Electromechanical Energy Conversion Systems (EECS)
Niroo Research Institute (NRI)
Vol. 3, No. 1, Autumn 2024, 18-28
DOI: 10.30503/eecs.2024.458334.1050
Original Article

Iron Loss Effect Compensation in Vector Control Axial Flux Permanent Magnet Motor by EKF-Based Speed Estimation

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Abstract:

Hall Effect sensors, Resolver sensor or other kind of sensors have conventional applications in vector control topologies of Axial Flux Permanent Magnet Motor (AFPM). In addition, sensorless systems can be used for vector control of AFPM. In this paper, Extended Kalman Filter (EKF) has been applied to AFPM position sensorless control and related algorithm was simulated. Since this observer operates based on state space variables variations, due to decrease total state variable numbers, core losses could be neglected in machine equivalent model and also in EKF algorithm. Special attention must be paid when core losses have been considered in machine model but have not been taken in to account in EKF realization, because this leads to some steady state error in control system performance. In this paper, the core losses have been considered in machine model without model order increasing. Simulation results prove the effectiveness of proposed method to reducing of speed error in EKF algorithm performance.

Keywords: Axial Flux Permanent Magnet, Sensorless Vector control, Extended Kalman Filter, Core losses, Iron losses

Received Date: 2024-05-18; Revised Date: 2024-07-01; Accepted Date: 2024-08-20.

Introduction

Axial Flux Permanent Magnet (AFPM) machines has various advantages of high-power density, relatively small moment of inertia, easy maintenance and reliability, high power factor, significant and high efficiency energy-saving effect. Also mentioned kind of machines has very good speed control performance and could be assembled in small volumes comparing them with other kind of electrical machines [1,2]. One of the most important elements used in applicable control topologies are various kind of speed sensors. These sensors are inherently expensive and environmental condition always has some influences on their performance and accuracy.

Recently AFPM drives without position and speed sensor have been attended. It is notable that, position sensorless control systems for AFPMs, including the machine state variables estimation for feedback control loop, are already developed more sophisticated. This estimation shall be done using full order state, if total state observation is necessary, or reduced order state observers, if some states are applicable only. Once reduced order observer estimates minimum number of states, it will be called as minimum order state observer [3,4]. Estimation could be carried out using open loop or close loop control systems. Main difference of mentioned control topologies is in how to consider estimated error signal in observer response adjustment [5].

In open loop base observers, machine parameter deviations have considerable effects on both steady state and transient response of machine, in low speeds specially, but one can improve this condition and also noise effects using close loop base observers.

Close loop base observers, generally called observers, are categorized according to observation parameter of system. If system is deterministic or real, observer should be deterministic one else in other cases, statistical observers can be used as estimator.

Conventional stochastic observers are Luenberger and Kalman Filter observers. Former one lies in deterministic and second one lies in non-deterministic and stochastic categories. Mentioned Kalman Filter is applicable only in non-deterministic linear systems. In case of non-linear systems, Extended Kalman Filter (EKF) base observers should be applied. EKFs not only can estimate state variables, but also can estimate machine parameters too. This observer is inherently kind of recursive filter that estimates above mentioned parameters based on measured

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noise or state statistical information in non-deterministic non-linear systems [3]. In comparison, Luenberger observer is applicable in deterministic, linear and time invariant systems. Extended Luenberger Observer (ELO) is applicable in non-deterministic, non-linear and time variant system [5]. In additional we can summarize that EKF and ELO observers are both non-linear type but EKF is applicable in statistical base systems and ELO is applicable in non-deterministic systems.

Finally, comparing these two observers, ELO has simple algorithm and easy to adjust but EKF is almost insensitive to system parameters variations and preferred for statistical base applications [6-7].

In this paper we have focused on a very important matter, which has not been investigated before in any work. Mentioned subject is power losses effect consideration in sensor-less vector control of AFPM.

Extended Kalman Filter is implemented as speed estimator, which functions based up on statistic information for estimation progress. At first, to clarify power losses effect importance, simulation results are presented while power losses have been modeled in AFPM modeling stage and simultaneously has not been considered in EKF algorithm. Then in second part, we show simulation results in which power losses have been considered in both machine model and EKF algorithm.

Clearly state space variables will increase in second case study. Alternatively, to solve this problem, an optimized model for AFPM is presented to decrease state space variable numbers while EKF algorithm and machine model remained accurate enough.

Simulation results of above-mentioned solution shows adequate corresponding with real state condition results. More over calculation time has been reduced due to this fact that state space variable has been scaled down.

1. AFPM EQUIVALENT CIRCUIT

1.1. AFPM d-q equivalent circuit without core losses

Fig.1 depicts AFPM machine's equivalent circuits in d-q axis rotating reference frame for both motor and generator operations regions.

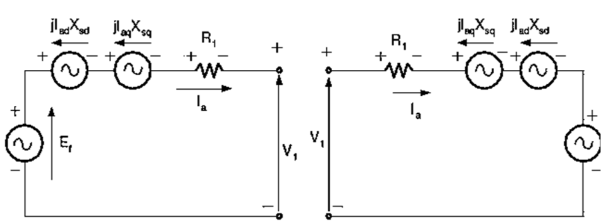


Fig.1. d-q equivalent circuits of AFPM machine without core losses

Compared with α-β coordinate system used in EKF algorithm in the literature, this article adopts d-q rotating coordinate system, so that it has better accuracy rather than α-β coordinate system because in d-q coordinate system all parameters are constant while in α-β coordinate system voltages and currents are variable parameters. Hysteresis power losses, called core losses, are not still taken in account. One can write voltage equations for a salient pole and magnetic rotor AFPM motor considering Fig.1 as [1,8-9]:

$$v_{1d} = R_1 i_{ad} + \frac{d\Psi_d}{dt} - \omega\Psi_q \quad (1)$$

$$v_{1q} = R_1 i_{aq} + \frac{d\Psi_q}{dt} + \omega\Psi_d \quad (2)$$

Flux linkage in d and q axis can be written as below:

