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Neural learning adaptive system using simplified reactive power reference model based speed estimation in sensorless indirect vector controlled induction motor drives

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Abstract: This paper presents a novel speed estimator using Reactive Power based Model Reference Neural Learning Adaptive System (RP-MRNLAS) for sensorless indirect vector controlled induction motor drives. The Model Reference Adaptive System (MRAS) based speed estimator using simplified reactive power equations is one of the speed estimation method used for sensor-less indirect vector controlled induction motor drives. The conventional MRAS speed estimator uses PI controller for adaptation mechanism. The nonlinear mapping capability of Neural Network (NN) and the powerful learning algorithms have increased the applications of NN in power electronics and drives. This paper proposes the use of neural learning algorithm for adaptation in a reactive power technique based MRAS for speed estimation. The proposed scheme combines the advantages of simplified reactive power technique and the capability of neural learning algorithm to form a scheme named "Reactive Power based Model Reference Neural Learning Adaptive System" (RP-MRNLAS) for speed estimator in Sensorless Indirect Vector Controlled Induction Motor Drives. The proposed RP-MRNLAS is compared in terms of accuracy, integrator drift problems and stator resistance versions with the commonly used Rotor Flux based MRNLAS (RF-MRNLAS) for the same system and validated through Matlab/Simulink. The superiority of the RP-MRNLAS technique is demonstrated.

Key words: sensorless indirect vector controlled IM drives, speed estimator, reactive power, MRAS, neural network, back propagation algorithm

1. Introduction

Induction motors are applied today, to a wide range of applications requiring variable speed. Accurate speed measurement is necessary to realize high performance and high-precision speed control operation of vector controlled induction motor drive. The speed is obtained by using mechanical sensors as resolver or pulse encoders. However, these sensors are usually expensive, bulky, and subject to failures under hostile industrial environments. Therefore, the cost and size of the drive systems are increased. Speed sensorless closed loop control of induction motor drives, leads to cheaper and reliable control. Therefore sensorless control of induction motor drives has become an active area of research. Advances in digital technology have made the sensorless control realizable by industries for high performance variable speed applications.

Since the late 1980s, speed-sensorless control methods of induction motors using the estimated speed instead of the measured speed have been reported. They have estimated speed from the instantaneous values of stator voltages and currents using induction motor model, which has difficulty in determining the instantaneous orientation of the flux vector. Other approaches to estimate speed use Rotor Slot Harmonic, Extended Kalman Filter (EKF), Extended Luenbergern Observer (ELO), Saliency Techniques and Model Reference Adaptive System (MRAS) [1-21]. MRAS schemes offer simpler implementation and require less computational effort compared to other methods and are therefore the most popular among the strategies used for sensor-less control IM drives [1-8, 10-12, 14-16].

In MRAS system, the outputs of two models, one independent of the rotor speed (reference model) and the other dependent (adjustable model) are used. The error vector is driven to zero by an adaptation mechanism (PI-controller) which yields the estimated rotor speed. Depending on the choice of output quantities that form the error vector (flux, stator current, back EMF, reactive power, etc), several MRAS structures are possible [1-4, 8-12, 21]. The most common MRAS structure is that based on the rotor flux error vector [1-4, 8-11]. The selection of reactive power as a function for MRAS based speed estimator deduces simpler system model equation independent of flux, which is easier to design and implement and become advantageous on real time applications [1, 2, 4]. For sensorless indirect vector controlled induction motor drives, the reactive power based MRAS makes the model equations much simpler for speed estimation [1]. Conventional MRAS schemes use PI controller as the adaptive mechanism for speed estimation.

Recently, the use of Neural Networks (NNs) for identification and control of nonlinear dynamic systems in power electronics and drives have been proposed as they are capable of approximating wide range of nonlinear functions to any desired degree of accuracy [5, 7, 14-17, 22]. Powerful learning algorithms have been developed for neural networks [23, 24].

This paper uses neural learning algorithm as an adaptation mechanism in MRAS instead of the PI controller. This method is named as “Model Reference Neural Learning Adaptive System” (MRNLAS). In MRNLAS based speed estimation, error between reference model and neural learning adaptive model is back propagated to adjust the weights of neural learning adaptive model to estimate the speed of an induction motor drive. A number of learning algorithms are available for supervised learning of NN. As this application requires on-line learning the back propagation with momentum algorithm is chosen as it the simplest algorithm with minimum time for convergence.

The learning algorithm is based on powerful steepest descent method [23, 24]. In this method, the weights of NN are adjusted in steps to minimize performance index: mean squared error. The learning rate employed in the algorithm determines the step size. Larger value of learning rate means faster learning of NN. But, this can lead to oscillations in the output and miss the global minimum point. To overcome this difficulty and reduce oscillations in the output, a momentum term is added to smoothen the oscillations and accelerate the convergence.

Hence, in this paper a novel speed estimator using simplified Reactive Power based MRNLAS (RP-MRNLAS) is proposed. The proposed scheme combines the advantages of reactive power technique and the capability of neural learning algorithm to form a scheme named "Reactive Power based Model Reference Neural Learning Adaptive System" (RP-MRNLAS) for speed estimator in Sensorless Indirect Vector Controlled Induction Motor Drives. The proposed RP-MRNLAS is compared in terms of accuracy, integrator drift problems and stator resistance versions with commonly used Rotor Flux based MRNLAS (RF-MRNLAS) for the same system and validated through Matlab/Simulink to identify the most suitable speed estimation method for sensorless indirect vector controlled induction motor drives.

