Optimal Parameter Estimation of Permanent Magnet Synchronous Motor by Using Moth-Flame Optimization Algorithm

Abdolmajid Dejamkhooy, Sajjad Asefi

***Abstract*— Precision of model parameters is vital in a permanent magnet synchronous motor high performance and controllability. Since these parameters are affected by different operation conditions and load changings, then an accurate estimation strategy is quite necessary. In this paper, stator resistance and disturbed load torque, which assumed to be variable, are estimated. For this purpose, optimal parameter estimation problem is constructed as a least squares one. In the next step, the parameter identification as an optimization problem is solved by Moth-flame optimization, which is a novel nature-inspired heuristic algorithm. Simulation results and their comparison with Particle Swarm Optimization based method show high performance and good ability of the proposed method in PMSM parameter estimation.**

***Index Terms*— Permanent magnet synchronous motor, Model parameter estimation, Moth-flame optimization, Particle swarm optimization**

I. Introduction

Recently, permanent magnet synchronous motors (PMSMs) have been widely used in high performance industrial applications, due to their high efficiency, high ratio of torque-to-inertia, suitable power factor, faster response and tough construction. The PMSMs have increasingly been utilized in electrical vehicles, aircraft, nuclear power stations, submarines, robotic applications, medical and industrial servo drives [1]. PMSMs can provide significant Performance improvement in many variable speed applications [2].

To provide fast and precise response, advanced control strategies require quick disturbance recovery, and parameter variations insensitivity. Accurate model construction for under study system is usually the important part in control system design [3]. In practical cases, the model parameters are not known exactly and/or may vary slowly. This fact may be due to a variable operating point or a fault [4]. From this point of view, the parameter estimation can be divided into online and offline methods.

For linear systems, model parameter estimation is relatively easy task. However, the most practical systems show non-linear behaviors. These nonlinearities are usually ignored. So, the linear system identification methods are applied to find approximate solution. However, they are inadequate in high-performance applications. Therefore, advanced approaches, which are specialized for nonlinear system identification, should be addressed [3].

So far, several methods have been presented to estimate the machine parameters of a permanent magnet synchronous machine. After applying voltage or current pulse to machine windings, the parameters have been calculated by using recorded data [5], [6]. These studies have not considered space harmonics. Thereby, a similar research has been presented, which focused on the harmonic effects and utilized Fast Fourier Transform (FFT) to calculate magnitude and phase of the fundamental harmonics [7]. Also, other signal processing methods such as Goertzel algorithm have been applied for this purpose [8]. The main disadvantage of these methods is that the parameters are estimated all at one in steady state. In other words, different operation conditions and load change effects are not considered in these methods. Other methods based on high carrier-frequency injection (CFI) technique, where the signal is superimposed onto the fundamental phase voltages, have been introduced [9–12]. The injection signal is usually a sinusoidal voltage. Therefore, it may cause acoustic noise, a motor current distortion, torque pulsation and large harmonic losses.

System identification methods have been widely employed to estimate PMSM parameters. Robust rotor position estimator based on the Sliding Mode Observer (SMO) has been proposed [13]. Also, Extended Kalman Filter (EKF) has been used to same purpose in sensorless PMSM [14]. Although, EKF method is less sensitive to the unknown measurement noise, but requires high computing capacity because of matrix calculations and particularly matrix inversions. Model reference adaptive system based mechanisms have shown good performance in the estimation of the parameters [1], [15]. A model reference based online identification method with its stability analysis and comparing with EKF has been

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developed in [4]. Despite expanded mathematical analysis, this method is seems too rough for practical applications.

Parameter estimation for a system with known model structure can be transferred to an optimization problem. The objective of the optimization problem is proximity of the system and model outputs. Therefore, the fitness function, which should be minimized, deals with difference between the real system and the estimated model outputs. On the other hand, evolutionary and swarm intelligence based algorithms are widely used to solve different types of optimization problems. Due to their advantages, they have been applied to model parameter estimation of PMSM. Particle Swarm Optimization (PSO) [3] and Differential Evolution (DE) [16] have been utilized for this purpose. Since these studies have been successful in PMSM parameter estimation, real-time implementation of the PSO based estimation has been investigated [17]. Afterward, the same methodology has been developed for fault diagnosis of PMSM [18].

