ON LINE PARAMETER ESTIMATION OF AN INDUCTION MOTOR USING RECURSIVE LEAST SQUARES METHOD

Abou-Hashema M. El-sayed and Yehia S. Mohamed

Electrical Engineering Department, Faculty of Engineering, El-Minia University, El-Minia Egypt

Received 9 October 2013; accepted 20 November 2013

ABSTRACT

This paper presents linear estimation techniques used to identify the stator resistance, the stator leakage inductance (transient inductance), the stator self inductance and rotor time constant of an induction motor with measuring its speed. Such estimation is important in the determination of the achieve performance for induction motor drives. The discrete-time parameter estimation models express the relationships of the dynamic machine model in terms of measurable stator voltages, stator currents and an estimated motor speed. These models are represented by linear regression equations from which the machine parameter vectors can be obtained using a recursive least squares (RLS) estimation algorithm. Simulation results are presented to validate the proposed estimation algorithm with reasonable accuracy of the estimated parameters regardless of load conditions. Comparisons between experimental and calculated steady-state performances using the estimated parameters are also presented.

1. Introduction

Induction motors are known to be superior to their DC counterparts concerning, ruggedness, reliability, cost, size and output power per unit weight. This resulted in increasing use and necessitated the study of induction motor performance in various drives [1-3]. In variable speed induction motor drives, it is often to know the accurate values of motor parameters to realize high performance drive systems calculation.

Traditionally, machine parameters have been determined by performing no-load tests and locked rotor tests. These experiments are not convenient because they require a human operator for electrical measurements and for intervention on the machine. The machine service must be interrupted while the tests are performed. This is in addition to the difficulty to perform the locked rotor tests on large power machines [4]. Moreover, the locked rotor test gives a very high slip frequency, which increases the skin-effect influence on the rotor resistance. Thus, they can lead to inadequate operating conditions and results in an inaccurate parameter estimation. In [5] a review of numerous methods to identify the motor parameters is introduced. In most of these methods, only one parameter (rotor time constant or resistance) estimation is considered.

The use of parameter estimation techniques in the characterization of an induction machine has been reported by many research teams [6]-[11]. The main problems associated with these techniques are:

1) The use of special test signals [6], [8] and [10]; 2) the requirement of special operating conditions, such as keeping the machine at standstill [10]; and 3) the need of several operating points when the machine is supplied with sinusoidal pulse width modulated (PWM) waveforms [11].

Recent works for estimating the induction motor parameters show that the extended Kalman filter can be successfully applied to simultaneous estimation of all electrical parameters [12-14]. The main advantage of this method is to allow regular operating conditions, without disturbing test signals. This is very important for on-line estimation and real-time controller tuning. However, this method is computationally demanding, as estimator uses a fifth-order state-space model of the induction machine and the algorithm involves a significant number of matrix multiplications and additions. This motivates the development of a suitable method for on-line estimation of all electrical machine parameters that can reduce the amount of calculations.

This paper presents models and procedures used to estimate most of the electrical parameters of an induction motor. These parameters are namely, the stator resistance, the stator leakage inductance, the stator self inductance and rotor time constant. Such parameters are important for the determination of the performance of induction motor drives. The presented models are derived from the dynamical machine model. These models are represented by linear regression equations from which machine parameter vectors may be obtained using the RLS estimation algorithm. The different estimation algorithms can provide good estimation accuracy of parameters at any load conditions. The results clarify satisfactory operation of the proposed scheme and reasonable accuracy of estimated machine parameters. Comparisons between experimental and calculated steady-state performances using the estimated parameters are also presented.

2. Dynamic Model of an Induction Motor

The mathematical model of an induction motor in a stationary $\alpha-\beta$ reference frame can be described by a state-space equation as [4]:

$$px(t) = A\,x(t) + B\,u(t) \tag{1}$$

where $x = \begin{bmatrix} i_s & \psi_r \end{bmatrix}^T$ and $u = V_s$

The state space vectors are complex quantities defined as:

$$i_s = i_{\alpha s} + j\,i_{\beta s}\ , \qquad \psi_r = \psi_{\alpha r} + j\psi_{\beta r}$$

The input vector is also a complex quantity given by $V_s = V_{\alpha s} + jV_{\beta s}$

The dynamic matrix *A* and the input matrix *B* of equation (1) are given by

$$A = \begin{bmatrix} -\dfrac{\left(R_s + R_r\,(L^2{}_m / L^2{}_r)\right)}{\sigma L_s} & \dfrac{L_m}{T_r} \\ \dfrac{L_m}{T_r} & -\dfrac{1}{T_r} + j\omega_r \end{bmatrix}^T \quad \text{and} \quad B = \begin{bmatrix} \dfrac{1}{\sigma L_s} & 0 \end{bmatrix}^T$$

The use of system estimation techniques in this work are based on a discrete-time representation of the induction motor behavior. To derive the discrete-time version of equation (1) it is assumed that the stator voltage vector is supplied to the motor through a voltage source inverter. Furthermore, the motor speed ω_r is assumed to remain constant during the sampling interval Δt, i.e. the mechanical modes are slower than the electrical ones. Under these assumptions, the discrete-time representation of equation (1) is expressed as [15]:

$$\delta x(t) = F x(t) + G u(t) \tag{2}$$

where δ is the delta operator, $\delta x(t) = (x(t+\Delta t) - x(t))/\Delta t$ or $\delta = q - 1/\Delta t$ where Δt is the sampling period and q is the shift operator.