Section 2 briefly outlines the proposed RP-MRNLAS based speed estimator utilizing simplified reactive power equations for both the reference model and neural learning adaptive model and commonly used Rotor Flux based MRNLAS model (RF-MRNLAS). Section 3 describes the closed loop operation of speed sensor-less indirect vector controlled induction motor drives. Section 4 details the simulation results obtained for the proposed RP-MRNLAS based speed estimator. Section 5 compares the proposed RP-MRNLAS with commonly used RF-MRNLAS. Section 6 concludes the paper.

2. Model reference neural learning adaptive system (MRNLAS) based speed estimator

2.1. Rotor Flux based MRNLAS Structure (RF-MRNLAS)

The speed of an induction motor can be estimated using the neural learning algorithm based MRAS system as illustrated in Figure 1. In this method of speed estimation, the rotor fluxes of the induction motor are selected to represent the actual and estimated state variables. Two independent observers are used to estimate the rotor flux of the induction motor. Equation (1) based on stator voltages and currents called as voltage model equation (reference model) which is independent of speed and Equation (2) is based on stator currents and rotor speed called as current model equations. The current model equations are represented as the neural learning adaptive model [7, 14, 15]. The Neural Learning Algorithm is used as an adaptive mechanism for rotor speed estimation.

The flux estimation using voltage model equations are used as the reference value and the flux estimation using neural representation of current model equations are used as estimated value. The difference between these state variables is then used by the neural learning mechanism (adaptation mechanism) to track the actual speed. The learning continues until the performance index is met.

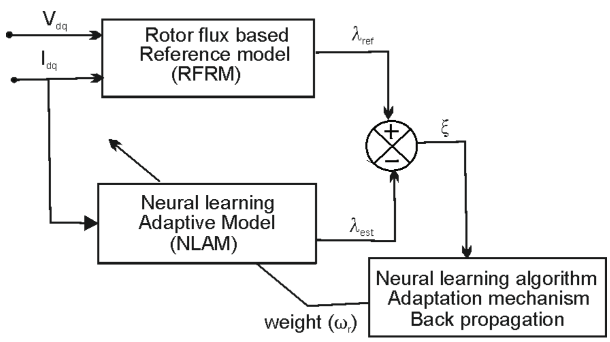

Fig. 1. Speed estimation using rotor flux based MRNLAS (RF-MRNLAS)

Voltage Model

$$\begin{bmatrix} \dfrac{d\lambda_{dr}}{dt} \\ \dfrac{d\lambda_{qr}}{dt} \end{bmatrix} = \frac{L_r}{L_m}\left[\begin{bmatrix} V_{ds} \\ V_{qs} \end{bmatrix} - \begin{bmatrix} R_s + s\sigma L_s & 0 \\ 0 & R_s + s\sigma L_s \end{bmatrix}\begin{bmatrix} I_{ds} \\ I_{qs} \end{bmatrix}\right]. \tag{1}$$

Current Model

$$\begin{bmatrix} \dfrac{d\lambda_{dr}}{dt} \\ \dfrac{d\lambda_{qr}}{dt} \end{bmatrix} = \begin{bmatrix} \dfrac{-1}{T_r} & -\omega_r \\ \omega_r & \dfrac{-1}{T_r} \end{bmatrix}\begin{bmatrix} \lambda_{dr} \\ \lambda_{qr} \end{bmatrix} + \frac{L_m}{T_r}\begin{bmatrix} I_{ds} \\ I_{qs} \end{bmatrix}. \tag{2}$$

$$\lambda_{dr}(k) = W_1\lambda_{dr}(k-1) - W_2\lambda_{qr}(k-1) + W_3\lambda_{ds}(k-1), \tag{3}$$

$$\lambda_{qr}(k) = W_1\lambda_{qr}(k-1) - W_2\lambda_{dr}(k-1) + W_3\lambda_{qs}(k-1), \tag{4}$$

where,

$$W_1 = 1 - (T_s/T_r), \quad W_2 = \omega_r T_s \quad and \quad W_3 = ((L_m T_s)/T_r,$$

T_s is the sampling time.

The update equations for rotor speed estimation of RF-MRNLAS are given in [7, 14, 15]. The reference model of commonly used RF-MRNLAS schemes depends on pure integrators and stator resistance, because it is voltage model of induction motor. The selection of reactive power as a function for MRNLAS (RP-MRNLAS) based speed estimator deduces simpler system model, which is easier to design and implement and become advantageous on real time applications [1, 2, 4]. The reference and adaptive model equations of proposed RP-MRNLAS schemes are derived using reactive power which is independent of the flux, pure integrator, stator resistance and derivative terms.

2.2. Proposed speed estimator using simplified reactive power based MRNLAS structure (RP-MRNLAS)

The state variable used is the reactive power. The reference model and neural learning adaptive model compute instantaneous reactive power (Q_{ref}) and steady-state reactive power (Q_{est}) respectively. The reference model is independent of ω_e where as the adjustable model depends on ω_e. The error signal ($\xi = Q_{ref} - Q_{est}$) is back propagated to adjust the weight ($\omega_e =$ $= Weight$) of the neural learning adaptive model. The rotor speed (ω_r) is then computed using $\omega_r = \omega_e - \omega_{sl}$, where, ω_e is stator frequency and ω_{sl} is slip frequency.

The block diagram of proposed Reactive Power based MRNLAS (RP-MRNLAS) system for rotor/motor speed estimation is illustrated in Figure 2. The equations defining the induction motor reference model and adjustable model based on reactive power are given below.