In this paper, PSMS, which applied to a variable frequency drive system with cascaded PI controllers, is investigated. Stator resistance and disturbed load torque are estimated by the proposed method. Disturbed load torque is defined as summation of the actual load torque, and the disturbances caused by inertia and frictional coefficient. Indeed, stator resistance is directly related to motor operating temperature. Its value may increase to twice of its nominal value. Similarly, the rotor inertia and the frictional coefficient may vary as they are coupled with load torques of the motor. Unlike the more reviewed researches, these parameters are assumed to be variable depend on the motor operation conditions in this study. For this purpose, optimal parameter estimation problem is constructed as a minimizing problem. The fitness function is defined in the manner of summation of difference between state variable values of real and estimated systems. In the next step, the parameter identification as an optimization problem is solved by Moth-flame optimization, which is a novel nature-inspired heuristic algorithm. Simulation results and their comparison with PSO based method show high performance and good ability of the proposed method in PMSM parameter estimation.

The rest of the manuscript is organized as follows. In the next section, studied PMSM model and also parameter estimation strategy are described. A brief introduce to the Moth-flame optimization algorithm is expressed in section 3. Simulation results, comparisons and discussions are presented in the section 4. Finally, the section 5 gives a conclusion of the paper.

II. PMSM MODEL AND ESTIMATION STRATEGY

A. Model description

The two-axis dq-model is the most commonly used model for variable speed PMSM drive control studies. PMSM is described by nonlinear differential equations. The system of nonlinear equations can be divided into two subsystems, i.e. electrical and mechanical system. The electrical system in rotating reference frame is as

$$\frac{di_d^r}{dt} = \frac{1}{L_d}\left[v_d^r - R_s i_d^r + \omega_r L_q i_q^r\right] \tag{1}$$

$$\frac{di_q^r}{dt} = \frac{1}{L_q}\left[v_q^r - R_s i_q^r - \omega_r L_d i_d^r - \omega_r \psi_{mag}\right] \tag{2}$$

where i_{dr}, i_{qr}, v_{dr}, and v_{qr} are the dq-components of the stator currents and voltages; ω_r is the rotor electrical angular speed; parameters R_s, L_q, L_d are the stator resistance, d-axis and q-axis inductance, and is the permanent magnet flux linkage.

The mechanical system includes two equations, which deal with Newton's law and produced electromechanical torque as

$$\frac{d\omega_r}{dt} = n_p \frac{1}{J}\left[T_e - B\frac{\omega_r}{n_p} - T_L\right] \tag{3}$$

$$T_e = \frac{3}{2} n_p \left[i_q^r \psi_{mag} + \left(L_d - L_q\right) i_q^r i_d^r\right] \tag{4}$$

i_{dr}, i_{qr} and ω_r are taken as the state variables/outputs. Also, v_{dr} and v_{qr} are chosen as control signals/inputs. Other parameters and coefficients are usually adopted as constant values. This assumption causes to inaccuracy in high performance applications and advanced control schedules. In practice, PMSM operates under various operating conditions, where different disturbances and parameter variations are unavoidable and immeasurable. For example, J and B vary by changing load level. Similarly, R_s , which is directly related to temperature, may rise to twice of its nominal value. Therefore, precise model parameter estimation strategy is required to achieve a successful tracking and control of PMSM.

B. Parameter estimation strategy

As the system model is known but the parameters are unknown, this parameter identification problem can be treated as an optimization problem. The main idea is comparison of the main and the estimated system outputs. The difference between the output values is considered as an index to make the objective function, which should be minimized by the heuristic algorithm. In other words, the best solution is accrued when the fitness function value is minimum. This ideal condition deals with matching the outputs. The structure of the parameter estimation approach is demonstrated in Figure 1.

It is clear that the estimated model has the same structure of the main system. Also, same input signal is fed into the both systems. P is defined as vector of the undetermined parameters, which should be estimated i.e. $\hat{P}$. Stator resistance (R_s) and disturbed load torque (T_{Ld}) are parameters which estimated in this study. Therefore P can be constructed as $P = [R_s \; T_{Ld}]^T$.

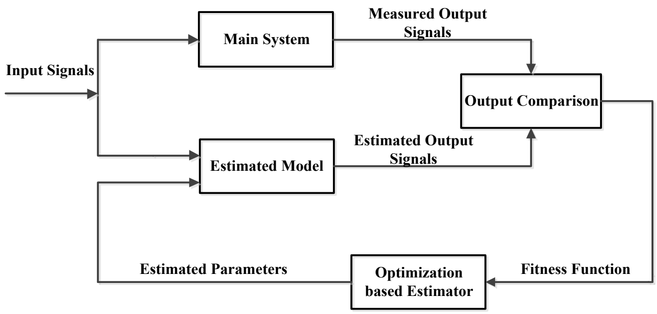

Fig. 1.Block diagram of the parameter estimation strategy

In fact, J and B appear in T_{Ld}. Disturbed load torque is the summation of the actual load torque (T_L), and the disturbances caused by inertia and frictional coefficient variations, as

$$T_{Ld} = T_L + \tilde{J}\frac{1}{n_p}\frac{d\omega_r}{dt} + \tilde{B}\frac{1}{n_p}\omega_r \tag{5}$$

where $\tilde{J} = J - J_0$ and $\tilde{B} = B - B_0$. J_0 and B_0 denote the nominal values of motor inertia and viscous friction coefficient.