The matrices F and G of the discrete-time model are determined by:

$$\boldsymbol{F} = \frac{e^{A\Delta t} - \boldsymbol{I}}{\Delta t} \quad \text{and} \quad \boldsymbol{G} = \boldsymbol{A}^{-1}\left(\frac{e^{A\Delta t} - \boldsymbol{I}}{\Delta t}\right)\boldsymbol{B} \tag{3}$$

From equation (3), it is clear that $\lim_{\Delta t \to 0} F = A$ and $\lim_{\Delta t \to 0} G = B$ it high sampling rates

The discrete-time model can be replaced by its continuous-time counter part using the power series expression of $e^{A\Delta t}$. As a result F and G can also be expressed by:

$$F = \sum_{n=0}^{\infty} \frac{A^{n+1}\Delta t^{n}}{(n+1)!} \quad \text{and} \quad G = \sum_{n=0}^{\infty} \frac{(A\Delta t)^{n}}{(n+1)!} B \tag{4}$$

Equation (2) may be expanded, by using the complex quantities defined previously [15] and may be rewritten as:

$$\begin{bmatrix} \delta i_s \\ \delta \psi_r \end{bmatrix} = \begin{bmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{bmatrix} \begin{bmatrix} i_s \\ \psi_r \end{bmatrix} + \begin{bmatrix} g_{11} \\ g_{21} \end{bmatrix} V_s \tag{5}$$

where $f_{mn} = f_{mnx} + jf_{mny}$, $g_{m1} = g_{m1x} + jg_{m1y}$, *m=1, 2, n=1, 2.*

After some algebraic manipulations, it is possible to eliminate the rotor flux terms from equation (5), resulting in

$$\delta^2 i^2{}_s = f_1 \delta i_s + f_0 i_s + g_1 \delta V_s + g_0 V_s \tag{6}$$

where $f_1 = f_{11} + f_{22} = f_{1x} + jf_{1y}$, (7)

$$f_0 = f_{12} f_{21} - f_{22} f_{11} = f_{0x} + jf_{0y} \ , \tag{8}$$

$$g_1 = g_{11} = g_{1x} + jg_{1y} \ , \tag{9}$$

and $g_0 = f_{12} g_{21} - f_{22} g_{11} = g_{0x} + jg_{0y}$ (10)

Equation (6) represents the basic equation used to formulate the parameter estimation problem. It is possible to show that some parameters of the state-space model (equation (2) or equation (5)) can be recovered once the parameters of equation (6) have been determined. By assuming that f_1, f_0, g_1 and g_0 are determined, it is possible to calculate

$$g_{11} = g_1 \tag{11}$$

If the sampling rate is sufficiently high, the discrete-time model can be approximated by its continuous-time counter part, i.e., *F=A* and *G=B* and consequently $g_{21} = B_{21} = 0$ which yields

$$f_{22} = -g_0 / g_1 \tag{12}$$

$$f_{11} = f_1 + g_0 / g_1 \tag{13}$$

$$f_{12} f_{21} = f_0 - \frac{g_0}{g_1}\left(f_1 + g_0 / g_1\right) \tag{14}$$

and then, the model given by equation (6) becomes

$$\begin{aligned} \delta^2 i_s = &-\left(\frac{R_s + L_s / T_r}{\sigma L_s} + j\omega_r\right)\delta i_s - \frac{R_s}{\sigma L_s}\left(\frac{1}{T_r} + j\,\omega_r\right) i_s \\ &+ \frac{1}{\sigma L_s}\delta V_s + \frac{1}{\sigma L_s}\left(\frac{1}{T_r} + j\,\omega_r\right) V_s \end{aligned} \tag{15}$$

In terms of the real and imaginary components of V_s and i_s vectors, the continuous-time model given by equation (15) can be rewritten as:

$$\begin{aligned} \begin{bmatrix} \delta^2 i_{\alpha s} \\ \delta^2 i_{\beta s} \end{bmatrix} = &\begin{bmatrix} -\left(\frac{R_s + L_s / T_r}{\sigma L_s}\right) & -\omega_r \\ \omega_r & -\left(\frac{R_s + L_s / T_r}{\sigma L_s}\right) \end{bmatrix} \begin{bmatrix} \delta i_{\alpha s} \\ \delta i_{\beta s} \end{bmatrix} + \begin{bmatrix} -\frac{R_s}{\sigma L_s T_r} & -\frac{\omega_r R_s}{\sigma L_s} \\ \frac{\omega_r R_s}{\sigma L_s} & -\frac{R_s}{\sigma L_s T_r} \end{bmatrix} \begin{bmatrix} i_{\alpha s} \\ i_{\beta s} \end{bmatrix} \\ &+ \begin{bmatrix} \frac{1}{\sigma L_s} & 0 \\ 0 & \frac{1}{\sigma L_s} \end{bmatrix} \begin{bmatrix} \delta V_{\alpha s} \\ \delta V_{\beta s} \end{bmatrix} + \begin{bmatrix} \frac{R_s}{\sigma L_s T_r} & \frac{\omega_r}{\sigma L_s} \\ -\frac{\omega_r}{\sigma L_s} & \frac{R_s}{\sigma L_s T_r} \end{bmatrix} \begin{bmatrix} V_{\alpha s} \\ V_{\beta s} \end{bmatrix} \end{aligned} \tag{16}$$

This also indicates that $\delta\, x(t) = p\, x(t)$, where *p=d/dt*, since the delta operator can be interpreted as the forward-difference approximation of the differential operator.

3. Real Time Parameter Estimation Based on RLS Algorithm

To estimate the motor parameters using the RLS algorithm, it is necessary to rewrite the model equation (16) in the form of a regression equation such as:

$$y(t) = \Gamma(t)\beta \tag{17}$$

where $y(t)$, $\Gamma(t)$ and β are the prediction vector, the regression matrix and the unknown parameters vector respectively. Equation (16) may be rewritten as linear regression model simply by defining

$$y(t) = \begin{bmatrix} \delta^2 i_{\alpha s} \\ \delta^2 i_{\beta s} \end{bmatrix} \quad , \tag{18}$$

$$\Gamma(t) = \begin{bmatrix} -\delta i_{\alpha s} & -\delta i_{\beta s} & -i_{\alpha s} & -i_{\beta s} & -\delta V_{\alpha s} & V_{\alpha s} & V_{\beta s} \\ -\delta i_{\beta s} & \delta i_{\alpha s} & -i_{\beta s} & i_{\alpha s} & \delta V_{\beta s} & V_{\beta s} & -V_{\alpha s} \end{bmatrix} \tag{19}$$

and $$\beta = \begin{bmatrix} \frac{R_s L_r + R_r L_s}{\sigma L_s L_r} & \omega_r & \frac{R_s}{\sigma L_s T_r} & \frac{R_s \omega_r}{\sigma L_s} & \frac{1}{\sigma L_s} & \frac{1}{\sigma L_s T_r} & \frac{\omega_r}{\sigma L_s} \end{bmatrix} \tag{20}$$

The RLS algorithm for a regression model computes the unknown estimated parameters vectors $\hat{\beta}(N)$ in such a way that the weighted quadratic cost function (21) is minimized for *N* successive instants samples:

$$C = \sum_{n=1}^{N} \left| y(n) - \Gamma(n)\hat{\beta}(n) \right|^2 \tag{21}$$

The basic equations of the RLS estimation algorithm used to calculate the unknown parameters $\hat{\beta}$ can be found in [15]. In this algorithm, the time variation of the parameters is taken into account by the forgetting factor $\alpha(n)$. The forgetting factor is used to track the time variation of the unknown parameters.

Figure 1 shows the complete scheme of the electrical parameters estimator. In this scheme, the stator inputs phase voltages and line currents signals are measured simultaneously as well as the motor output speed. The measured stator voltage and current signals are transformed to d^s and q^s signals with stationary reference frame. The linear regression model (predictor) is fed by calculated d^s and q^s axis voltage and current signals in addition to motor speed ω_r. The error between the measured output of the actual motor model as influenced by saturation $y(t)$ and the (predicted model output) $\hat{y}(t)$ is then calculated. A weighted sum of the errors defined as the quadratic cost function is computed after completion of the simulation interval (t). The cost function is used to feed the full electrical parameter estimator based on RLS for estimating the vector $\hat{\beta}$ which in turn updates the parameters of linear regression model. This process continues until the sum of these errors is minimized.

