

## Particle swarm optimization-based stator resistance observer for speed sensorless induction motor drive

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### ABSTRACT

This paper presents a different technique for the online stator resistance estimation using a particle swarm optimization (PSO) based algorithm for rotor flux oriented control schemes of induction motor drives without a rotor speed sensor. First, a conventional proportional-integral controller-based stator resistance estimation technique is used for a speed sensorless control scheme with two different model reference adaptive system (MRAS) concepts. Finally, a novel method for the stator resistance estimation based on the PSO algorithm is presented for the two MRAS-type observers. Simulation results in the Matlab/Simulink environment show good adaptability of the proposed estimation model while the stator resistance is varied to 200% of the nominal value. The results also confirm more accurate stator resistance and rotor speed estimation in comparison with the conventional technique.

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## 1. INTRODUCTION

The rotor flux oriented control (RFOC) has been developed and employed widely in an enormous number of industrial applications with induction motors (IM) [1, 2]. Furthermore, numerous speed sensorless control schemes have been applied for the RFOC systems because of recent significant enhancements in the computational power of modern generations of microprocessors. One of the popular techniques is the model reference adaptive system (MRAS) concept, which could provide the correct and stable estimated rotor speed in a wide operating range [3-8]. Nevertheless, both the systems: the RFOC and rotor speed estimation based on the MRAS are so sensitive to the IM parameters, such as the stator and rotor resistance. These parameters are affected by the IM particular operating temperature. The difference between the real and estimated values leads to the unintended operational status and hence, to the poor dynamic performance of the drive. Therefore, the issues of the IM parameters variation and their impact on the performance of IM drives belong to the actual research topics in recent years [5-18].

A review on the subject of the stator and rotor resistances estimation for speed sensorless IM drives is reported in [9]. In [10], a closed-loop stator flux estimator in stator flux oriented control systems assumed that the stator resistance variations caused flux calculation errors. In [11], a MRAS based rotor speed and stator resistance estimator is presented. A first-order adaptive observer is suggested in [12] to estimate the error dynamics, while in [13, 14], an adaptive full-order observer is used. In general, in [10-14], an adaptive reference model with proportional-integral (PI) or integrated controller is proposed.

In recent years, artificial intelligence (AI) based techniques and soft computing methods such as fuzzy logic (FL) systems, artificial neural networks (ANNs), neural-fuzzy (NF) systems, genetic algorithms (GA), particle swarm optimization (PSO) methods, etc., have been widely used for recognition and control of nonlinear dynamic systems in power electronics and AC drives as presented in [5, 15-29]. Some of these methods are universal function approximators, the others are general-purpose stochastic optimization methods etc. and their application in the field of electrical drives can lead to better performance of electrical drives than conventional control methods. The problem of IM parameters estimation is discussed in [16], where authors proposed a new method which combines ANNs and NF to estimate the stator and rotor resistance simultaneously whilst in [17], only ANNs are used to estimate the stator and rotor resistance for a speed sensorless RFOC system. Similar to [17], authors in [18] also utilizes ANNs for the online estimation of the stator resistance for Direct Torque Control (DTC) of IM drives without a speed sensor.

The PSO algorithm was first introduced by Kennedy and Eberhart in 1995 [21, 22]. It is characterized as simple in concept, easy to implement, and computationally efficient more than many other heuristic techniques. This paper proposes a novel method of the online stator resistance estimation using the PSO algorithm for MRAS based speed sensorless RFOC schemes of IM drives. Concepts in [11, 17, 18] are considered to suggest a simple method concerning the online stator resistance and rotor speed estimation simultaneously. First, to check the correct function of the presented method, two rotor speed observers (rotor flux-based MRAS (RF-MRAS) and current-based MRAS (CB-MRAS) are sequentially applied with a conventional PI-based stator resistance estimator (PI-SRE, described in [11]).

Finally, the proposed technique using the PSO algorithm based stator resistance estimator (PSO-SRE) is also applied with the same conditions as the PI-SRE. Simulation results in the Matlab/Simulink environment confirm a better performance of the PSO-SRE for the RF-MRAS and CB-MRAS observers in comparison with the conventional PI-SRE (see chapter 4 for the simulation results).

## 2. CONVENTIONAL MRAS FOR ROTOR SPEED AND STATOR RESISTANCE ESTIMATION

The block diagrams of the MRAS schemes for the rotor speed and stator resistance estimation are presented in Figures 1 and 2. In these schemes, the conventional PI-based mechanism stator resistance estimator (PI-SRE) with rotor speed estimation mechanisms based on the RF-MRAS and CB-MRAS are sequentially presented. The principle of the RF-MRAS, CB-MRAS, and PI-SRE are discussed in the following subsections.