To find out the unknown parameters the output of the systems are compared. If y and $\hat{y}$ denote main and estimated system outputs respectively, a fitness or cost function can be define to transform the parameter identification problem to an optimization problem. The function may be considered as the weighted quadratic function which is defined as follows

$$C(\hat{p}) = \int_t (y - \hat{y})^T W (y - \hat{y})\, dt \tag{6}$$

where $y = [i_{abc}\ \omega_r]^T$ and W is a positive matrix as weighted factor.

It is worth to mention that eventually the fitness function depends on the parameters which will be estimated. In other words, by minimizing the fitness function, the optimum values for the parameters are yields.

For this investigation (6) is rewritten as

$$C(\hat{R}_s, \hat{T}_{Ld}) = \sum_{k=1}^{n} \begin{bmatrix} \left(i_a(k) - \hat{i}_a(k)\right)^2 + \left(i_b(k) - \hat{i}_b(k)\right)^2 \\ + \left(i_c(k) - \hat{i}_c(k)\right)^2 + w\left(\omega_r(k) - \hat{\omega}_r(k)\right)^2 \end{bmatrix} \tag{7}$$

where i_{abc} and ω_r are phase currents and rotor speed of the main system (outputs of the main system), while $\hat{i}_{abc}$ and $\hat{\omega}_r$ are the output values for the estimated system. R_s and T_{Ld} are the unknown parameters which are going to be identified, and W is the weighting factor that has been assumed as ratio of stator current magnitude to rotor speed magnitude.

To minimize the fitness function and yield the optimized parameter values, moth-flame optimization algorithm is utilized. It is a novel nature-inspired heuristic method which has shown high ability in solving rough optimization problems [19]. Also, the problem is accomplished and compared by PSO method. In the next section, a brief introduce to moth-flame optimization algorithm is presented.

III. MOTH-FLAME OPTIMIZATION ALGORITHM

Recently, a new swarm intelligence based algorithm known as Moth Flame Optimization Algorithm (MFOA) has been developed [19]. The inspiration source of the algorithm is the lateral movement of moths around a bright object such as candle, which is found in nature. Moths have a special movement mechanism i.e. transverse orientation. This ability helps them to fly at night. To this aim, they keep a fixed angle with respect to moon. In order to move in a straight line, this method is very helpful, considering that light source is far away. If the moths be closer to the light source, again they will try to keep a constant angle regarding this light source. Since, the distance between them is not far enough, it results a spiral movement of moths around the candle. Finally, after a few rounds they will converge to light source.

In MFO algorithm moths and flames play the main roles and both of them are considered as a result for this algorithm. In each iteration, their update mechanism is different. Moths are the search agents. They contain values of the problem's parameters. Flames are the best position of moths throughout the search space. In other words, moths pin the best obtained solution by using flames. So, each moth flies through the search space, finds solutions and updates itself. The set of moths can be presented as

$$M = \begin{bmatrix} m_{1,1} & m_{1,2} & \cdots & \cdots & m_{1,d} \\ m_{2,1} & m_{2,2} & \cdots & \cdots & m_{2,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ m_{n,1} & m_{n,2} & \cdots & \cdots & m_{n,d} \end{bmatrix} \tag{8}$$

where n is the number of moths and d is the number of variables. Also, the fitness values for all the moths are stated as

$$OM = \begin{bmatrix} OM_1 \\ OM_2 \\ \vdots \\ OM_n \end{bmatrix} \tag{9}$$

Flames and their corresponding fitness function values can be stored as

$$F = \begin{bmatrix} F_{1,1} & F_{1,2} & \cdots & \cdots & F_{1,d} \\ F_{2,1} & F_{2,2} & \cdots & \cdots & F_{2,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ F_{n,1} & F_{n,2} & \cdots & \cdots & F_{n,d} \end{bmatrix} \tag{10}$$

and

$$OF = \begin{bmatrix} OF_1 \\ OF_2 \\ \vdots \\ OF_n \end{bmatrix} \tag{11}$$

respectively.