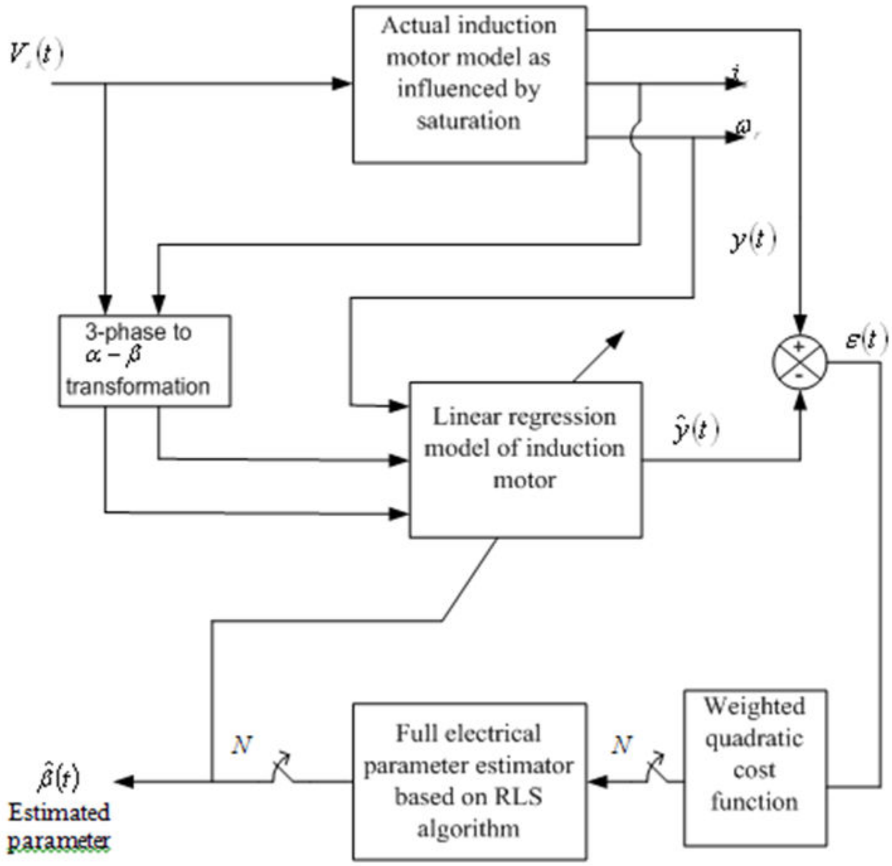

Fig. 1. Block diagram of the parameter estimator.

3.1 Estimation model of stator resistance

The stator resistance estimation together with the other parameters may cause in general an inaccurate estimation. Then, it is wise to develop a model to estimate the stator resistance independently of other parameters. If the machine is supplied with dc quantities, i.e. the stator frequency $\omega_s = 0$, equation (16) can be written as follows:

$$V_s = R_s i_s \tag{21}$$

Then, the regression model may be represented by

$$y(t) = \begin{bmatrix} V_{\alpha s} & V_{\beta s} \end{bmatrix}^T \tag{22}$$

$$\Gamma(t) = \begin{bmatrix} i_{\alpha s} & i_{\beta s} \end{bmatrix}^T \tag{23}$$

and

$$\beta = \begin{bmatrix} R_s \end{bmatrix} \tag{24}$$

The stator resistance estimator is accomplished online by adding a dc bias to the reference signals. This estimated value is considered when the stator windings are supplied with PWM waveforms and the machine is running under normal operating conditions.

3.2 Estimation model of stator leakage inductance

From equation (16) it is possible to derive the following regression model if the stator resistance has already been estimated.

$$y(t) = \begin{bmatrix} -\delta u_{\alpha s} - \omega_r u_{\beta s} \\ -\delta u_{\beta s} + \omega_r u_{\beta s} \end{bmatrix} \tag{25}$$

$$\Gamma(t) = \begin{bmatrix} -\delta^2 i_{\alpha s} - \omega_r \delta i_{\beta s} & u_{\alpha s} & -\delta i_{\alpha s} \\ -\delta^2 i_{\beta s} + \omega_r \delta i_{\alpha s} & u_{\beta s} & -\delta i_{\beta s} \end{bmatrix} \tag{26}$$

$$\beta = \begin{bmatrix} \sigma L_s & \dfrac{1}{T_r} & \dfrac{L_s}{T_r} \end{bmatrix}^T \tag{27}$$

where $u_{\alpha s} = V_{\alpha s} - R_s i_{\alpha s}$ and $u_{\beta s} = V_{\beta s} - R_s i_{\beta s}$

When the machine is supplied with sinusoidal PMW waveform, only the leakage inductance can be estimated with good accuracy. Due to high frequency components present in the voltage and current waveforms, the ratio $\dfrac{\partial \hat{y}(t)}{\partial(\sigma L_s)}$ becomes dominant over the other terms of the regression model.

By using equations (25)-(27), one may obtain σL_s as long as ω_r is available from speed estimator. A simpler model to determine σL_s independently of ω_r is possible. If the excitation frequency is sufficiently high such that $\omega_s \quad \omega_r$, the model given by (16) can be approximated by

$$V_{sh} = \sigma L_s \, \delta i_{sh} \tag{28}$$

where the subscript *h* in the above equation stands for the high frequency components of voltages and currents.

Then, from equation (28) the following regression model can be obtained

$$y(t) = \begin{bmatrix} V_{shd} & V_{shq} \end{bmatrix}^T \tag{29}$$

$$\Gamma(t) = \begin{bmatrix} \delta i_{shd} & \delta i_{shq} \end{bmatrix} \tag{30}$$

$$\beta = \begin{bmatrix} \sigma L_s \end{bmatrix} \tag{31}$$

3.3 Estimation model of rotor time constant and stator self inductance

To derive the equations for this model, it is assumed that the stator resistance and leakage inductance have been previously estimated.