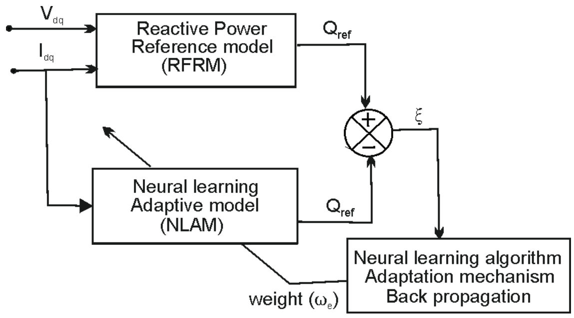

Fig. 2. Speed estimator using reactive power based MRNLAS (RP-MRNLAS)

The d and q axis stator voltages of an induction motor can be expressed on synchronously rotating reference frame as given in (5) and (6).

$$V_{ds} = R_s I_{ds} + \sigma L_s \frac{d}{dt} I_{ds} + \frac{L_m}{L_r}\frac{d}{dt}\lambda_{dr} - \sigma L_s \omega_e I_{qs} - \omega_e \frac{L_m}{L_r}\lambda_{qr}, \tag{5}$$

$$V_{qs} = R_s I_{qs} + \sigma L_s \frac{d}{dt} I_{qs} + \frac{L_m}{L_r}\frac{d}{dt}\lambda_{qr} - \sigma L_s \omega_e I_{ds} - \omega_e \frac{L_m}{L_r}\lambda_{dr}, \tag{6}$$

The actual instantaneous reactive power (Q_{ref}) absorbed by the induction motor can be expressed as in (7). Using the flux and parameter of the induction motor, the estimated reactive power (Q_{est}) can be expressed as (8).

$$Q_{ref} = V_{qs} I_{ds} - V_{ds} I_{qs} \tag{7}$$

$$Q_{est} = \omega_e \sigma L_s \left(I_{ds}^2 + I_{qs}^2\right) + \omega_e \frac{L_m}{L_r}\left(\lambda_{qs} I_{qs} + \lambda_{qs} I_{qs}\right). \tag{8}$$

Substituting the condition $\lambda_{dr} = L_m I_{ds}$ and $\lambda_{qr} = 0$ for the indirect field oriented control (IFOC) IM drive in (8), the more simplified expression of Q is (9, 10). The Equation (9) is rewritten in the form of neural network and is presented in (11)

$$Q_{est} = \sigma L_s \omega_e \left(I_{ds}^2 + I_{qs}^2\right) + \omega_e \frac{L_m^2}{L_r} I_{ds}^2, \tag{9}$$

$$Q_{est} = \omega_e \left(\sigma L_s \left(I_{ds}^2 + I_{qs}^2\right) + \frac{L_m^2}{L_r} I_{ds}^2 \right), \tag{10}$$

$$Q_{est} = W_1 P, \tag{11}$$

where:

$$W_1 = \omega_e \quad \text{and} \quad P = \sigma L_s \left(I_{ds}^2 + I_{qs}^2\right) + \frac{L_m^2}{L_r} I_{ds}^2.$$

The neural learning algorithm is obtained for the model represented by the Equation (11), where W_1 represents the weight of the network and P is a function of currents and parameters of the induction motor. The input to the neural learning adaptive model is current as shown in Figure 2. The energy function E minimizes the difference between actual and estimated reactive power and is given in equation (12). The Back-propagation learning rule with momentum is used to minimize the energy function. For the neural learning adaptive model the change in weight is given in Equation (13). The stability of the neural learning adaptive mechanism depends on learning rate (α) and momentum (η). Appropriate choice of learning rate (α) and momentum (η) will yield the best results. The learning rate (α) and momentum (η) should lie between 0 to 1 for the system to be stable. The weight update equations are given in Equation (14). The estimated stator frequency (ω_e) can be calculated from W_1 and rotor speed (ω_r) is obtained using the relation $\omega_r = \omega_e - \omega_{sl}$.

$$E = \frac{1}{2}\left(Q_{ref} - Q_{est}\right)^2, \tag{12}$$

$$\Delta W_1(k) = \alpha \left[E \; P\right], \tag{13}$$

$$W_1(k) = W_1(k-1) + \Delta W_1(k) + \eta \, \Delta W_1(k-1). \tag{14}$$

3. Sensorless indirect vector controlled IM drives with proposed RP-MRNLAS

The speed sensorless vector control presented here is indirect field oriented control (rotor flux oriented control). Figure 3 shows the overall block diagram of the speed sensorless drive system of an induction motor using an RP-MRNLAS speed estimator. The system consists of a solid state IM drive system, rotor flux oriented control, and RP-MRNLAS speed estimator. RP-MRNLAS speed estimator as explained in section II. Rotor flux oriented control consists of a PI speed controller, a current controller, and PWM generator.

The torque command is generated as a function of the speed error signal, generally processed through a PI controller. The torque and flux command are processed in the calculation block. The three phase reference current generated from the functional block is compared with the actual current in the hysteresis band current controller and the controller takes the necessary action to produce PWM pulses. The PWM pulses are used to trigger the current source inverter to drive the Induction motor.

