_m} i_{\beta s} + \frac{R_{fe}}{l_{ms}}.i_{\beta r} - \frac{R_{fe}}{l_m} i_{\beta m}
\end{aligned} \tag{9}
$$

### 3.2 Field oriented control with core loss

It's known that the vector control scheme has been derived from the equivalent circuit in the synchronous frame by applying the field orientation requirements. If the core loss resistance is introduced in the equivalent circuit, indeed a current will flow this branch. This current is not considered by the classical FOC. Consequently the desired decoupling between the torque and the rotor flux is not achieved. It's clear that the core loss can be considered as a source of detuning which causes degradation in transient as well as in steady state operation. In fact, rather than the loss of decoupling and mismatch in electromagnetic torque control will result.

Levi *et al* [10] has developed a new decoupling scheme which is based on the new equivalent circuit of field oriented control that compensates for the current through the core resistance branch.

The modified indirect field oriented controller maintains the decoupling by introducing two new torque and flux producing components respectively ($i_{qm}$, $i_{dm}$) and compensation of core loss resistance's effect is done by calculating the required stator components that will be the inputs for the current controlled PWM inverter after conversion to the stationary reference frame.

### 3.3 Speed estimation without core loss compensation

Simulation results for indirect vector scheme, using the model for the induction motor, have shown that an error due to the core loss resistance is created between the actual and the estimated rotor speed. The scheme used for this simulation was the current controlled PWM inverter with PI speed controller. Figure 3 (b) and (c) show that the error is about 1rad/s or 10 RPM which is considerable for most applications. This has been obtained even though; the classical indirect field oriented controller was replaced by the modified one [10], to overcome the flux orientation detuning.

This error is simply due to the fact that the induction motor model, from which the EKF is derived, neglects the core loss resistance. Nevertheless the flux producing current component (or $i_{dm}$ in modified indirect vector control scheme [10]) is well controlled; the power delivered to the rotor yielding the electromagnetic torque within the motor is different from that in the Extended Kalman Filter model.

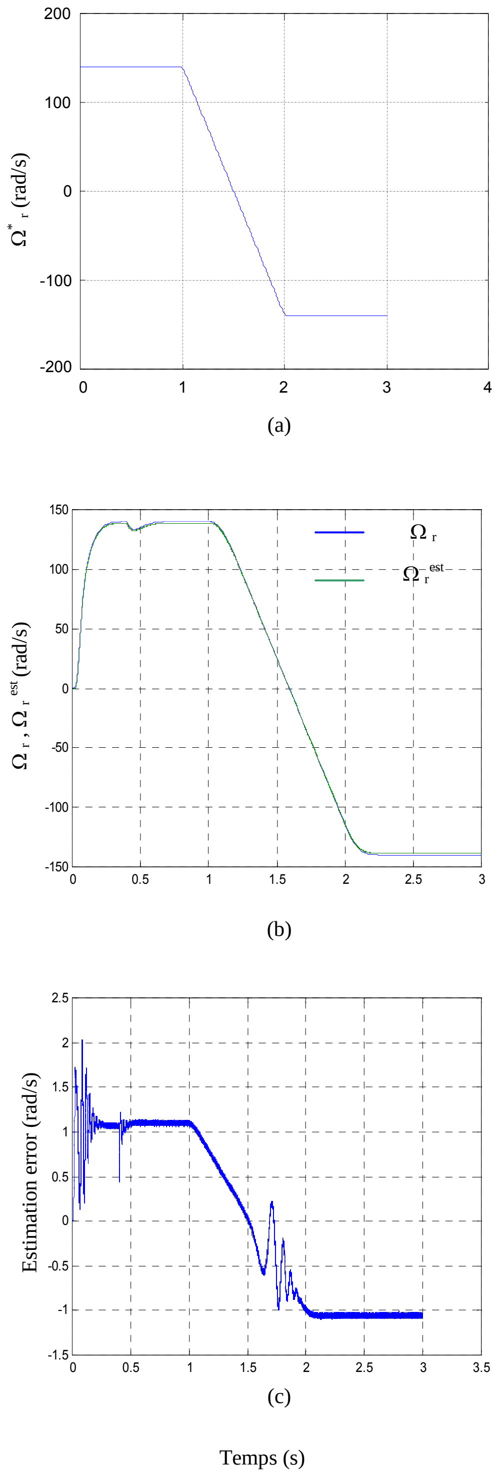



Fig. 3 Sensorless indirect vector control, without core loss compensation

## 4. Compensation of Core Loss effect

We can obviously notice that modifying the EKF algorithm to take care of core loss will increase substantially the computational time. To address this problem without increasing the computational time and avoid consequently the fastidious task, *i.e.* retuning the covariance matrices, one can take advantage from the previous results, by changing the inputs of the EKF in such a way the core loss current is not fed to the observer. By using the equivalent circuit of IMs in steady state (Fig.4.a) and we ignore the voltage drop across the stator leakage inductance $l_{fs}$ when compared to that due to $R_s$, a new equivalent circuit is obtained. This scheme allows us to eliminate the core loss from input power by using equations (10) deduced from Fig.4 (b)