In this case, one may derive from (16) the following regression model

$$y(t) = \begin{bmatrix} \delta^2 i_{\alpha s} - \dfrac{1}{\sigma L_s}\delta u_{\alpha s} - \omega_r \delta i_{\beta s} - \dfrac{\omega_r}{\sigma L_s} u_{\beta s} \\ \delta^2 i_{\beta s} - \dfrac{1}{\sigma L_s}\delta u_{\beta s} - \omega_r \delta i_{\alpha s} + \dfrac{\omega_r}{\sigma L_s} u_{\sigma s} \end{bmatrix} \tag{32}$$

$$\Gamma(t) = \begin{bmatrix} -\dfrac{1}{\sigma L_s}\delta i_{\alpha s} & \dfrac{1}{\sigma L_s} u_{\alpha s} \\ -\dfrac{1}{\sigma L_s}\delta i_{\beta s} & \dfrac{1}{\sigma L_s} u_{\beta s} \end{bmatrix} \tag{33}$$

and

$$\beta = \begin{bmatrix} \dfrac{L_s}{T_r} & \dfrac{1}{T_r} \end{bmatrix}^T \tag{34}$$

The unknown parameters β of the discrete-time model can be determined using equations (32)-(34).

4. Simulation and Experimental Results

In order to verify the validity and the performance of the proposed scheme of figure 1, computer simulations have been carried out using Matlab software. The test motor was a 9.8 H.P, 220 V, 50 Hz, delta connected, slip-ring induction motor. The rated current per phase was 15.1 A at 1450 rpm. Coupled to the motor was a DC generator of about the same rating. The equivalent circuit parameters for the motor were determined by the no-load and locked rotor tests (standard tests), in the usual manner.

The parameter estimation procedure is carried out using the presented regression equations and the RLS algorithm with forgetting factor. The sampling time is set to $\Delta t = 40\,\mu\text{sec}$ and the forgetting factor =0.99. The parameter estimation algorithm runs with the data generated by simulation program.

Table 1 illustrates the estimated mean values of electrical motor parameters obtained using the RLS algorithm and those obtained experimentally (standard tests). The third row shows the percentage error results. It can be noted that it is possible to estimate all electrical parameters with good precision (estimation errors between 2-4 %). These errors are small and tolerated to get good parameters estimation.

Table 1.
Estimated and standard induction motor parameters

Electrical parameters	R_s (Ohm)	σL_s (Henry)	L_s (Henry)	T_r (Sec.)
Using RLS algorithm	0.5300	0.0073	0.1165	0.2290
Experimentally	0.5150	0.0070	0.1210	0.2339
% |error|	2.9 %	4 %	3.7 %	2.1 %

Figure 2 shows the simulation results for stator resistance estimation with dc + sinusoidal waveform using the estimated model of equations (21)-(23). The estimation of the stator resistance in this case is obtained using a first-order low pass filter with suitable cutoff frequency to reduce the estimation time. The average value of the estimated stator resistance ($\hat{R}_s$ = 0.530 ohm) is in reasonable agreement with the measured one.

Figure 3 shows the simulation results for stator leakage inductance estimation with model given by equations (24)-(26). The previously estimated stator resistance is employed in this model. From this figure, it can be seen that the estimates converge quickly to the measured one and only the initial high transient peak (about 0.05 henry) due to the startup of the RLS algorithm is observed.

Figures 4 and 5 show the simulation results for the rotor time constant and the stator self inductance estimations as obtained from equations (27)-(29). The previously estimated values of stator leakage inductance and stator resistance are used with this model. It can be seen from these figures that the estimated values of rotor time constant and stator self inductance provide good performance i.e. fast convergence time and limited estimation errors.

From these figures 2-5, it can be seen that, the different estimated parameters follow the measured one very closely which indicates that the presented estimation procedure worked successful for motor parameter estimation. These results are confirmed by Table1

The validity of the presented method of estimating parameters is checked by comparing the calculated steady-state performance characteristics using estimated parameters and standard ones with those measured experimentally when the source voltage and frequency are maintained at their rated values.

Figure 6 shows that standard, estimated and experimental values of the motor per-unit speed versus motor torque. From this figure, it can be noted that the estimated values of motor speed and measured one have small deviation. The discrepancy between standard, estimated and experimental speed values, especially at high values of motor torque, is attributed to the mechanical loss which is disregarded from the machine model.

Figure 7 and Figure 8 show that standard, estimated and experimental value of stator current and input power factor. These figures indicate that, the estimated values are well matched and agree with their measured ones. On the other hand, large deviation between the standard values of stator current and input power factor and their experimental ones is due to the consideration that the machine parameters values are assumed to be constant at all operating conditions.

Figure 9 shows that standard, estimated and experimental values of the motor efficiency versus motor torque. From this figure, it can be noted that the estimated values of motor efficiency and measured one have small deviation. The discrepancy between estimated and experimental efficiency values, especially at high values of motor torque, is attributed to the mechanical loss which is disregarded from the equivalent circuit.