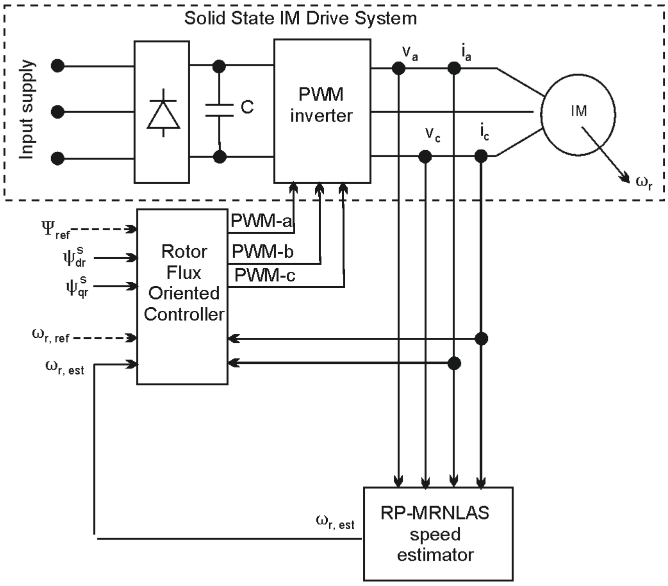

Fig. 3. Sensor-less indirect vector controlled IM drives with proposed RP-MRNLAS speed estimators

4. Simulation results and discussion of proposed RP-MRNLAS

The performance of proposed RP-MRNLAS based rotor speed estimation utilizing the reactive power technique for sensorless indirect vector controlled induction motor drives is analyzed extensively under various operating conditions through Matlab/Simulink. The sample results for proposed RP-MRNLAS model are shown for the following operating conditions as listed below:

4.1. Test 1. Stair case speed transients from 50 to 0 to −50 rad/sec at no load

In this test, the IM drive is subjected to a stair case speed commands from 50 rad/sec to zero speed in a series of five 25 rad/sec steps continuing to −50 rad/sec, at no load. The performance of proposed speed estimation scheme is shown in Figure 4(a). The mismatch error curve between actual and estimated speed is presented in Figure 4(b). The speed estimated from the proposed speed estimation scheme is found to closely match with the actual speed in steady state. Also the results depict stable operation for the proposed speed estimation scheme, particularly around zero speed.

4.2. Test 2. Load torque impact of 100% at 100 rad/sec

The test condition 2 examines the load torque disturbance capability of the proposed speed estimation scheme. The drive is operated with reference speed of 100 rad/sec. 100% step change in load torque is applied at 2.5 sec and rejected at 4 sec. The proposed speed estimation scheme shows better steady state and dynamic performance with negligible steady state error between the actual and estimated speed, as shown in Figure 5(a) and Figure 5(b).

4.3. Test 3. Low speed operation with effect of loading

The load torque disturbance capability of the proposed speed estimation scheme at very low speed of 10 rad/sec with load is examined. The proposed speed estimation scheme estimate speed with good accuracy even in the case of very low speed under 50% load condition as presented in Figure 6(a). The speed estimation error between actual and estimated speed is observed in Figure 6(b). It is noticed that the estimation error is negligible at steady state.

4.4. Test 4. ±100 rad/sec speed at no load

The high speed reversal capability of proposed speed estimation scheme is presented in test condition 4. Initially, the drive is operated with the speed command of 100 rad/sec and the speed command is gradually reduced to –100 rad/sec. The performance of proposed speed estimation scheme is shown in Figure 7(a). It is noticed that the sensorless drive is operated with full stability in the speed reversal mode. The steady state error between the actual and estimated speed is very small and it is presented in Figure 7(b). The estimated speed follows the actual speed with good accuracy under speed reversal mode also. The proposed speed estimation scheme shows better performance and found to estimate speed with negligible error.

4.5. Test 5. ±1 rad/sec speed at no load

This condition deals the performance of proposed speed estimation scheme for very low speed reversal under no load. Initially, the drive is operated with the speed command of 1 rad/sec up to 3 sec and the speed command is gradually reduced to –1 rad/sec. The performance of proposed speed estimation scheme is shown in Figure 8(a). The proposed speed estimation scheme performance better under steady state with negligible error and the estimated speed closely matches the actual speed. The error between actual and estimated speed is shown in Figure 8(b).

4.6. Test 6. Zero speed operation

The performance of the proposed estimator at zero speed is tested through simulation and the results are presented in Figure 9(a) and error curve is shown in Figure 9(b). The drive is operated at zero speed from 3 to 5 sec. It is observed that the estimated speed follows the actual speed with good accuracy.

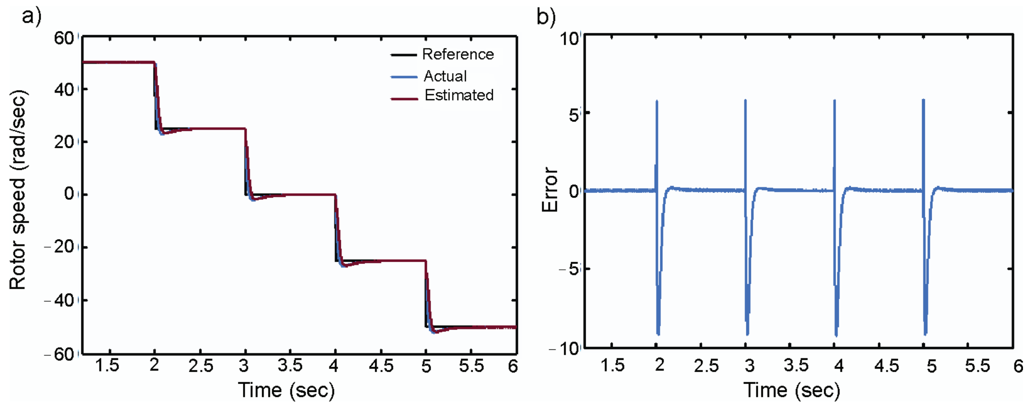

Fig. 4. Performance curves for test condition-1: (a) actual and estimated speed, (b) error between actual and estimated