### 2.1. Rotor speed estimation based on RF-MRAS

As shown in Figure 1, the structure of the RF-MRAS includes two models: the reference (voltage) model uses the stator voltages ( $u_{S\alpha}$ ,  $u_{S\beta}$ ) and stator currents ( $i_{S\alpha}$ ,  $i_{S\beta}$ ) to calculate the components of the rotor flux vector ( $\psi_{R\alpha}^V$ ,  $\psi_{R\beta}^V$ ) while the adaptive (current) model uses the stator currents and estimated rotor speed  $\hat{\omega}_R$  to calculate the rotor flux components ( $\psi_{R\alpha}^I$ ,  $\psi_{R\beta}^I$ ) too.

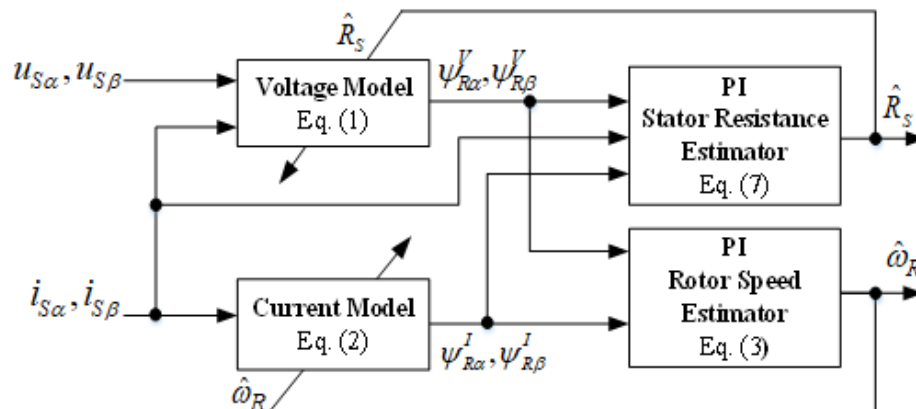


Figure 1. Block diagram of RF-MRAS with PI-SRE

The error of the estimated rotor flux components between these two models  $\varepsilon_\omega$  is used as an input signal to the PI mechanism for tracking the estimated rotor speed  $\hat{\omega}_R$ , as follows [3]:

$$\begin{aligned} \psi_{R\alpha}^V &= \frac{L_R}{L_m} \int (u_{S\alpha} - \hat{R}_S i_{S\alpha}) dt - \sigma L_S i_{S\alpha} \\ \psi_{R\beta}^V &= \frac{L_R}{L_m} \int (u_{S\beta} - \hat{R}_S i_{S\beta}) dt - \sigma L_S i_{S\beta} \end{aligned} \tag{1}$$

$$\begin{aligned} \psi_{R\alpha}^I &= \int \left( \frac{L_m}{T_R} i_{S\alpha} - \frac{1}{T_R} \psi_{R\alpha}^I - \hat{\omega}_R \hat{\psi}_{R\beta} \right) dt \\ \psi_{R\beta}^I &= \int \left( \frac{L_m}{T_R} i_{S\beta} - \frac{1}{T_R} \psi_{R\beta}^I + \hat{\omega}_R \hat{\psi}_{R\alpha} \right) dt \end{aligned} \tag{2}$$

$$\begin{aligned} \varepsilon_\omega &= \psi_{R\alpha}^I \psi_{R\beta}^V - \psi_{R\beta}^I \psi_{R\alpha}^V \\ \hat{\omega}_R &= K_{P\omega} \varepsilon_\omega + K_{I\omega} \int_0^t \varepsilon_\omega dt \\ K_{P\omega} > 0; K_{I\omega} > 0 \end{aligned} \tag{3}$$

where

- $\hat{R}_S, R_R$  = estimated stator resistance and rotor resistance,
- $L_S, L_R$  = stator and rotor inductance,
- $L_m$  = mutual inductance,
- $T_R = L_R/R_R$  = rotor time constant,
- $\sigma = 1 - L_m^2/(L_S L_R)$  = total leakage factor.

### 2.2. Rotor speed estimation based on CB-MRAS

The CB-MRAS structure for the rotor speed estimation with the stator resistance adaptation is presented in Figure 2.

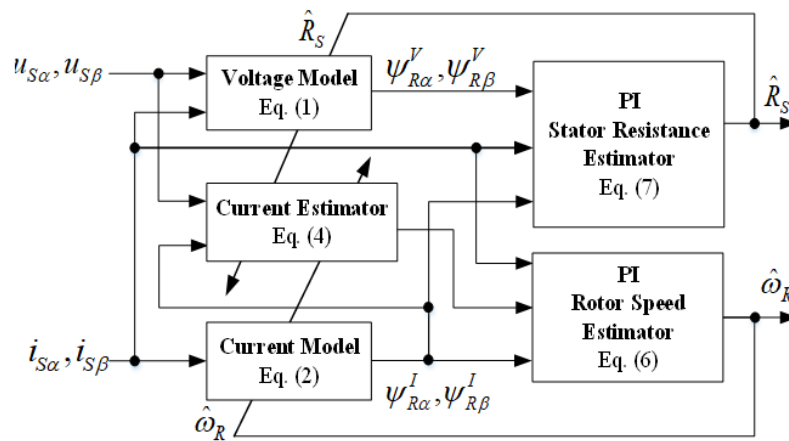


Figure 2. Block diagram of CB-MRAS with PI-SRE

This scheme has one more block for the current estimation and a different adaptive mechanism for the rotor speed estimation compared to the RF-MRAS, as follows [20]:

$$\begin{aligned} \hat{i}_{S\alpha} &= \frac{1}{T_i} \int \left( K_1 u_{S\alpha} + K_2 \psi_{R\alpha}^I + K_3 \hat{\omega}_R \psi_{R\beta}^I - \hat{i}_{S\alpha} \right) dt \\ \hat{i}_{S\beta} &= \frac{1}{T_i} \int \left( K_1 u_{S\beta} + K_2 \psi_{R\beta}^I - K_3 \hat{\omega}_R \psi_{R\alpha}^I - \hat{i}_{S\beta} \right) dt \end{aligned} \tag{4}$$

where

$$K_1 = \frac{L_r}{C_1 L_m}, K_2 = \frac{L_m}{L_r R_S T_R + L_m^2}, K_3 = \frac{1}{C_1}, C_1 = \frac{L_R \hat{R}_S}{L_m} + \frac{L_m}{T_R}, T_i = \frac{L_S L_R - L_m^2}{C_1 L_m}, \tag{5}$$

and

$$\begin{aligned} \varepsilon_\omega &= (i_{S\alpha} - \hat{i}_{S\alpha})\psi_{R\beta}^I - (i_{S\beta} - \hat{i}_{S\beta})\psi_{R\alpha}^I \\ \hat{\omega}_R &= K_{P\omega}\varepsilon_\omega + K_{I\omega} \int_0^t \varepsilon_\omega dt \end{aligned} \tag{6}$$

**2.3. PI-based mechanism for stator resistance estimator**

The PI-SRE was proposed and evaluated for the stability according to Popov’s criterion by the authors in [11]. This block uses the estimated rotor flux components from the voltage  $(\psi_{R\alpha}^V, \psi_{R\beta}^V)$  and current model  $(\psi_{R\alpha}^I, \psi_{R\beta}^I)$  to estimate the stator resistance via the error signal  $\varepsilon_{Rs}$ , which is defined as (7) [11]:

$$\begin{aligned} \varepsilon_{Rs} &= (\psi_{R\alpha}^V - \psi_{R\alpha}^I)i_{S\alpha} + (\psi_{R\beta}^V - \psi_{R\beta}^I)i_{S\beta} \\ \hat{R}_S &= K_{PRs}\varepsilon_{Rs} + K_{IRs} \int_0^t \varepsilon_{Rs} dt \\ K_{PRs} &> 0; K_{IRs} > 0 \end{aligned} \tag{7}$$

**3. PROPOSED STATOR RESISTANCE ESTIMATION BASED ON PSO ALGORITHM**

**3.1. PSO algorithm**

The PSO algorithm is an excellent computational optimization method motivated by the process of hunting food of a flock of birds or fish in the wild [21, 22]. With the advantages such as simplicity, stable convergence and good computational efficiency etc., the PSO has been popularly applied to resolve a large range of optimization problems, such as adaptive tuning of controller gains [23-25], parameters identification [26], loss minimization of electric drive [27]. In the PSO, the bird is called “particle” and constitute a swarm. Each particle indicates a candidate solution to the problem. The particles adjust their positions by travelling through a multidimensional specified searching range. While the journey, each particle adjusts its location according to the previous best position of each individual (called as *Pbest*) and the global best position (called as *Gbest*) as shown in Figure 3.

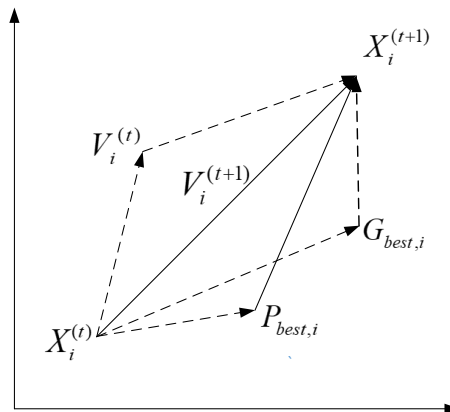


Figure 3. Illustration of adjusting velocity and particle position of PSO algorithm [21]

In each iteration, the modification of velocity and location of each agent can be determined by employing the current speed and the distance from *Pbest* to *Gbest*, as presented in the following equations [22]:

$$\begin{aligned} V_i^{(k+1)} &= wV_i^{(k)} + c_1 \text{Rand}_1 (Pbest_i - X_i^{(k)}) + c_2 \text{Rand}_2 (Gbest_i - X_i^{(k)}) \\ X_i^{(k+1)} &= X_i^{(k)} + V_i^{(k+1)} \end{aligned} \quad (8)$$

where

- $i$  = denote each particle,
- $k$  = discrete time index,
- $X_i$  = position of  $i^{\text{th}}$  particle,
- $V_i$  = velocity of  $i^{\text{th}}$  particle,
- $w$  = inertia function,
- $c_{1,2}$  = acceleration constants (self-confidence),
- $\text{Rand}_{1,2}$  = a random number on an interval [0,1],
- $Pbest_i$  = best position found by  $i^{\text{th}}$  particle (personal best),
- $Gbest_i$  = best position found by swarm (global best).