$$\Psi_d = (L_{ad} + L_l) i_{ad} + \psi_f = L_{sd} i_{ad} + \Psi_f \quad (3)$$

$$\Psi_q = (L_{aq} + L_l) i_{aq} = L_{sd} i_{ad} \quad (4)$$

Where in above equations v_{1d} and v_{1q} is d and q axis first harmony of terminal voltages respectively. R_s is armature winding total resistance and L_{ad} and L_{aq} are d and q axis self inductances in rotor reference frame and L_l is leakage inductance of stator winding. Also Ψ_f is maximum flux linkage per phase produced by field excitation circuit. $\omega = 2\pi f$ is rotational frequency of i_{ad} and i_{aq} armature currents. For synchronous inductances in d and q axis, we have:

$$L_{sd} = L_{ad} + L_l \quad (5)$$

$$L_{sq} = L_{aq} + L_l \quad (6)$$

In addition, one can write flux linkage in term of field current as:

$$\Psi_f = L_{fd} I_f \quad (7)$$

In this equation L_{fd} is for mutual inductance between field and armature circuits. Substituting recent equations in general, voltage equations of (1) and (2) will result as:

$$v_{1d} = R_1 i_{ad} + \frac{di_{ad}}{dt} L_{sd} - \omega L_{sq} i_{aq} \quad (8)$$

$$v_{1q} = R_1 i_{aq} + \frac{di_{aq}}{dt} L_{sq} + \omega L_{sd} i_{ad} + \omega\Psi_f \quad (9)$$

Since in steady state operation of machine there is no variation in first order derivative of above equations, steady state of machine can be described by:

$$\frac{d}{dt}(L_{sd} i_{ad}) = \frac{d}{dt}(L_{sq} i_{aq}) = 0 \quad (10)$$

$$I_a = I_{ad} + jI_{aq} \quad (11)$$

$$V_1 = V_{1d} + jV_{1q} \quad (12)$$

$$i_{ad} = \sqrt{2} I_{ad} \quad ; \quad v_{1d} = \sqrt{2} V_{1d}$$
$$i_{aq} = \sqrt{2} I_{aq} \quad ; \quad v_{1q} = \sqrt{2} V_{1q} \quad (13)$$

$$E_f = \frac{\omega L_{fd} I_f}{\sqrt{2}} = \frac{\omega\psi_f}{\sqrt{2}} \quad (14)$$

In above equations I_a and V_1 are reference vector current and voltage of machine. Instantaneous input power of motor can be written as:

$$p_{in} = \frac{m_1}{2}(v_{1d}i_{ad} + v_{1q}i_{aq}) \quad (15)$$

Since there are no power losses in core, input and output instantaneous power shall be equal. Resultant electromagnetic power and torque equations for an AFPM machine with p pole pairs can be written there as:

$$p_{elm} = \frac{3}{2}\omega[\Psi_f + (L_{sd} - L_{sq})i_{ad}]i_{aq} \quad (16)$$

$$T_e = p\frac{p_{elm}}{\omega} = \frac{3}{2}p[\Psi_f + (L_{sd} - L_{sq})i_{ad}]i_{aq} \quad (17)$$

Applying park transformation [10], one can write below equations for i_{ad} and i_{aq}:

$$i_{ad} = \frac{2}{3}\left[i_{aA}\cos(\omega t) + i_{aB}\cos\left(\omega t - \frac{2\pi}{3}\right) + i_{aC}\cos\left(\omega t + \frac{2\pi}{3}\right)\right] \quad (18)$$

$$i_{aq} = -\frac{2}{3}\left[i_{aA}\sin(\omega t) + i_{aB}\sin\left(\omega t - \frac{2\pi}{3}\right) + i_{aC}\sin\left(\omega t + \frac{2\pi}{3}\right)\right] \quad (19)$$

Vice versa, using reverse park transformation, three phase currents of AFPM machine in abc reference frame can be written as:

$$i_{aA} = i_{ad}\cos(\omega t) - i_{aq}\sin(\omega t) \quad (20)$$
$$i_{aB} = i_{ad}\cos\left(\omega t - \frac{2\pi}{3}\right) - i_{aq}\sin\left(\omega t - \frac{2\pi}{3}\right)$$
$$i_{aC} = i_{ad}\cos\left(\omega t + \frac{2\pi}{3}\right) - i_{aq}\sin\left(\omega t + \frac{2\pi}{3}\right)$$

1.2. AFPM d-q equivalent circuit with core losses

Fig. 2a and 2b are salient pole AFPM equivalent circuits for q and d axis respectively. Writing KVL equations in Fig.2 shows that:

$$KVL\ I) \quad V_q = R_S I_{qs} + SL_{lq}I_{qs} + R_c(I_{qs} - I_q) \quad (21)$$

$$KVL\ II) \quad I_q = \frac{1}{R_{S+}SL_{aq}}(R_c I_{qs} - L_{ad}\omega_e I_d - 1\omega_e\Psi_f) \quad (22)$$

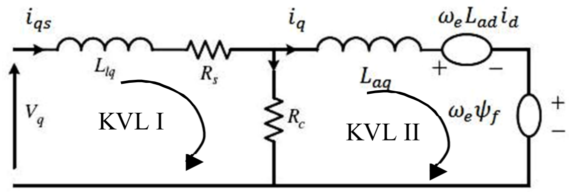
In above equations R_S is armature winding total resistant and S stands for Laplace operator and L_{lq} is leakage inductance. In addition, R_c is for core losses equivalent resistant and ω_e is electrical rotational frequency speed.

Substituting equation (22) in equation (21), first loop's KVL equation would be completed. In the same way, d axis equations could be written as:

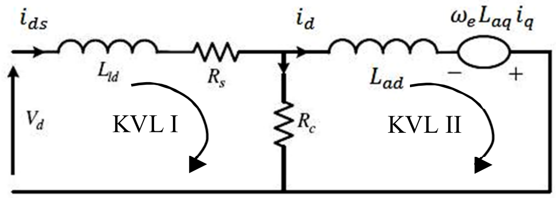
$$KVL\ I)\ V_d = R_s I_{ds} + SL_{ld}I_{ds} + R_c(I_{ds} - I_d) \quad (23)$$
$$KVL\ II)\ SL_{ad}I_d - \omega_e L_{aq}I_q + R_c(I_d - I_{ds}) = 0 \quad (24)$$

I_d can be obtained from KVL-II of above equations as:

$$I_d = \frac{R_c}{R_c + SL_{ad}}I_{ds} + \frac{L_{aq}}{R_c + SL_{ad}}\omega_e I_q \quad (25)$$



(a)



(b)

Fig.2. Equivalent circuit of AFPM considering core losses. (a) q-axis. (b) d-axis.