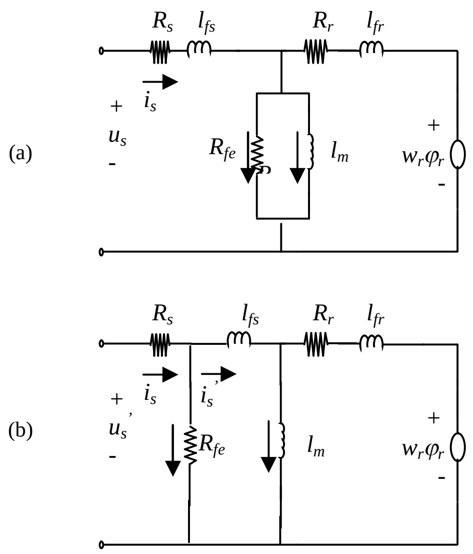



Fig.4 Steady state equivalent circuit of IM: (a) before and (b) after modification

$$u_{\alpha s}' = u_{\alpha s}$$

$$u_{\beta s}' = u_{\beta s}$$

$$i_{\alpha s}' = i_{\alpha s} - \frac{u_{\alpha s} - R_s.i_{\alpha s}}{R_{fe}} \tag{10}$$

$$i_{\beta s}' = i_{\beta s} - \frac{u_{\beta s} - R_s.i_{\beta s}}{R_{fe}}$$

By using the new input to observer, a new configuration system for sensorless indirect vector controlled induction motor is obtained (Fig. 5).

Simulation has been performed for the same motor parameters and the same speed reference. The obtained results are shown in fig.6 (a) and (b). As regards, the extended Kalman matrices, namely $A_d$, $B_d$ and $C_d$, there are no changes neither in their dimension nor their parameters. Therefore the required computational time will not change.

It can be noticed from Eq.(10) that the voltage is maintained since the core loss component is a parallel branch, whereas the current inputs to the extended Kalman filter have been changed so that the power dissipated by $R_{fe}$ is taken into account. Simulation results, Fig. 6, show that for the same desired speed reference, one can realize that the estimation error is considerably decreased for Fig.6 (b), in others words, the estimation accuracy has been maintained though the presence of the core loss resistance.

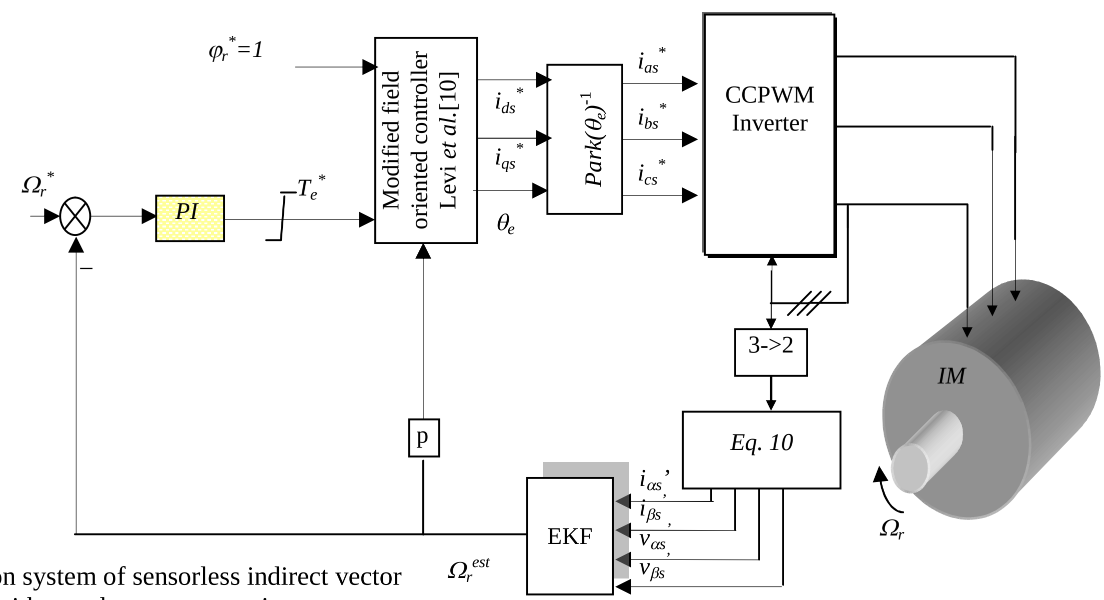
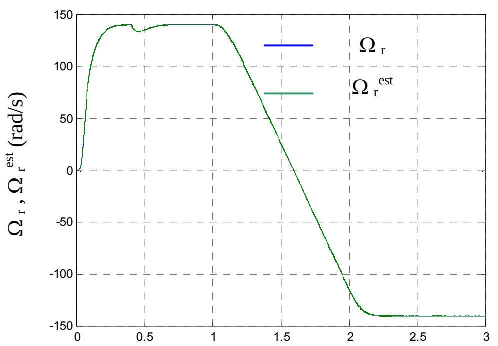
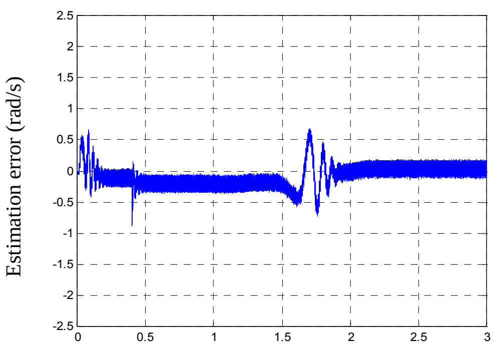