In Figure 4, the major steps in the procedure of the PSO are described as follows [21]:

- Step1: Generate a population of particles with random locations and velocities in d dimensions of the problem space within the allowable range.
- Step 2: Evaluate the objective function of each particle in the swarm. If the current value is better than the previous Pbest, then Pbest is replaced by the current value. If the best value of Pbest is better than the previous Gbest, the Gbest value is replaced by the best value, and the location of a particle with the best value is stored.
- Step 3: Modify the searching point of each particle according to (8).
- Step 4: The loop terminating condition is checked to determine if it has been achieved (based on objective function values or number of interaction), if not satisfied, then the process is repeated from step 2. Otherwise, the algorithm is stopped.

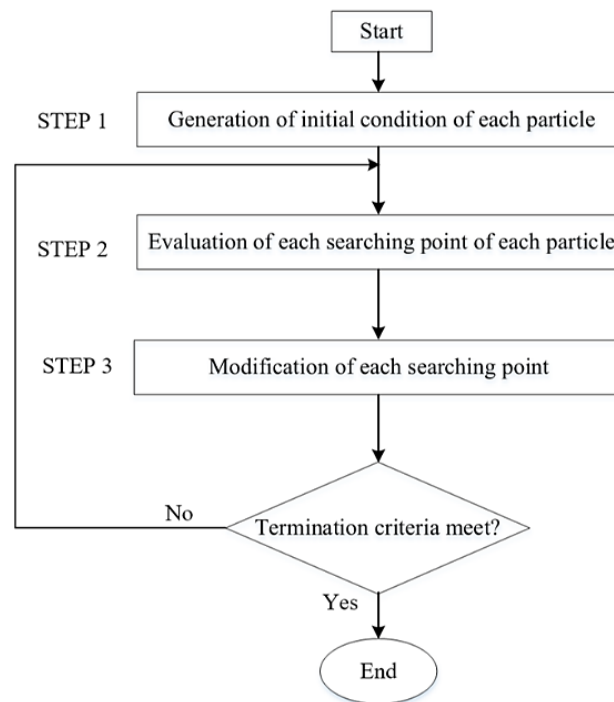


Figure 4. Steps in PSO algorithm

### 3.2. PSO-based stator resistance estimation mechanism

In this research, the PSO-SRE as shown in Figure 5 is suggested to replace the PI-SRE, and its principle is discussed below. Equations (1) and (2) from section 2 can be rewritten as:

$$\begin{aligned}\frac{d\psi_{R\alpha}^V}{dt} &= \frac{L_R}{L_m} \left( u_{S\alpha} - \hat{R}_S i_{S\alpha} - \sigma L_S \frac{di_{S\alpha}}{dt} \right) \\ \frac{d\psi_{R\beta}^V}{dt} &= \frac{L_R}{L_m} \left( u_{S\beta} - \hat{R}_S i_{S\beta} - \sigma L_S \frac{di_{S\beta}}{dt} \right)\end{aligned}\quad (9)$$

$$\begin{aligned}\frac{d\psi_{R\alpha}^I}{dt} &= \frac{1}{T_R} \left( L_m i_{S\alpha} - \psi_{R\alpha}^I - \hat{\omega}_R T_R \psi_{R\beta}^I \right) \\ \frac{d\psi_{R\beta}^I}{dt} &= \frac{1}{T_R} \left( L_m i_{S\beta} - \psi_{R\beta}^I + \hat{\omega}_R T_R \psi_{R\alpha}^I \right)\end{aligned}\quad (10)$$

Assuming that the obtained rotor flux components from the voltage and current model are equal. From (9) and (10), the following equations can be obtained:

$$\sigma L_S \frac{di_{S\alpha}}{dt} = u_{S\alpha} - \hat{R}_S i_{S\alpha} - \frac{L_m^2}{L_R T_R} i_{S\alpha} + \frac{L_m}{L_R T_R} \psi_{R\alpha}^I + \frac{L_m}{L_R} \hat{\omega}_R \psi_{R\beta}^I \quad (11)$$

$$\sigma L_S \frac{di_{S\beta}}{dt} = u_{S\beta} - \hat{R}_S i_{S\beta} - \frac{L_m^2}{L_R T_R} i_{S\beta} + \frac{L_m}{L_R T_R} \psi_{R\beta}^I - \frac{L_m}{L_R} \hat{\omega}_R \psi_{R\alpha}^I \quad (12)$$