2. CONTROL STRATEGY

2.1. Extended kalman filter theory

A discrete time, Standardized KF estimates $x(k)\epsilon R^n$ state (in which, n is number of state variable). In most applications, dynamical systems and miscellaneous sensors used are not linear at all. Therefore, standardized KF is not satisfying in mentioned systems due to non-linear properties of system. As previously described, EKF is a recursive filter (based on the knowledge of statistics of both state and measurement noise), which can estimate non-linear system parameters and states taking in to account any probable noise signals. This estimation carried out in four recursive steps [11]. Primarily, initial condition would be assigned for state space variables and also state covariance matrix, which is called estimation stage. Then depending up on previous stage, Kalman filter's gain would be determined. At second stage, considering measured parameters of machine, they should be updated. At third stage, considering input parameters and also machine model, which is already linearized via Jacobian method, estimated state space variables and also estimated state covariance will be modified. Finally, according to modified parameters, Kalman filter's gain would be re-determined and would be used for next estimations. These steps can be divided in to two main parts. Initially, estimation stage shall be done then filtering should be carried out as second step. In former stage, next step's amount of state variables X(k+1) and matrix named P, will be estimated. To achieve this goal, Q and previous amount of state variables should be taken into account (Predictive step or Time Update).

$$X(k+1|k) = X(k+1)$$
$$= X(k|k) + T.f[X(k+1|k) + Bu(k)]$$

$$P(k+1|k) = P(k|k) + T^2.f(k+1|k)P(k|k)f^T(k+1|k) + Q \quad (26)$$

Where

$$f(k+1|k) = \frac{\partial F(X)}{\partial X}\Big|_{X=X(k+1|k)}$$

$$Q = Cov\ (W\ (t)) = E\ (WW^T\ )$$

Also in later stage, filtered states of $\hat{x}$ from foreseen estimations will be applied (Corrective Step or Measurement Update).

$$\hat{X}(k+1|k) = X(k+1|k) + K(k+1|k).\left[Y(k+1|k) - \hat{Y}(k+1|k)\right]$$

$$\hat{P}(k+1|k) = P(k+1|k) - K(k+1|k).C.P(k+1|k) \quad (27)$$

The Kalman gain is calculated by

$$K(k+1|k) = \frac{P(k+1|k).C}{C.P(k+1|k).C^T + R}$$

$$R = Cov\ (V\ (t)) = E\ (VV^T\ ) \quad (28)$$

2.2. Schematic diagram of sensorless vector control

Sensorless control topology has been presented in Fig.3. Here in this control strategy, direct axis current (i_d) shall be set to zero or negative value to achieve maximum torque per ampere state[12,13]. Although, a look up table (current space vector's angle is produced to generate reference current signals) is already applied for instances that speed passed over nominal speed but simulated motor's speed shall not be in over nominal values.

3. EKF APPLICATION IN AFPM CONTROL

As discussed, EKF application in AFPM control consists of four general steps. If core losses should be considered, state variables will increase in comparison with core loss less case. Here in this paper, we will consider core losses.

3.1. Introduction time domain of machine model

State space equations of AFPM can be summarized as below:

$$\dot{X} = F(X) + Bu + V(t) \quad (29)$$

$$Y = CX + W(t) \quad (30)$$

Also, we have:

$$\dot{X} = \left[\dot{I_{ds}} \quad \dot{I_{qs}} \quad \dot{I_d} \quad \dot{I_q} \quad \dot{\omega_r} \quad \dot{\theta_r}\right]^T$$

where W_r and θr are rotor speed and rotor position (angle) respectively.
Considering these figures, one can write:

$$\dot{I_{ds}} = \frac{1}{L_{ld}}V_d - \frac{R_s + R_C}{L_{ld}}I_{ds} + \frac{R_c}{L_{ld}}I_d \quad (31)$$

$$\dot{I_{qs}} = \frac{1}{L_{lq}}V_d - \frac{R_s + R_c}{L_{lq}}I_{qs} + \frac{R_c}{L_{lq}}I_q \quad (32)$$

$$\dot{I_d} = \frac{R_c}{L_{md}}I_{ds} + \frac{L_{sq}}{L_{md}}\omega_r I_q - \frac{R_c}{L_{md}}I_d \quad (33)$$

$$\dot{I_q} = \frac{R_c}{L_{mq}}I_{qs} - \frac{L_{sd}}{L_{mq}}\omega_r I_d - \frac{R_c}{L_{mq}}I_d - \frac{1}{L_{mq}}\omega_r\psi_f \quad (34)$$

$$\dot{\omega_r} = \frac{P}{2J}(T_e - T_L) - \frac{B_m}{J}\omega_r \quad (35)$$

$$\dot{\theta_r} = \omega_r \quad (36)$$

Also:

$$L_{sd} = L_{ld} + L_{md}$$
$$L_{sq} = L_{lq} + L_{mq} \quad (37)$$

Where L_{ld}, L_{lq}, L_{md} and L_{mq} are d, q axis leakage inductances and magnetic inductances respectively.