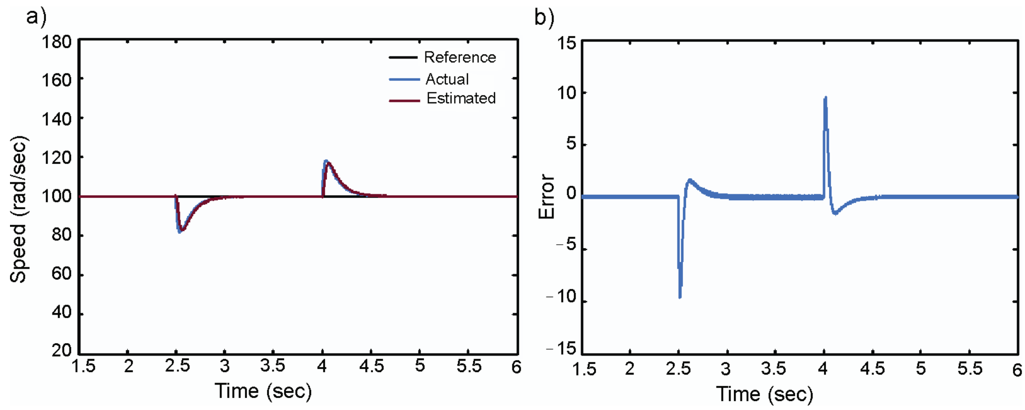

Fig. 5. Performance curves for test condition-2: (a) actual and estimated speed, (b) error between actual and estimated

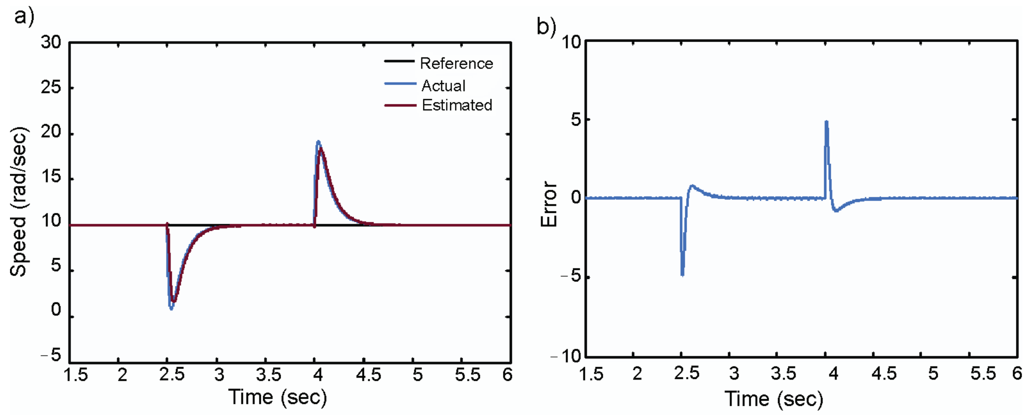

Fig. 6. Performance curves for test condition-3: (a) actual and estimated speed, (b) error between actual and estimated

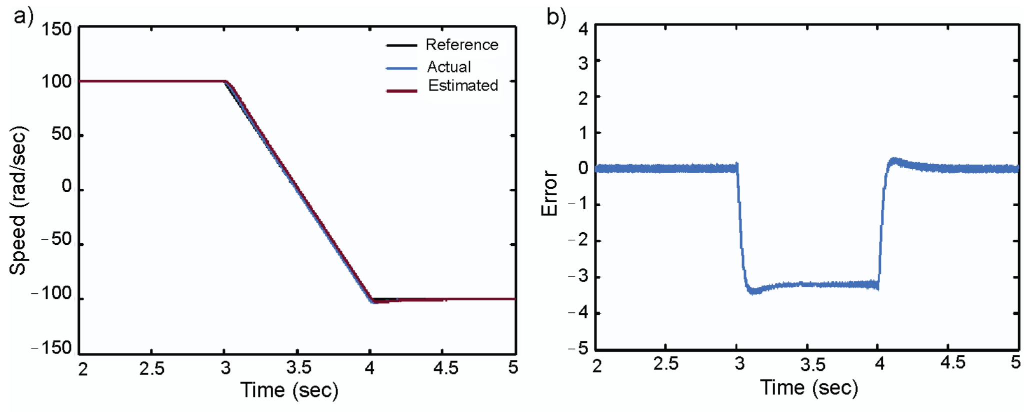

Fig. 7. Performance curves for test condition-4: (a) actual and estimated speed, (b) error between actual and estimated

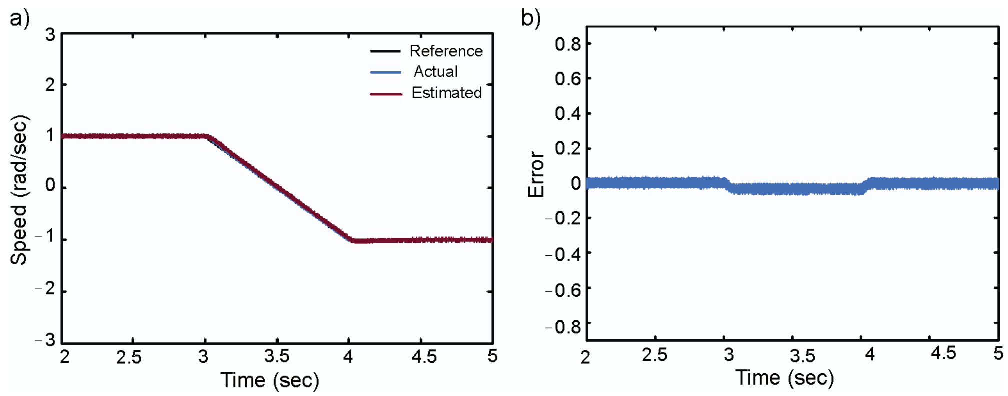

Fig. 8. Performance curves for test condition-5: (a) actual and estimated speed, (b) error between actual and estimated