Transformation of (11) to a discrete type is defined as:

$$\hat{i}_{S\alpha}(k) = B_1 \psi_{R\alpha}^I(k-1) + B_2 \psi_{R\beta}^I(k-1) + B_3 u_{S\alpha}(k-1) + B_4 \hat{i}_{S\alpha}(k-1) \quad (13)$$

where

$$\begin{aligned}B_1 &= [T_S / (\sigma L_S)] [L_m / (L_R T_R)] \\ B_2 &= [T_S / (\sigma L_S)] [(L_m / L_R) \hat{\omega}_R] \\ B_3 &= T_S / (\sigma L_S) \\ B_4 &= [1 - (T_S / \sigma L_S) \hat{R}_S - (T_S / \sigma L_S) (L_m^2 / (L_R T_R))]\end{aligned}\quad (14)$$

Equation (14) shows how to estimate the stator current while the stator resistance is variable. The weights  $B_1$ ,  $B_2$ ,  $B_3$  are directly computed from the rotor speed, motor parameters, and sampling time. All motor parameters are assumed to remain unchanged during the operational conditions except the stator resistance.

The error function of the current  $i_{S\alpha}$  is given:

$$E_\alpha = \frac{1}{2} \varepsilon_\alpha^2 = \frac{1}{2} (i_{S\alpha}(k) - \hat{i}_{S\alpha}(k))^2 \quad (15)$$

Similarly, transformation of (12) to a discrete type is defined as:

$$\hat{i}_{S\beta}(k) = B_1 \psi_{R\beta}^I(k-1) - B_2 \psi_{R\alpha}^I(k-1) + B_3 u_{S\beta}(k-1) + B_4 \hat{i}_{S\beta}(k-1) \quad (16)$$

$$E_\beta = \frac{1}{2} \varepsilon_\beta^2 = \frac{1}{2} (i_{S\beta}(k) - \hat{i}_{S\beta}(k))^2 \quad (17)$$

With the proposed PSO algorithm, the  $R_S$  value of  $B_4$  weight will be searched so that the fitness function  $F$  is minimized:

$$F = E_\alpha + E_\beta \quad (18)$$

The procedure of the PSO algorithm for the stator resistance estimation as shown in Figure 5 is also based on the same procedure as described in the previous subsection 3.1, see Figure 4, including the steps as follows:

- Formulate the initial population and initial position randomly of each particle ( $R_s$ ) in a range of the searching space (from 0.5 to 2.5 of the nominal stator resistance value).
- Calculate the fitness function of each particle using (13) to (18).
- Find the individual best of each particle.
- Find the global best in the entire population.
- Update the velocity and position of each particle according to (8).
- Repeat step 2 to step 5 until the criterion is satisfied.
- Apply the optimized stator resistance value to the system.

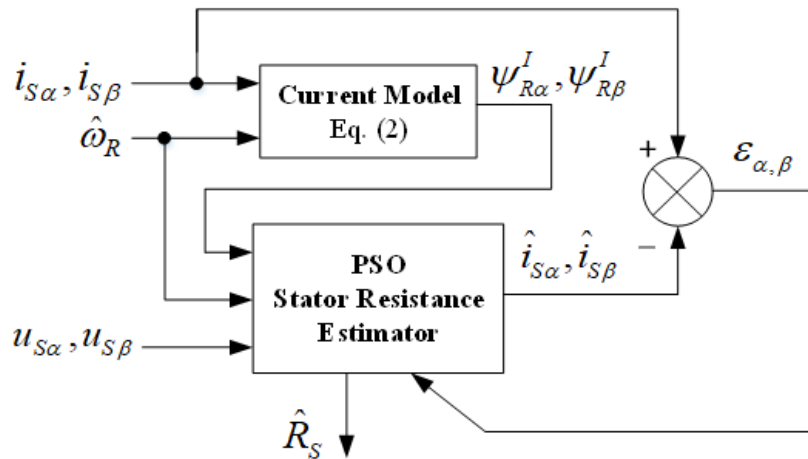


Figure 5. Structure of PSO-based stator resistance estimator

#### 4. SIMULATION RESULTS

The proposed algorithm is implemented in the Matlab/Simulink environment to obtain the simulation results. The mentioned techniques for the online stator resistance estimation (PI-SRE and PSO-SRE) are sequentially tested with the speed sensorless control schemes (RF-MRAS and CB-MRAS) for the RFOC system of the IM drive according to a block diagram shown in Figure 6 (see in appendix).