Matrix form of state equations would be:

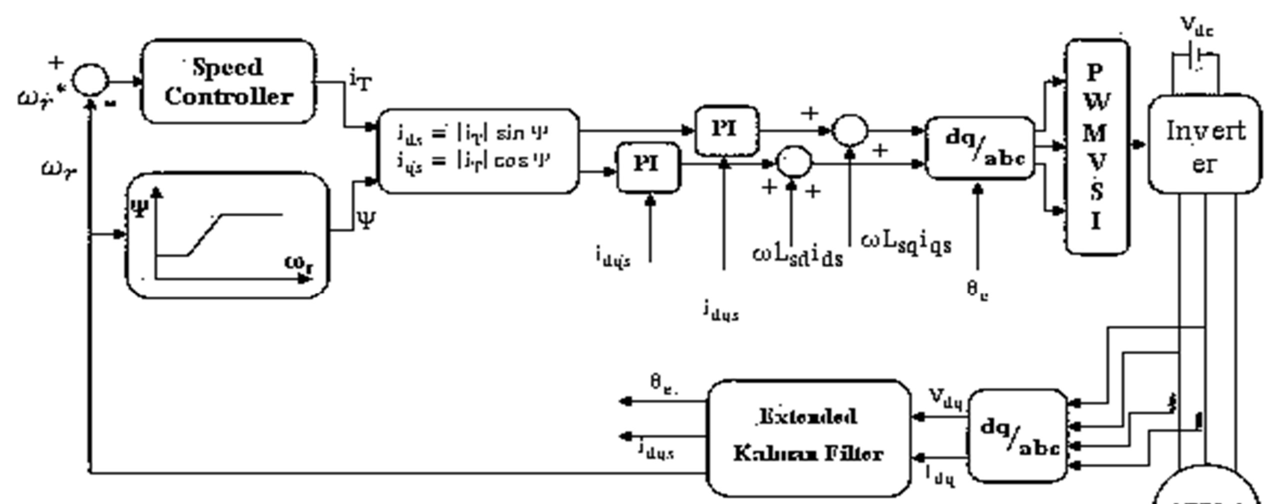


Fig.3. Block diagram for sensorless control system of AFPM machine

$$F(X)=\begin{bmatrix} \frac{R_c}{L_{ld}}I_d-\frac{R_s+R_c}{L_{ld}}I_{ds} \\ \frac{R_c}{L_{lq}}I_q-\frac{R_s+R_c}{L_{lq}}I_{qs} \\ \frac{R_c}{L_{md}}I_{ds}+\frac{L_{sq}}{L_{md}}\omega_r I_q-\frac{R_c}{L_{md}}I_d \\ \frac{R_c}{L_{mq}}I_{qs}-\frac{L_{sd}}{L_{mq}}\omega_r I_d-\frac{R_c}{L_{mq}}I_d-\frac{1}{L_{mq}}\omega_r\Psi_f \\ \frac{P}{2J}\cdot\left[\frac{3}{2}\frac{P}{2}\left(\Psi_f+\left(L_{md}-L_{mq}\right)I_{ds}\right)I_{qs}\right]-\frac{B_m}{J}\omega_r \\ \omega_r \end{bmatrix} \tag{38}$$

$$B=\begin{bmatrix} \frac{1}{L_{ld}} & 0 & 0 \\ 0 & \frac{1}{L_{lq}} & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & -\frac{P}{2J} \\ 0 & 0 & 0 \end{bmatrix} \tag{39}$$

$$U=[V_d \quad V_q \quad T_l]^T$$

$$C=\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$Y=[I_{ds} \quad I_{qs}]^T$$

3.2. Discrete state space model of AFPM

In this step, for simplicity F(x) should be in form of linear using Jacobian matrices as [14-16]:

$$F_{Jacob}=\frac{\partial F(X)}{\partial X}=\begin{bmatrix} F_{X_{11}} & F_{X_{21}} & F_{X_{31}} & F_{X_{41}} & F_{X_{51}} & F_{X_{16}} \\ F_{X_{12}} & F_{X_{22}} & F_{X_{32}} & F_{X_{42}} & F_{X_{52}} & F_{X_{26}} \\ F_{X_{13}} & F_{X_{23}} & F_{X_{33}} & F_{X_{43}} & F_{X_{53}} & F_{X_{36}} \\ F_{X_{14}} & F_{X_{24}} & F_{X_{34}} & F_{X_{44}} & F_{X_{54}} & F_{X_{46}} \\ F_{X_{15}} & F_{X_{25}} & F_{X_{35}} & F_{X_{45}} & F_{X_{55}} & F_{X_{56}} \\ F_{X_{16}} & F_{X_{26}} & F_{X_{36}} & F_{X_{46}} & F_{X_{56}} & F_{X_{66}} \end{bmatrix} \tag{40}$$

Calculated $F_{x_{i,j}}$ can be found in appendix A. Finally, we can write final discrete model equations as below:

$$\dot{X}=X+T\cdot F_{Jacob}\times X+T\cdot Bu+V \tag{41}$$

$$Y=CX+W \tag{42}$$

3.3. Noise and covariance matrices of P, Q, R determination

As illustrated before, considering core losses in model of AFPM will cause increases in matrices dimensions, i.e. total number of states will increase accordingly. For instance, Q and P will be 6×6 and R will be 2×2 matrices. It means that 76 no. of variables will appear in equations. Special attention should be paid to this matter that noise signals are independent. This will cause to shrinkage in variable numbers. For instance, in P and Q these No. will be limited to six numbers or the diagonal matrices with six elements.

Finally, it is remarkable that if R increases, K will decrease and transient response will be swift. Also, if Q increases, K will increase too. Therefore, transient response will be slow. Also, if Q increases much more than limited bound or R is very small, there may some un-stability problems [2,12,17].

4. Model Validation

In this paper MATLAB/Simulink has been used for AFPM sensorless control system's simulation.

Machine parameters are presented in Table I.

TABLE I. AFPM parameters

Components	Unit	Rating values
P_{out}	KW	1.1
V_{L-L}	V	220
R_S	Ω	2.875
Ψ_f	mWb	175
L_{ad}	mH	8
L_{aq}	mH	8
L_{ld}	mH	0.5
L_{lq}	mH	0.5
J	$Kg.m^3$	0.001
P	No.	8
B_m	N.s/rad	0.0022
N_s	RPM	3000
TL	N.m	3.5
R_c	Ω	2500
f	Hz	50

When core losses are neglected, R and Q that are covariance matrices will be as below for mentioned machine parameters:

$$R=\begin{bmatrix} 0.01 & 0 \\ 0 & 0.01 \end{bmatrix}$$

$$Q=\begin{bmatrix} 100 & 0 & 0 & 0 \\ 0 & 200 & 0 & 0 \\ 0 & 0 & 20 & 0 \\ 0 & 0 & 0 & 10 \end{bmatrix}$$