Figure 10 shows that standard, estimated and experimental value of the motor input power versus motor torque. From this figure it clears that, the estimated values of the motor input power and measured one have small deviation. On the other hand large deviation between the standard values of the motor input power and their experimental ones are due to the mechanical loss which is disregarded from the equivalent circuit.

From these figures (6-10) it can be seen that, using estimated parameter provide good calculation of the performance characteristics of induction motor. This indicates that the presented estimation procedure worked successful for motor parameter estimation.

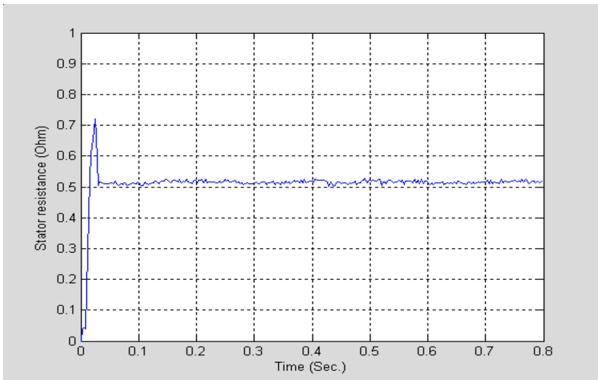

Fig. 2. Simulation results of stator resistance estimation

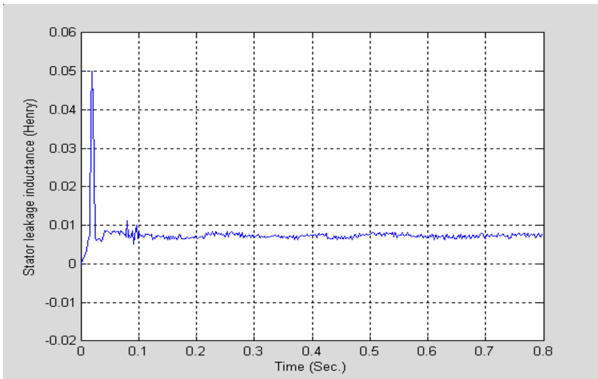

Fig. 3. Simulation results of stator leakage inductance estimation

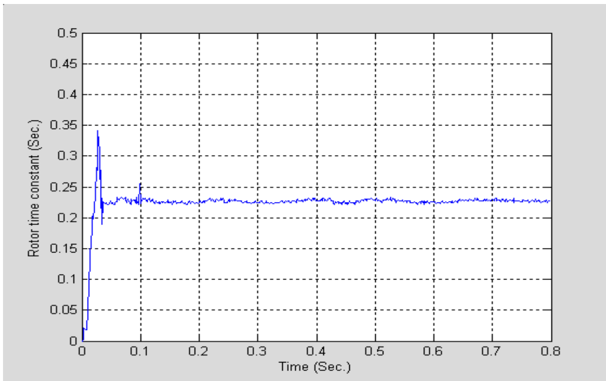

Fig. 4. Simulation results of rotor time constant estimation

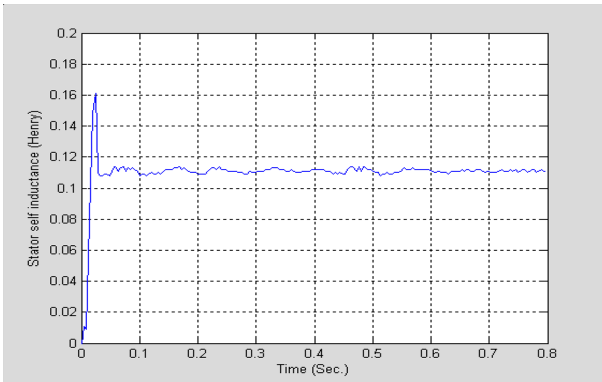

Fig. 5. Simulation results of stator self inductance estimation

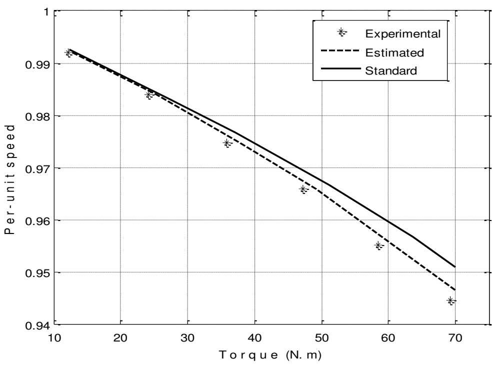

Fig. 6. Speed-Torque characteristics of induction motor.