The simulation is carried out on a three-phase squirrel cage IM, whose parameters are given in Table 1. Figure 7(a) illustrates the ratio of step changes of the stator resistance, and the references of the rotor speed and load torque are shown in Figure 7(b). In Figure 8, the ratio between the estimated and actual values of the stator resistance using the PI-SRE and PSO-SRE for the RF-MRAS are presented, respectively. Similarly, Figure 9 displays the PI-SRE and PSO-SRE for the CB-MRAS. Figures 10 and 11 shows the errors of the actual and estimated rotor speed of the two MRAS-type observers when using the PI-SRE and PSO-SRE, sequentially. The results of the rotor speed and motor torque responds are shown in Figures 12 and 13 for the PI/PSO-SRE and the RF/CB-MRAS, respectively.

Table 1. Parameters of induction motor

Symbol	Quantity	Values
$P_n$	rated power	3.3 kW
$V_n$	rated voltage	380 V
$R_s$	stator resistance	4.179 $\Omega$
$L_s$	stator inductance	0.209 H
$R_r$	rotor resistance	2.118 $\Omega$
$L_r$	rotor inductance	0.209 H
$L_m$	mutual inductance	0.192 H
$p$	pole pair number	2
$J$	moment of inertia	0,047 kg.m <sup>2</sup>

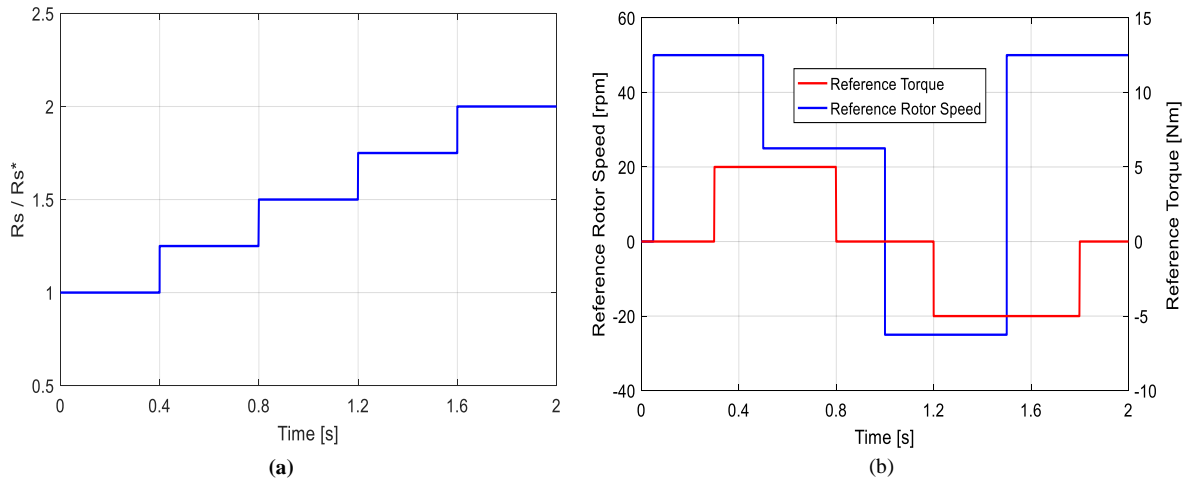


Figure 7. (a) Illustration of variation ratio between changed and nominal stator resistance, (b) References of rotor speed and load torque

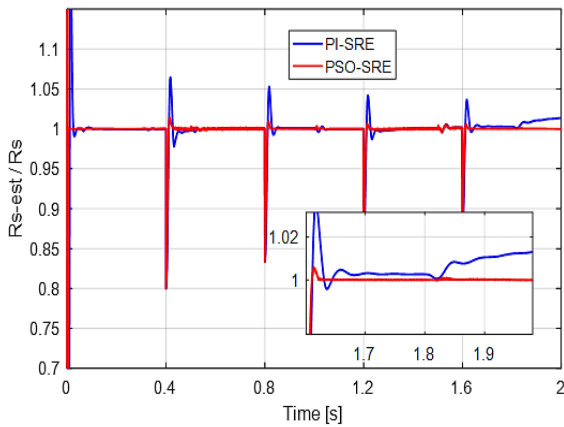


Figure 8. Ratio of estimated and actual values of stator resistance for RF-MRAS with PI-SRE and PSO-SRE

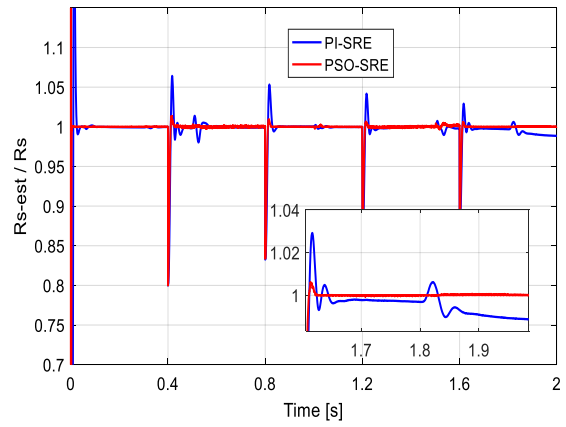


Figure 9. Ratio of estimated and actual values of stator resistance for CB-MRAS with PI-SRE and PSO-SRE