Moreover, sample time is:

$$T_s=\frac{8.5^{\,mH}}{2.875^{\,\Omega}}\times 0.01$$

Speed control loop's PI regulator parameter has been chosen to be as:

$$K_{Iw}=0.8 \quad \text{and} \quad K_{Pw}=90$$

There K_{Iw} is integral gain and K_{Pw} is proportion gain of speed loop. Also, current control loop's PI regulator parameter has been chosen to be as:

$$K_{Id}=2.5 \quad \text{and} \quad K_{Pd}=80$$
$$K_{Iq}=2.5 \quad \text{and} \quad K_{Pq}=20$$

Fig. 5 depicts estimated speed, produced by Kalman filter, and simulated speed of rotor by machine model, when core losses are neglected. As shown in this figure, speed error exists. Fig. 6 shows estimated and simulated speed of rotor from starting moment while core losses have been neglected. Also, Fig. 7 displays rotor speed's first and second overshoot, Fig. 8 depicts simulated and estimated results for rotor nominal speed, and Fig. 9a and 9b show

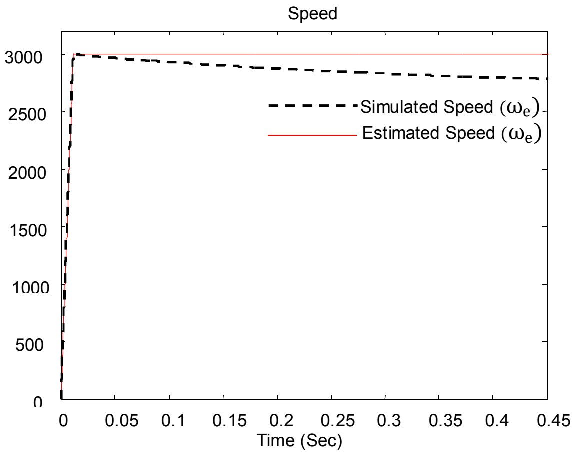


Fig.5. Estimated and simulated speed of rotor in nominal condition

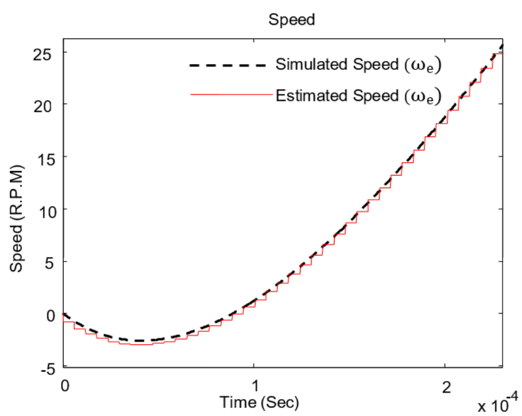


Fig.6. Estimated and simulated speed of rotor in starting condition

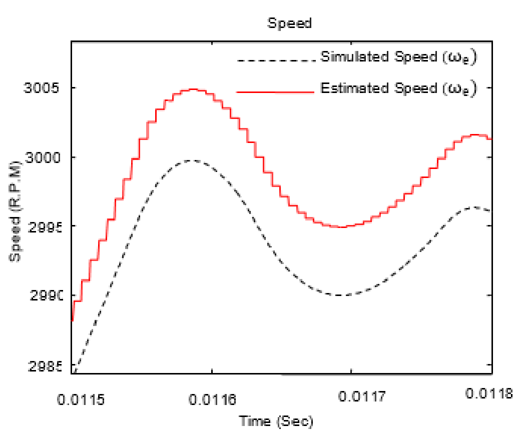


Fig.7. Estimated and simulated speed of rotor in first and second overshoot

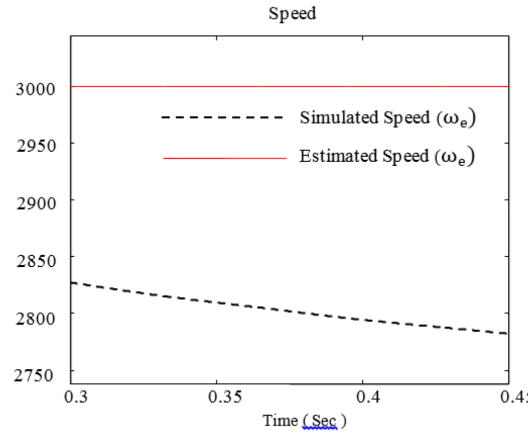
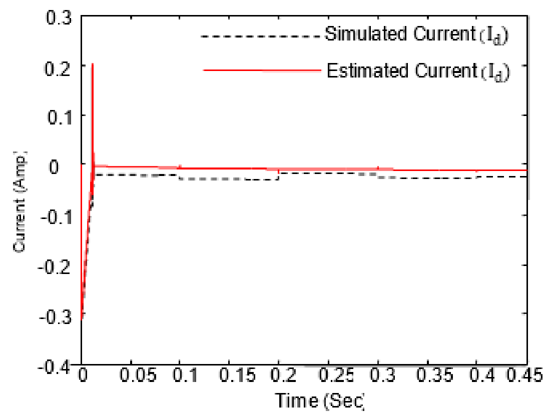
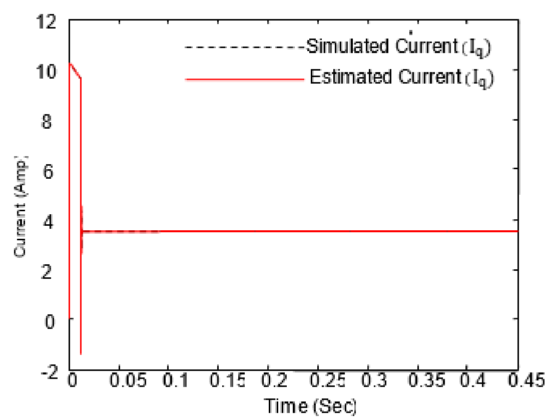


Fig.8. Estimated and simulated speed of rotor in steady state



(a)



(b)

Fig.9. Simulated and estimated currents. (a) Id. (b) Iq.