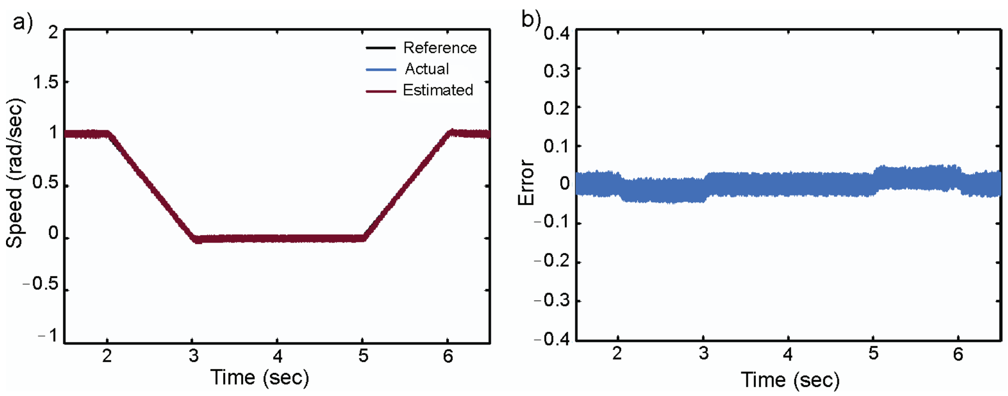

Fig. 9. Performance curves for test condition-6: (a) actual and estimated speed, (b) error between actual and estimated

5. Performance comparison of proposed RP-MRNLAS and RF-MRNLAS speed estimator for stator resistance variation and integrator drift problems

The comparisons of proposed RP-MRNLAS and commonly used RF-MRNLAS for speed estimation in sensorless indirect vector controlled induction motor drives under steady state are carried out at 0% and 100% loaded conditions. The results obtained are consolidated and presented in Table 1 and Table 2.

Table 1. Performance of the proposed RP-MRNLAS and RF-MRNLAS based speed estimator for various speed commands under 0% load condition

Reference speed	Actual speed (rad/sec)	RP-MRNLAS		RF-MRNLAS	
		Estimated speed (rad/sec)	% Error (rad/sec)	Estimated speed (rad/sec)	% Error (rad/sec)
145	145.001	144.998	0.002	145.033	−0.022
125	125.003	125.075	−0.057	125.042	−0.031
100	99.998	99.943	0.055	100.031	−0.088
75	75.004	75.025	−0.027	75.029	−0.033
50	49.995	49.984	0.022	50.026	−0.062
25	25.006	24.981	0.099	25.032	−0.103
5	4.999	4.980	0.380	5.007	−0.160
1	0.999	1.004	**−0.500**	0.984	**1.501**

Table 2. Performance of the proposed RP-MRNLAS and RF-MRNLAS based speed estimator for various speed commands under 100% load condition

Reference speed	Actual speed (rad/sec)	RP-MRNLAS		RF-MRNLAS	
		Estimated speed (rad/sec)	% Error (rad/sec)	Estimated speed (rad/sec)	% Error (rad/sec)
145	145.001	145.012	−0.007	145.025	−0.016
125	124.998	124.984	0.011	125.011	−0.010
100	100.000	100.124	−0.124	100.003	0.120
75	74.999	74.929	0.093	75.002	−0.004
50	49.999	50.031	−0.064	50,009	−0.020
25	25.000	25.039	−0.156	25.019	−0.076
5	5.003	5.008	−0.099	5.025	−0.439
1	0.999	1.001	−**0.200**	0.989	**1.001**

From the Tables, it is observed that MRNLAS schemes based speed estimator works very well for a wide range of operating conditions from 1 rad/sec to 145 rad/sec. The error between the actual and estimated speed from the proposed RP-MRNLAS and commonly used RF-MRNLAS for various operating conditions is computed at 0% and 100% loaded conditions under steady state and is presented in Tables 1 and 2. The error in the speed estimation from the commonly used RF-MRNLAS scheme under no load condition is found to be within ± 0.1% for normal operating speed range and maximum value of ± 1.5% at low and very low speeds. Under full load condition, the error in the speed estimation from the commonly used RF-MRNLAS scheme always lies within ± 0.1% for normal operating speed range and ± 1% for low and very low speeds. The proposed RP-MRNLAS estimates the speed under no load condition with an accuracy of ± 0.09% for normal operating speed range and maximum value of ± 0.5% at low and very low speed. The error in the speed estimated from the proposed RP-MRNLAS scheme under full load condition is found to be within ±0.1% for normal operating speed range and ±0.2% for low and very low speeds. From the Tables 1 and 2, it is clear that proposed RP-MRNLAS model has same accuracy as that of RF-MRNLAS, but for implementation it is required less complex model. The RP-MRNLAS is simpler and easy to implement in the low cost digital hardware when compared to commonly used RF-MRNLAS.

The performance comparisons of proposed RP-MRNLAS and commonly used RF-MRNLAS for speed estimation in sensorless indirect vector controlled induction motor drives for stator resistance (R_s) variation and integrated drift problems under steady state are also carried out in Matlab/Simulink and the results obtained are consolidated and presented.

5.1. Stator resistance variation

The performance of proposed RP-MRNLAS and commonly used RF-MRNLAS is tested for step change in stator resistance variation. Of course, in a real drive, the stator resistance never undergoes abrupt variations in response to temperature change due to the large thermal time constant. The step variation represents an extreme case and is used to show the robustness of the proposed RP-MRNLAS based speed estimation scheme. The effect of R_s variation is investigated at very low speed of 1 rad/sec with 50% load condition. Two different cases for stator resistance detuning are considered.