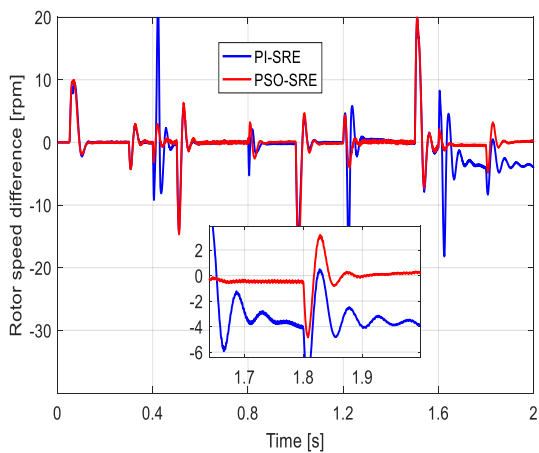


Figure 10. Error of actual and estimated rotor speed for RF-MRAS with PI-SRE and PSO-SRE

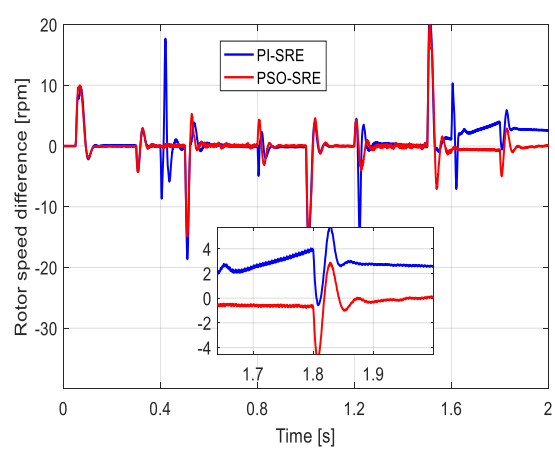


Figure 11. Error of actual and estimated rotor speed for CB-MRAS with PI-SRE and PSO-SRE



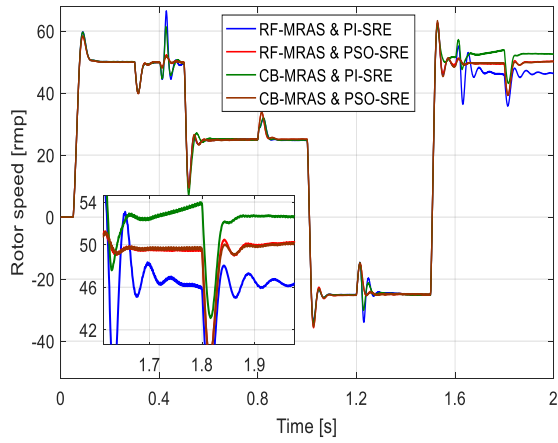


Figure 12. Rotor speed responds of RF-MRAS and CB-MRAS using PI-SRE and PSO-SRE

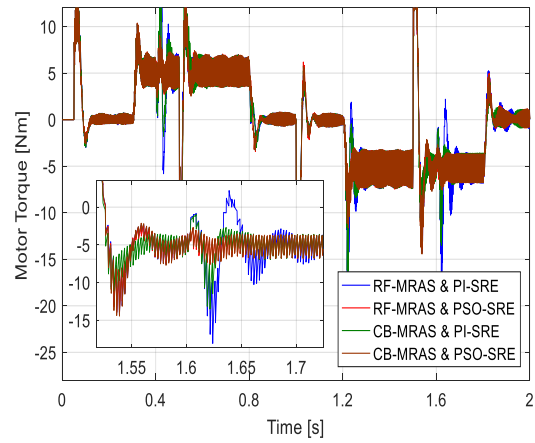


Figure 13. Motor torque responds of RF-MRAS and CB-MRAS using PI-SRE and PSO-SRE

To show more clearly the performance of the above mentioned estimators, we apply the Integral of the time weighted absolute error (ITAE) criterion (defined by (19)) to evaluate the error between the estimated and real value of the stator resistance (ESR), rotor speed difference (RSD), and the error between the reference and real motor torque (EMT). These factors are presented in Table 2.

$$ITAE = \int_0^{\infty} t |e(t)| dt \tag{19}$$

where  $t$  is the time and  $e(t)$  is the difference between a set point and controlled variable.

As shown in Figure 8 and 9 and the first row in Table 2, it indicates that the proposed PSO-SRE gives more accurate and stable responses of the stator resistance estimation than the conventional PI-SRE does. Each time the stator resistance has a step change (at  $t = 0.4; 0.8; 1.2; 1.6$  s, see Figure 7 a)), as well as the rotor speed and torque changes as shown in Figure 7 b), the PSO-SRE oscillates slightly for a very short time and stabilizes quickly with excellent tracking, even when the stator resistance increases twice the original value. Meanwhile, the PI-SRE gives more overshoots, fluctuation, and worse responsive tracking, especially during 200% of the nominal stator resistance (at  $t = 1.6$  to 2 s).