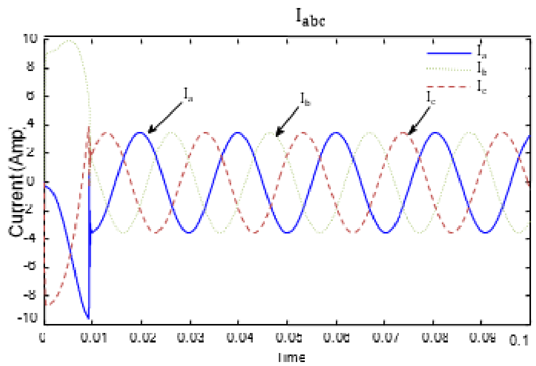


Fig.10. Simulated phase currents (Iabc)

simulated currents produced by machine model and estimated currents produced by EKF. Fig. 10 depicts phase currents of AFPM motor, when estimated values are used by EKF in feedback loop of vector control.

When core losses been considered, R and Q will be:

$$R = \begin{bmatrix} 0.01 & 0 \\ 0 & 0.01 \end{bmatrix}$$

$$Q = \begin{bmatrix} 100 & 0 & 0 & 0 & 0 & 0 \\ 0 & 200 & 0 & 0 & 0 & 0 \\ 0 & 0 & 200 & 0 & 0 & 0 \\ 0 & 0 & 0 & 200 & 0 & 0 \\ 0 & 0 & 0 & 0 & 20 & 0 \\ 0 & 0 & 0 & 0 & 0 & 10 \end{bmatrix}$$

Moreover, sample time would be:

$$T_s = \left(\frac{8.5^{\,mH}}{2.875^{\,\Omega}} \times 0.001 \right) / 5$$

$$K_{Iw} = 0.8 \quad \text{and} \quad K_{Pw} = 90$$

$$K_{Id} = 2.5 \quad \text{and} \quad K_{Pd} = 80.0$$

$$K_{Iq} = 2.5 \quad \text{and} \quad K_{Pq} = 80.0$$

Fig. 11a - 11d depict estimated and simulated speed of rotor in nominal condition, starting time, first and second overshoot and steady state condition respectively.

As shown in these figures, by considering core losses in Kalman filter's algorithm, speed curve has been improved. In comparison with case that core losses neglected, speed variations and even steady state error has been corrected.

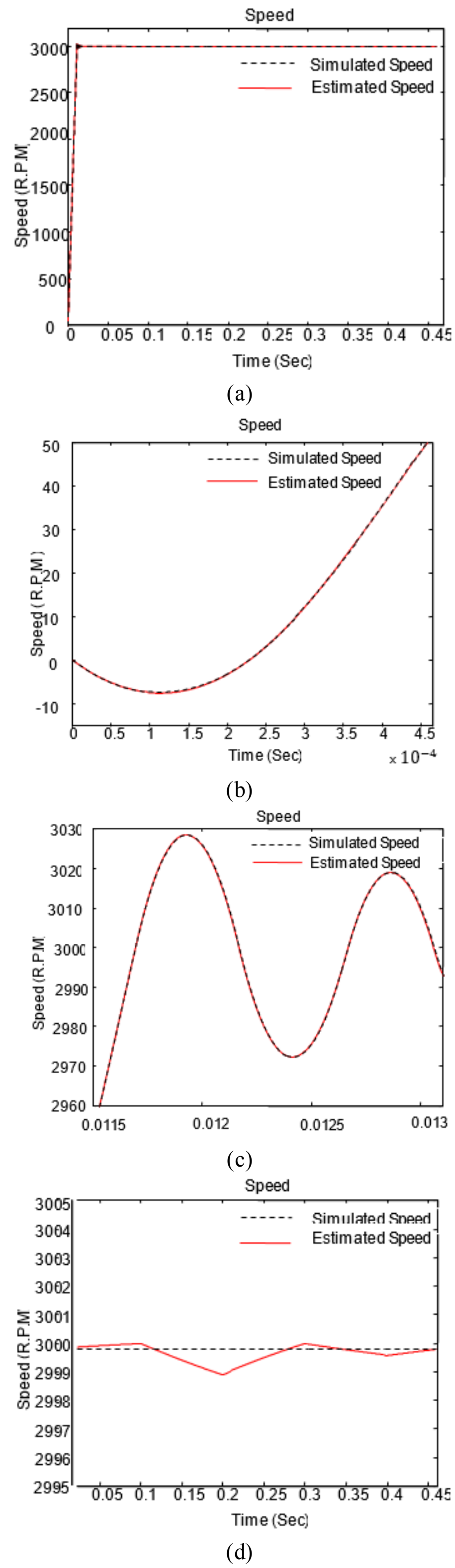


Fig.11. Estimated and simulated speed of rotor (a) Nominal condition (b) Starting condition (c) Overshoots (d) Steady state condition