Fig.5 Configuration system of sensorless indirect vector control with core loss compensation




(a)




(b)

Fig.6 Sensorless field-oriented control, with core loss compensation

## 5. Conclusion

In the paper, the effect of core loss on the Extended Kalman Filter is analysed. The main advantage of such observer is the ability to deal with noisy systems and its robustness against parameters uncertainties. This is the main raison to find it in sensorless speed control of induction motor drives. However, it has been shown that the core loss decreases the estimation accuracy and consequently degrades sensorless induction motor drives particularly when used in position control. In this work, it has been suggested a mechanism based on the dq modelling of IMs to reduce the core loss effect without retuning the covariance matrices of the observer (EKF).

This later is the most fastidious and time consuming task to design Kalman filter algorithm. The obtained results have witnessed the effectiveness of the suggested approach.

## References

1. W. Guanghui, “Speed senseless control of induction machine based on carrier signal injection and smooth-air-gap induction machine model”, Phd Dissertation, the Pennsylvania State University, 2004.
2. V. Peter, “Sensorless vector and direct torque control”, Oxford university press, 1998.
3. P.L. Jonson, R.D. Lorenz, “Transducerless position and velocity estimation in induction and salient AC machines”, IEEE Indus. Applica. Society Annual meeting, pp. 488-495, 1994.
4. C.Schauder, “Adaptive speed identification for vector control of induction motors without rotational transducers”, IEEE Transactions on Industry Applications, Vol. 28, pp. 1054-1061, 1992.
5. H Kubota, K Matsuse, T Nakano, “DSP-based adaptive flux observer of induction motors”, IEEE Transactions on Industry Applications, Vol. 29, pp. 344-348, 1993.
6. Li Jingchuan, “Adaptive sliding mode observer and loss minimizing for senseless field orientation control of induction machine” Phd Dissertation, The Ohio State University, 2005.
7. M.S.Nait Said, M.H. Benbouzid, A.Benchaib, “Detection of brocken bars in induction motors using an extended kalman filter for rotor resistance sensorless estimation”, IEEE Trans. On Energy Conversion, Vol. 15, NO. 1, 2000.
8. A.V. Leite, R.E. Araujo, D. Freitas, “Full and reduced order extended Kalman filter for speed estimation in induction motor drives: a comparison study”, IEEE Power Electronics Specialists Conference, Aachen, Germany, pp. 2293-2299, 2004.
9. M.A. Ouhrouche, “Estimation of speed, rotor flux and rotor resistance in cage induction motor using the EKF algorithm”, International Journal of Power and Energy Systems, 2002.
10. E.Levi, M.Sokola, A.Boglietti, M.Pastrolli, “Iron loss in rotor flux oriented induction machines: Identification, Assessment of detaining and Compensation”, IEEE Trans. on Power Electronics. Vol.11, n°05, pp.698-709, 1996.
11. S. Lim and K. Nam, “Loss-minimising control scheme for induction motors”, IEE Proc.-Electr. Power Appl., Vol. 151, No. 4, 2002, pp. 385-397.
12. B.Chetate, A. Kheldoun, “A method of minimizing the power losses in an induction motor with a squirrel-cage with vector control”, Electrical Technology Russia, ISSN: 1028-7957, N° 4, 2004, pp. 154-165.