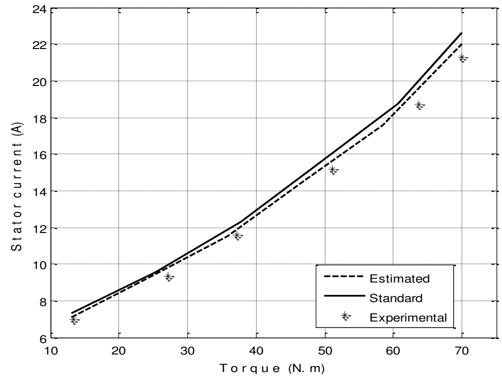

Fig. 7. Stator current versus torque characteristics of induction motor.

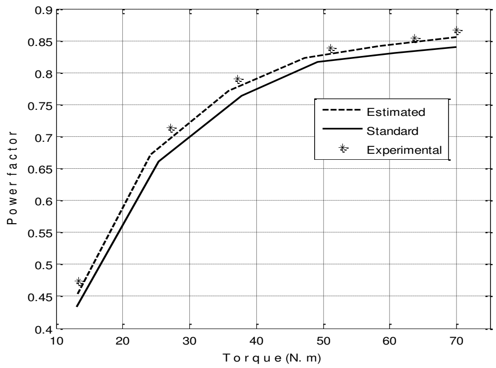

Fig. 8. Power factor versus torque characteristics of induction motor.

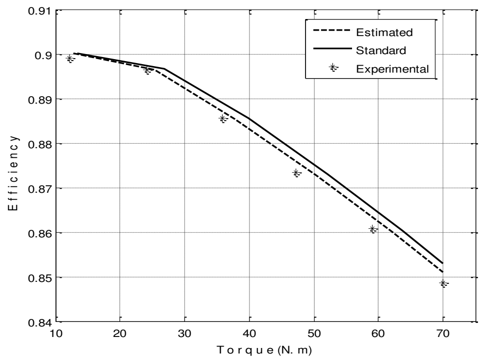

Fig. 9. Motor efficiency versus torque characteristics of induction motor.

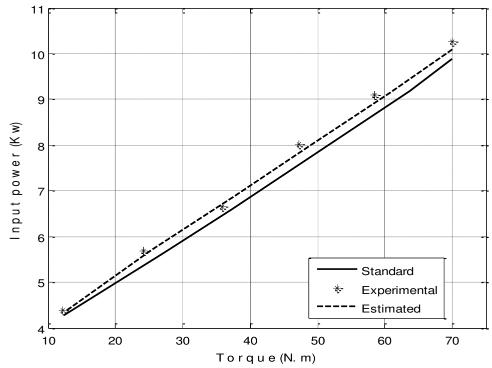

Fig. 10. Input power versus torque characteristics of induction motor.

5. Conclusion

This paper presents, an efficient methodology to online estimation of the basic electrical parameter set ($R_s, \sigma L_s, L_s$ and T_r) of an induction motor using linear estimation techniques. These parameters are important for high performance of induction motor drives. The estimation models take the form of linear regression equations which are derived from the dynamical machine model. The RLS algorithm is applied successfully for estimating the machine parameter vectors of the linear regression equations using the measurements of stator voltages, currents and motor speed. The estimation is carried out by using PWM voltage waveform. The accuracy of the estimated parameters using the proposed technique is in reasonable agreement with those obtained experimentally. It can be seen from the experimental results that the performance characteristics which is obtained using estimated parameters follow the experimental ones very closely. This indicates that the proposed identification procedure worked successfully for induction motor parameters estimation.

From the present analysis, one can draw the following main conclusions:

1- The special procedure that uses a small dc bias and a low pass filter to estimate the stator resistance gives good results.

2- The estimated parameters ($R_s, \sigma L_s, L_s$ and T_r) have provided good performances, i.e. fast convergence time and track well their standard ones with small estimation errors.

3- The presented regression models have provided good estimation accuracy regardless of load conditions.

4- Good agreements between experimental and calculated steady-state performances using the estimated parameters demonstrate the effectiveness of the proposed identification algorithm.

6. References

[1] C. L. Becnel, J. W. Kilgrore and E. F. Merrill, " Determining Motor Efficiency by Field Testing " IEEE Transactions on Industry Applications, Vol. IA-23, No. 3, pp. 440-443, 1987.