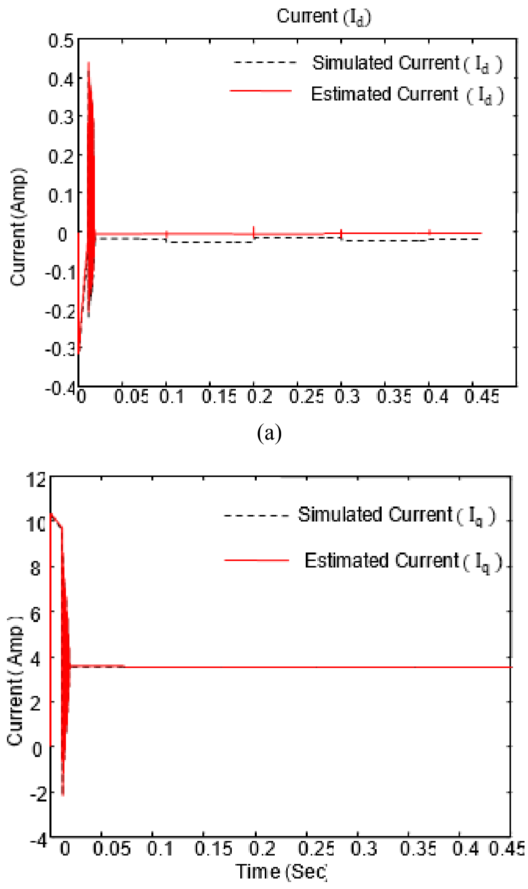


Fig.12. Simulated and estimated currents. (a) Id. (b) Iq

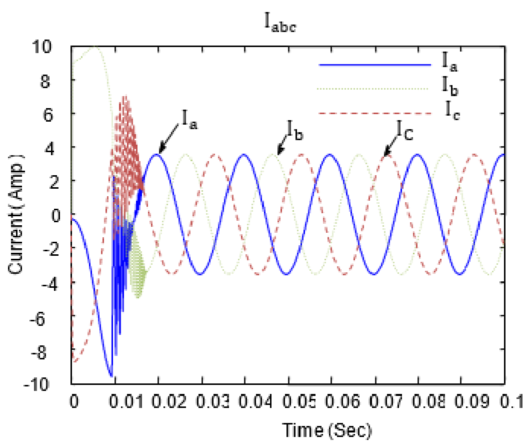


Fig.13. Three phases instantaneous currents

Comparing result obtained from with and without core losses compensation in EKF. One can investigate that in t=0.4 sec estimation error's reduction rate is $217.57^{r.p.m}$ while in start time, speed curves are similar. Also comparing Fig.9a and 9b with Fig.12a and 12b, it will be deduced that they are similar and also it is not clear in which curve core losses have been considered in machine model or not been taken into account in Kalman Filter realization. However, there is 0.0041offset between I_q in both conditions.

Moreover, sampling time is decreased 20 times smaller than former case which is a troublesome in practical realization of system. In contrary, when using modified model, simulation results depict acceptable accuracy with same sample time. In this case, sample time and PI regulator parameters and covariance matrices are similar to that case in which core losses were neglected in model.

5. Modified model for AFPM with core losses

Leakage inductances of AFPM model are effective only in starting moments while lead to increment of state space variable numbers. One can merge these leakage inductances with magnetizing inductance of machine and consequently power losses effect will affect machine performance in starting condition. Mentioned model, which are presented in Fig. 4a and 4b are very similar to induction machine [18]. State space variables to be implemented in EKF algorithm are as follow:

$$\dot{X} = [\dot{I_{ds}} \ \dot{I_{qs}} \ \dot{\omega_r}] \tag{43}$$

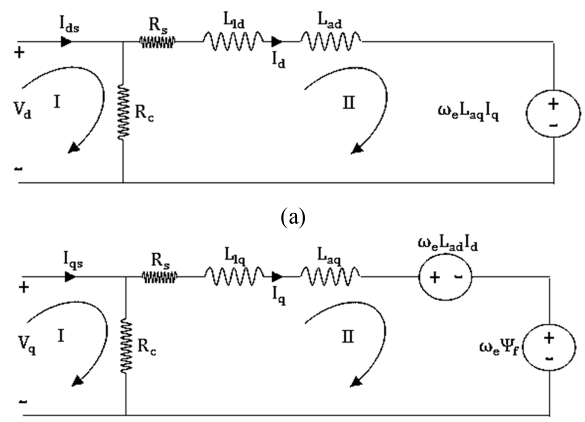


Fig.14. Equivalent circuit of modified AFPM considering core losses. (a) Axis-d. (b) Axis-q.

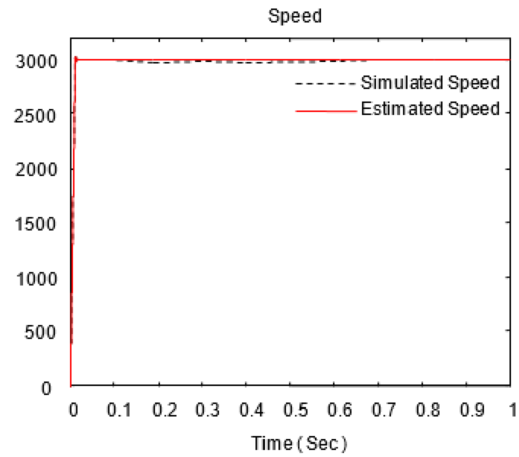
It is remarkable that electrical equations of mentioned model are same as that condition in which core losses has not been considered in EKF algorithm. Major differences are as below equations:

$$I_{ds} = \frac{V_d}{R_c} + I_d \tag{44}$$

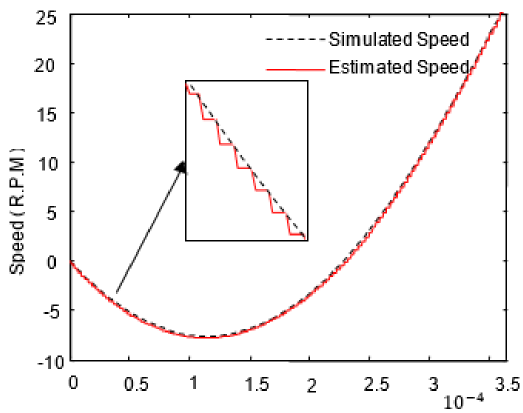
$$I_{qs} = \frac{V_q}{R_c} + I_q \tag{45}$$

Fig. 15a and 15b show estimated and simulated curves of rotor speed in respectively nominal condition then starting time, first and second overshoot and finally steady state condition. As illustrated in these figures, by considering modified model of core losses in Kalman filter's algorithm, speed curve will be improved.

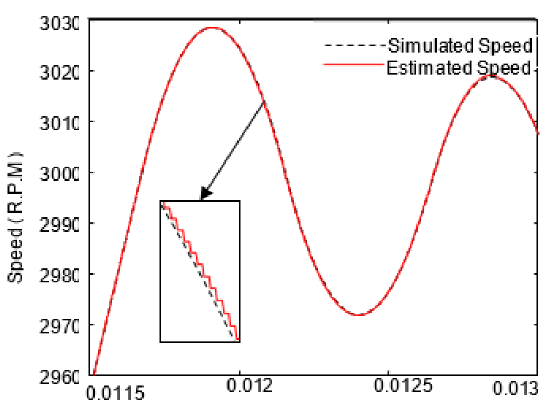
Comparing with precise model including core losses, results are almost similar.