Figures 10, 11 and the second row in Table 2 also prove the advantages in the rotor speed estimation of the both MRAS when operate with the proposed PSO-SRE. The RSD values obtained from the two MRAS-type observers with the PSO-SRE are smaller than those from the PI-SRE. The overshoot and oscillation of the RF/CB-MRAS with the PSO-SRE are always smaller and still keep the correct response in the wide range of the stator resistance values.

The EMT values provided by the both MRAS-type observers with the PI/PSO-SRE (the third row of Table 2) are almost equal, but the RF/CB-MRAS schemes using the PSO-SRE give better responses and smoother rotor speed and motor torque than those of the PI-SRE as shown in Figures 12 and 13.

Table 2. Comparisons of RF/CB-MRAS with PI/PSO-SRE

ITAE	RF-MRAS with PI-SRE	RF-MRAS with PSO-SRE	CB-MRAS with PI-SRE	CB-MRAS with PSO-SRE
ESR ( $\times 10^{-2}$ )	9.01	<b>2.87</b>	8.54	2.91
RSD	4.834	2.111	3.937	<b>2.105</b>
EMT	3.274	2.773	2.849	<b>2.746</b>

### 5. CONCLUSION

This study introduces a novel technique concerning the online estimation of the stator resistance using the PSO algorithm applied to the MRAS based speed sensorless RFOC of IM drives. The simulation results confirm that the proposed method is able to identify variations of the stator resistance and converge to a steady-state and stable value when the stator resistance increases to 200% of the nominal value. The proposed technique also shows the excellent dynamic respond of the rotor speed and stator resistance estimation in comparison with the conventional PI based mechanism.

## APPENDIX

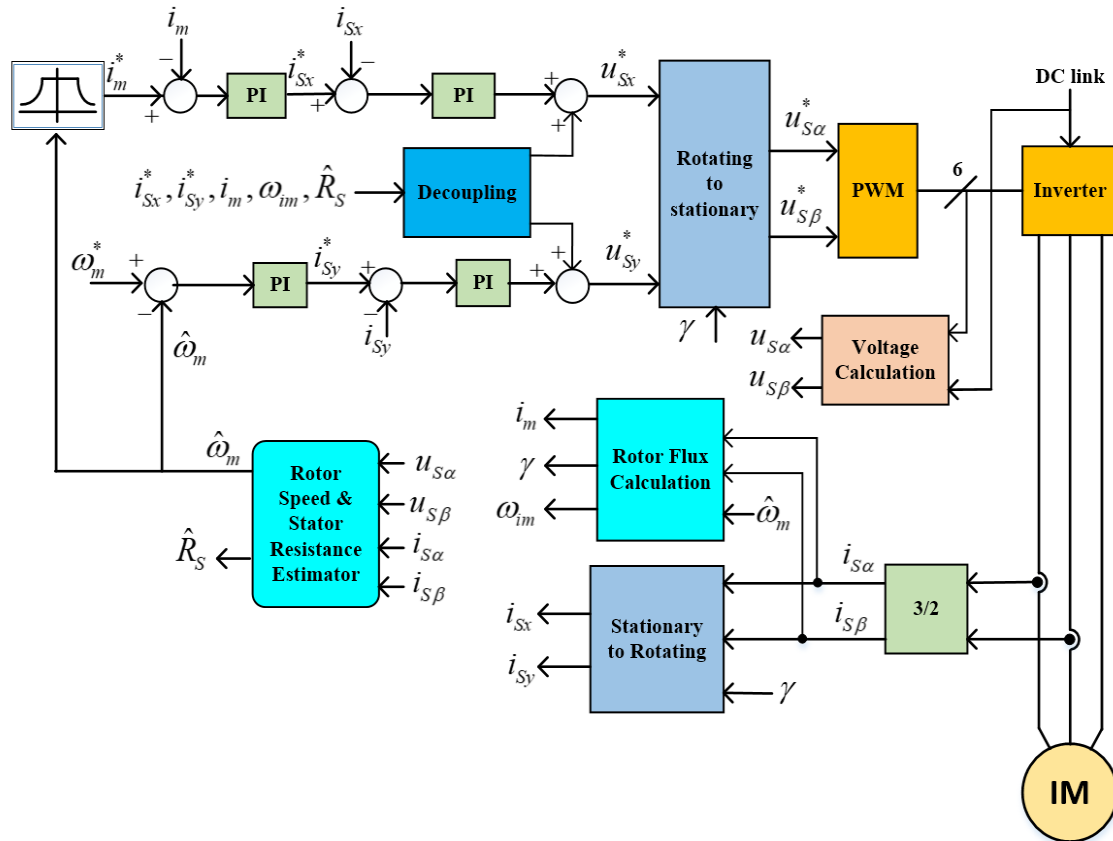


Figure 6. Block diagram of MRAS based sensorless RFOC of IM drive with SRE

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