[2] T. W. Jian, D. W. Novotny and N. L. Schmitz, " Characteristic Induction Motor Values for Variable Voltage Part Load Performance Optimization " IEEE Transactions on Power Apparatus and Systems, Vol. PAS-102, pp. 38-46, 1983.
[3] D. S. Kirschen, D. W. Novotny and T. A. Lipo, " Optimal Efficiency of an Induction Motor Drives, " IEEE Transactions on Energy Conversion, Vol. EC-2, No. 1, pp. 70-75, 1987.
[4] P. Vas, Parameter Estimation, Condition Monitoring, and Diagnosis of Electrical Machines, Oxford Science Publications, 1993.
[5] H. A. Toliyat, E. Levi, M. Raina, " A Review of RFO Induction Motor Parameter Estimation Techniques", IEEE Trans. On Energy Conversion, Vol. 18, No. 2, pp.271-283, 2003.
[6] K. Minami, M.Veles-Reyes, D. Elten, G. C. Verghese, and D. Filbert, "Multi-Stage Speed and Parameter Estimation for Induction Machines", in Proc. IEEE PESC'91, 1991, pp. 596-604.
[7] P. R. Nchez, et al., "Rotor-Resistance Estimation for Induction Machines with Indirect-Field Orientation", Control Engineering Practice, Elsevier, Vol.15, No.9, September 2007.
[8] H. B. Karayaka, M.N. Marwali, and A. Keyhani, "Induction Machines Parameter Tracking from Test Data Via PWM Inverters", in Conf. Rec. IEEE-IAS Annu. Meeting, 1997, pp.227-233.
[9] L. A. de S. Riberiro and A. M. N. Lima " Parameter Estimation of Induction Machines Under Sinusoidal PWM Excitation", IEEE Trans. On Energy Conversion, Vol. 14, No. 4, December 1999, pp. 1218-1223.
[10] Peretti, L.and Zigliotto, M., "Automatic procedure for induction motor parameter estimation at standstill", Electric Power Applications, IET Vol.6 , Issue. 4, pp. 214-224, April 2012.
[11] A. M. N. Lima, C. B. Jacobina, and E. B. de Souze Filho, "Nonlinear Parameter Estimation of Steady-state Induction Machine Models", IEEE Trans. Ind. Electron., Vol. 44, pp. 390-397, June 1997.
[12] Aksoy, S., Muhurcu, A., and Kizmaz, H., "State and parameter estimation in induction motor using the Extended Kalman Filtering algorithm, "Modern Electric Power Systems (MEPS), 2010 Proceedings of the International Symposium, pp. 1-5, 20-22 Sept. 2010.
[13] L. Loron and G. Laliberte, " Application of the Extended Kalman Filter to Parameter Estimation of Induction Motors, " The European Power Electronics Association, pp. 73-78, Sept. 1993.
[14] Barut, M., Demir, R. ; Zerdali, E., and Inan, R., "Real-Time Implementation of Bi Input-Extended Kalman Filter-Based Estimator for Speed-Sensorless Control of Induction Motors, " Industrial Electronics, IEEE Transactions on (Volume:59 , Issue: 11), pp. 4197 - 4206, Nov. 2012.
[15] R. H. Middeton and G. C. Goodwin, Digital Control and Estimation, Vol. 1, Prentice-Hall, Inc., Englewood Cliffs, New Jersey, First Edn., 1990.

Appendix I

Experimental Set-Up

A dc machine was mechanically coupled to a three-phase slip-ring induction motor to provide a mechanical load when operated in the generator mode. The armature current was changed by varying the load resistance to operate the induction motor in the stable portion of the torque-speed characteristics. The experimental values are listed in table I.1

Table 1.

Experimental results

Motor Torque (N.m)	12.3	24.11	35.7947	47.2671	58.4465	69.1672
Per unit speed	0.9447	0.9447	0.9660	0.9747	0.984	0.9920
Input current (A)	6.9589	9.3509	11.5993	15.1567	18.699	21.3
Input power factor	0.433	0.6614	0.763	0.816	0.830	0.84
Efficiency	0.8991	0.8964	0.8856	0.8733	0.8608	0.8485
Input power (kw)	4.3771	5.6862	6.6862	8.0146	9.1	10.2692

تقدير ثوابت معاملات المحرك الحثى أثناء التشغيل باستخدام الطريقة التكرارية لحساب اقل قيمة لحيود مجموع المربعات

الملخص العربى :

يقدم هذا البحث طريقة خطية لحساب ثوابت المعاملات الكهربية للمحرك الحثى وهذه الثوابت هى مقاومة العضو الثابت والحث المتسرب والحث الذاتى وكذلك ثابت الزمن لدائرة العضو الدوار .ويمثل حساب تلك الثوابت المذكورة اهمية كبرى عند تصميم نظم الدفع ذات الاداء العالى للمحركات الحثية .

تم عمل نماج لتقييم ثوابت المعاملات تعبر عن العلاقة بين النموذج الديناميكى للمحرك وقيم الجهود والتيارات المقاسة لدائرة العضو الثابت وكذلك سرعة المحرك .هذه النماذج يمكن تمثيلها بوسطة معادلات خطية وذلك للحصول على ثوابت معاملات الماكينة وذلك باستخدام الطريقة التكرارية لحساب اقل قيمة لحيود مجموع المربعات .طرق تقييم ثوابت المعاملات تعطى تقدير دقيق للثوابت دون النظر لقيمة الحمل ومن السهل ادخال الثوابت المقيمة مع انظمة التحكم المختلفة مثل التحكم الاتجاهى المباشر والغير مباشر وقد اثبتت النتائج العملية والتمثيلية التى تم طرحها فى هذا البحث جودة ودقة الطرق المقترحة فى حساب ثوابت المعاملات الكهربية وكذالك معرفة اداء خواص المحرك فى الحالة المستقرة عند جميع ظروف التحميل المختلف للمحرك.