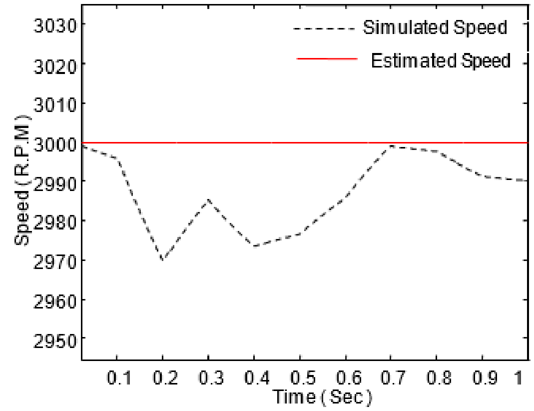
(a)



(b)



(c)



(d)

Fig.15. Rotor speed (a) Nominal condition (b) Starting condition (c) Overshoots (d) steady state condition

Unlike Fig. 5 and Fig. 11a, in Fig. 15a Simulation time is extended up to 1 second to illustrate steady state damping condition.

6. CONCLUSION

Generally, if core losses were considered in machine equivalent model while not been considered in Extended Kalman Filter algorithm, some disturbances in current and speed waves will appear. As shown in this paper, steady state error of current and speed in t=0.4 sec will be 0.0041Amp and 217.57 rpm respectively. As illustrated by simulation results, estimation will no longer accurate enough in case that core losses have not been considered in Kalman Filter Realization. To overcome states space variables multiplicity, and to rebate steady state errors in core loss effect neglected model, it would be better to implement modified model of core losses. This model is very similar to core losses effect neglected model and also it can be obtained with a few changes in conventional model. Simulation results depicted acceptable values for this model.

APPENDIX A

$$F_{X_{11}} = \frac{\partial F(X)}{\partial I_{ds}} = -\frac{R_s + R_c}{L_{ld}}$$

$$F_{X_{12}} = \frac{\partial F(X)}{\partial I_{qs}} = 0$$

$$F_{X_{13}} = \frac{\partial F(X)}{\partial I_d} = \frac{R_c}{L_{ld}}$$

$$F_{X_{14}} = \frac{\partial F(X)}{\partial I_q} = 0$$

$$F_{X_{15}} = \frac{\partial F(X)}{\partial \omega_r} = 0$$
$$F_{X_{16}} = \frac{\partial F(X)}{\partial \theta_r} = 0$$
$$F_{X_{21}} = \frac{\partial F(X)}{\partial I_{ds}} = 0$$
$$F_{X_{22}} = \frac{\partial F(X)}{\partial I_{qs}} = -\frac{R_s + R_c}{L_{ld}}$$
$$F_{X_{23}} = \frac{\partial F(X)}{\partial I_d} = 0$$
$$F_{X_{24}} = \frac{\partial F(X)}{\partial I_q} = \frac{R_c}{L_{lq}}$$
$$F_{X_{25}} = \frac{\partial F(X)}{\partial \omega_r} = 0$$
$$F_{X_{26}} = \frac{\partial F(X)}{\partial \theta_r} = 0$$
$$F_{X_{31}} = \frac{\partial F(X)}{\partial I_{ds}} = \frac{R_c}{L_{md}}$$
$$F_{X_{32}} = \frac{\partial F(X)}{\partial I_{qs}} = 0$$
$$F_{X_{33}} = \frac{\partial F(X)}{\partial I_d} = -\frac{R_c}{L_{md}}$$
$$F_{X_{33}} = \frac{\partial F(X)}{\partial I_d} = -\frac{R_c}{L_{md}}$$
$$F_{X_{34}} = \frac{\partial F(X)}{\partial I_q} = \frac{L_{sq}}{L_{md}} \omega_r$$
$$F_{X_{35}} = \frac{\partial F(X)}{\partial \omega_r} = \frac{L_{sq}}{L_{md}} I_q$$
$$F_{X_{36}} = \frac{\partial F(X)}{\partial \theta_r} = 0$$
$$F_{X_{41}} = \frac{\partial F(X)}{\partial I_{ds}} = 0$$
$$F_{X_{42}} = \frac{\partial F(X)}{\partial I_{qs}} = \frac{R_c}{L_{mq}}$$
$$F_{X_{43}} = \frac{\partial F(X)}{\partial I_d} = -\frac{L_{sd}}{L_{mq}} \omega_r$$
$$F_{X_{44}} = \frac{\partial F(X)}{\partial I_q} = -\frac{R_c}{L_{mq}}$$
$$F_{X_{45}} = \frac{\partial F(X)}{\partial \omega_r} = -\frac{\Psi_f + L_{sq} I_d}{L_{mq}}$$
$$F_{X_{46}} = \frac{\partial F(X)}{\partial \theta_r} = 0$$
$$F_{X_{51}} = \frac{\partial F(X)}{\partial I_{ds}} = K_e\left(L_{md} - L_{mq}\right) I_{qs}$$
$$F_{X_{52}} = \frac{\partial F(X)}{\partial I_{qs}} = K_e\left(\Psi_f + \left(L_{md} - L_{mq}\right) I_{ds}\right)$$
$$F_{X_{53}} = \frac{\partial F(X)}{\partial I_d} = 0$$
$$F_{X_{54}} = \frac{\partial F(X)}{\partial I_q} = 0$$
$$F_{X_{55}} = \frac{\partial F(X)}{\partial \omega_r} = -\frac{B_m}{J}$$
$$F_{X_{56}} = \frac{\partial F(X)}{\partial \theta_r} = 0$$
$$F_{X_{61}} = \frac{\partial F(X)}{\partial I_{ds}} = 0$$
$$F_{X_{62}} = \frac{\partial F(X)}{\partial I_{qs}} = 0$$
$$F_{X_{63}} = \frac{\partial F(X)}{\partial I_d} = 0$$
$$F_{X_{64}} = \frac{\partial F(X)}{\partial I_q} = 0$$
$$F_{X_{65}} = \frac{\partial F(X)}{\partial \omega_r} = 1$$
$$F_{X_{66}} = \frac{\partial F(X)}{\partial \theta_r} = 0$$

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