5.1.1. Slight R_s detuning

The actual R_s of the induction motor is slightly increased with respect to the nominal ones as follows:

$$\frac{\Delta R_s}{R_s} = -5\%.$$

In this case, the performance of proposed speed estimation scheme and commonly used speed estimation scheme is tested for 5% increase in stator resistance. 5% step change in R_s is effected at 2sec. The speed estimated from the proposed flux eliminated RP-MRNLAS model and commonly used RF-MRNLAS model is presented in Figure 10(a) and 10(b) respectively. From the results obtained, it is obvious that the speed estimated from the RP-MRNLAS model tracks closely the actual speed even when there is a change in the parameter and the error in the speed estimation is almost negligible whereas the speed estimated from the commonly used RF-MRNLAS model fluctuates between 0.557 rad/sec and 1.313 rad/sec. The flux eliminated RP-MRNLAS based speed estimation is shown to overcome the R_s variation problem.

5.1.2. Large R_s detuning

In many real applications, the R_s may vary on ranges which are larger than those considered in previous section. In order to check the robustness of the proposed speed estimator in the presence of larger detuning, the actual R_s of the induction motor is increased to a large value with respect to the nominal ones as follows:

$$\frac{\Delta R_s}{R_s} = -50\%.$$

50% step change in R_s is effected at 2 sec. The robust speed estimation is observed from the proposed RP-MRNLAS based speed estimator even in the case of large parameter tuning which is presented in Figure 11(a). Where as the oscillation in the speed estimated using the commonly used RF-MRNLAS model is observed to lie between 0.3 rad/sec and 3.563 rad/sec which is evident from Figure 11(b). The oscillation in the speed is keeps on increases with the increase in R_s. Thus the proposed RP-MRNLAS based speed estimator, exhibits robust speed estimation even in the presence of slight and large parameter variation of R_s.

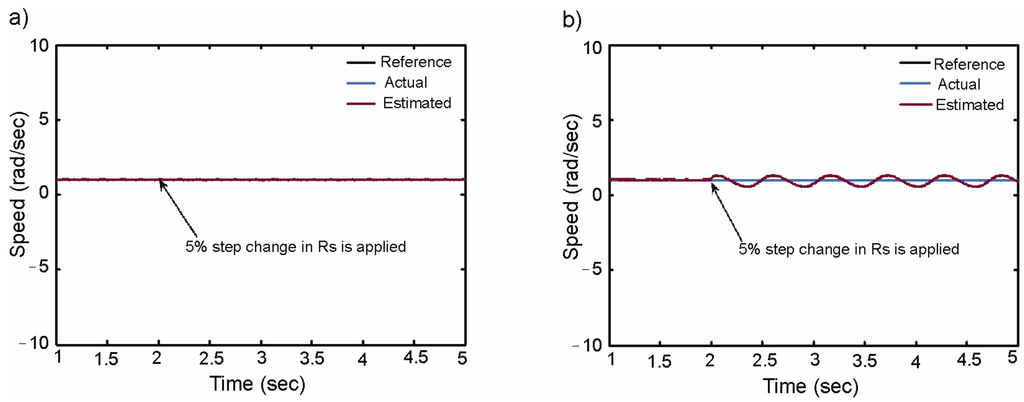

Fig. 10. Rotor speed with slight Rs detuning: (a) RP-MRNLAS (b) RF-MRNLAS

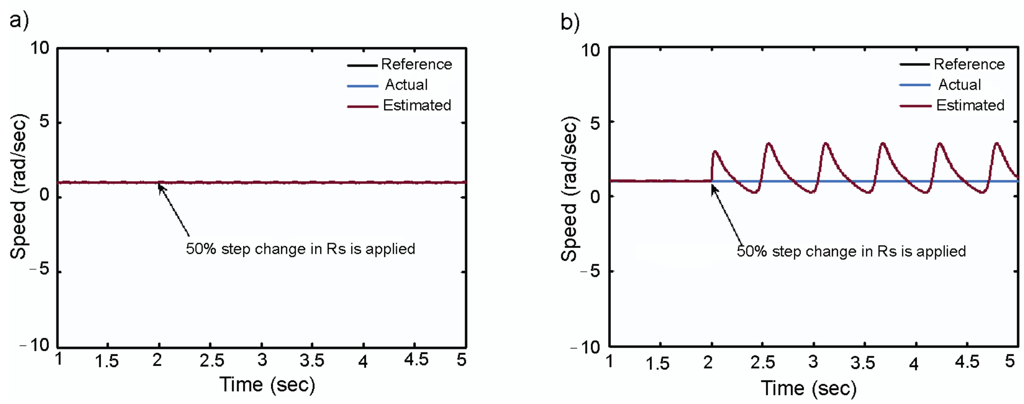

Fig. 11. Rotor speed with large Rs detuning: (a) RF-MRNLAS (b) RP-MRNLAS

5.2. Integrated drift problem

The performance of proposed RP-MRNLAS and commonly used RF-MRNLAS are also investigated for integrator drift problems. A dc bias in the measured signal for integration is inevitable, no matter how small it is, makes the estimated speed drift from the actual. The drift problem is investigated under very low speed of 10 rad/sec at no load condition. A dc bias of 2% is added to the input of the proposed RP-MRNLAS and RF-MRNLAS models at 3 sec.

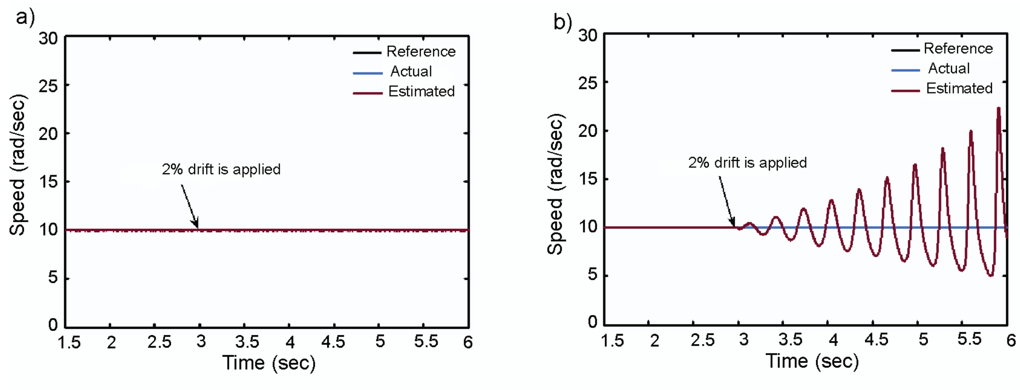

Fig. 12. Response of MRNLAS based speed estimator for integrator drift Problem: (a) RP-MRNLAS (b) RF-MRNLAS

The performance of proposed RP-MRNLAS and commonly used RF-MRNLAS for dc drift problem is presented in Figure 12(a) and Figure 12(b). For the comparison, both the figures are shown with same scale. From the results obtained, it is seen that the proposed RP-MRNLAS based speed estimation displays stable performance and tracks the actual speed very well whereas commonly used RF-MRNLAS becomes unstable and fails to estimate. Thus RP-MRNLAS based speed estimator is found to be less sensitive to dc bias problem. This is due to the inherent absence of integrator in the model equations of RP-MRNLAS, where as rotor speed estimated from the RF-MRNLAS gets deviated from the actual speed due to the presence of integrator in the reference model (voltage model). It is also noted that the error in the rotor speed keeps on increasing with time. Thus, from the above analysis, it is understood that RP-MRNLAS exhibits stable performance where as RF-MRNLAS shows unstable performance with the presence of small dc bias. The proposed RP-MRNLAS based speed estimator is accurate, less complex free from integrator drift problems and robust to R_s variation, so it is a promising alternative to commonly used RF-MRNLAS of speed estimators for sensor-less vector controlled IM drives.

6. Conclusion

This paper proposes a novel Reactive Power based MRNLAS (RP-MRNLAS) for speed estimation. The choice of reactive power as a functional candidate in RP-MRNLAS based speed estimation makes the system model equations independent of flux, simpler and easier to design. The proposed method is compared with commonly used Rotor Flux MRNLAS (RF-MRNLAS) in terms of accuracy, robustness to R_s variation and integrator drift problem. The error in the speed estimation from the commonly used RF-MRNLAS scheme under no load condition is found to be within ± 0.1% for normal operating speed range and maximum value of ± 1.5% at low and very low speeds. Under full load condition, the error in the speed estimation from the commonly used RF-MRNLAS scheme always lies within ± 0.1% for normal operating speed range and ± 1% for low and very low speeds. The proposed RP-MRNLAS estimates the speed under no load condition with an accuracy of ± 0.09% for normal operating speed range and maximum value of ± 0.5% at low and very low speed. The error in the speed estimated from the proposed RP-MRNLAS scheme under full load condition is found to be within ± 0.1% for normal operating speed range and ± 0.2% for low and very low speeds. It is concluded that proposed RP-MRNLAS provides the same accuracy as that of RF-MRNLAS for speed estimation in sensorless indirect vector controlled induction motor drives.

The robustness of proposed RP-MRNLAS based speed estimation scheme is illustrated with slight and large parameter variation of R_s and it is found to be outperforms the commonly used RF-MRNLAS based speed estimation scheme. The integrator drift problem of RP-MRNLAS and RF-MRNLAS are analyzed and the results obtained are presented. The RF-MRNLAS requires pure integrator in the reference model, where as the RP-MRNLAS based model is completely independent of integration problems. Hence at low speeds it is shown that RP-MRNLAS outperforms the RF-MRNLAS

The RP-MRNLAS based speed estimator utilizing reactive power and neural learning adaptation is shown to exhibit good performance over a wide operating range with good accuracy. The proposed RP-MRNLAS based speed estimator which is accurate, less complex, robust to integrator drift problems and R_s variations is a more promising alternative than the commonly used RF-MRNLAS based speed estimators for sensor-less indirect vector controlled IM drives.

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Appendix

The parameters of the induction machine used for simulation are given in the table shown below.

Induction Motor Parameters

Parameters	Values	Parameters	Values
Rated Power	1.1k W	Stator Resistance (R_s)	6.03 Ω
Rated voltage	415 V	Rotor Resistance (R_r)	6.085 Ω
Rated current	2.77 A	Magnetizing Inductance (L_m)	0.4893 H
Type	3 Ph	Stator Inductance (L_s)	0.5192 H
Frequency	50 Hz	Rotor Inductance (L_r)	0.5192 H
Number of poles	4	Total Inertia (J_T)	0.011787 Kg m^2
Rated Speed	1415 RPM	Friction Coefficient (B)	0.0027 Kg m^2/s

Nomenclature

V_{ds}, V_{qs} – d and q components of stator voltage; I_{ds}, I_{qs} – d and q components of stator current; λ_{dr}, λ_{qr} d and q components of rotor flux; L_s, L_r, L_m – stator, rotor and mutual inductances; R_s – resistance of stator phase winding; R_r – resistance of rotor phase winding; T_r – rotor time constant; $\sigma = 1 - (L_m^2/L_sL_r)$ – total leakage factor; ω_e – stator frequency; ω_{sl} – slip frequency; ω_r – rotor mechanical speed; Q – reactive power.

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