To model movement of the moths, the logarithmic spiral function is chosen to update position of moths as

$$M_i = S\left(M_i, F_j\right) = D_i\ e^{bt}\ \cos\left(2\pi t\right) + F_j \tag{12}$$

Here, D_i represents distance of the i-th moth from j-th flame, M_i indicates the i-th moth, F_j indicates the j-th flame, b is a constant for announcing the shape of the logarithmic spiral, and t is a random number in the range of [-1, 1]. D_i is calculated as

$$D_i = \left|F_j - M_i\right| \tag{13}$$

Basic method for updating of moths is logarithmic spiral. Not only logarithmic spiral can be used, but also other types of spiral have the ability to be used if they have the following conditions:

- Initial point of Spiral must start from the moth
- Final point of Spiral has to be the position of the flame
- Spiral oscillation limit must not exceed from the search space.

The position updating of moths with respect to n different locations in the search space degrades the exploitation of the best promising solutions. To overcome this problem, an adaptive mechanism has been proposed for the number of flames. The number of flames decreased over the course of iterations by

$$flame\ no = round\left(N - l * \frac{N-1}{T}\right) \tag{14}$$

where l, N and T are the current number of iteration, the maximum number of flames, and the maximum number of iterations, respectively.

The moths update their positions only with respect to the best flame in the final steps of iterations. The little change in number of flames results in balance in searching and finding the desired points within search space. Finally, the pseudo-code of the flame updating can be constructed as follows.

Update *flame no* using Equation (14)
OM = Fitness Function (*M*);
if iteration = = 1
    F = sort (*M*);
    OF = sort (*OM*);
else
    F = sort (M_{t-1}, M_t);
    OF = sort (OM_{t-1}, OM_t);
end
for *i* = 1 : *n*
    for j=1:d
    Update *t* and d
    Calculate *D* using Equation (13) with respect to the corresponding moth
    Update *M(i,j)* using Equation (12) with respect to the corresponding moth
    end
end

In the next section, to solve the optimization problem and yield the optimal estimation of the parameters, MFOA is employed. Also, to compare the results, same operation is conducted by PSO as another famous optimization algorithm.

IV. SIMULATION RESULTS

In this section, a three-phase PMSM with non-salient poles is investigated to demonstrate the performance of the proposed MFOA based approach to PMSM model parameter estimation. In this study, the motor is applied to a variable frequency drive system with cascaded PI controllers. This configuration is widely used in industrial motor drive applications. The general structure of the system is illustrated in Figure 2. This drive configuration includes two control loops. Outer and inner loop correspond with speed and current respectively. In the outer loop, PI controller produces q- axis of rotor current. On the other hand, d- axis of rotor current can be calculated by reference flux. Actual value of motor current are compared with dq-reference currents. The comparison result passes through PI controller and then dq-reference voltages are yielded. These voltage values are utilized for inverter switching control. Nominal parameters of the simulated PMSM are given in Table 1.

However, in this simulation, several parameters such as the stator resistance (R_s), motor inertia (J), and frictional coefficient (B), are assumed to be variables. In this situation, the proposed MFOA based method is applied to estimate and track theses parameters. According to (5), the time varying inertia and viscous frictional coefficient causes change in the disturbed load torque. Thereby, the stator resistance and the disturbed load torque should be identified.

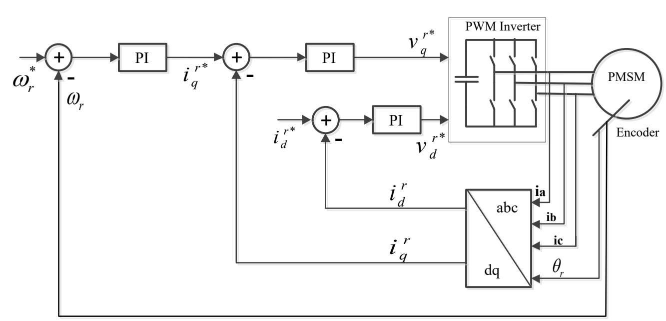

Fig. 2. PMSM current control in *dq*-reference frame

TABLE I
NOMINAL VALUE OF THE PMSM PARAMETERS

Parameter	Nominal values
Power rating P_r	19.8 (kW)
Rated rotor speed	1700 (rpm)
Current at rated speed I_r	41.56 (A)
Torque at rated speed T_r	67.27 (N m)
Voltage constant k_e	1.33 (V s/rad)
Torque constant k_t	1.629 (N m/A)
Max bus voltage V_{DC}	560 (V)
Pole pairs n_p	4
Stator resistance R_s	0.17 (Ω)
q-axis inductance L_q	1.9 (mH)
d-axis inductance L_d	1.9 (mH)
Static friction T_f	0.1483 (N m)
Damping coefficient B	0.00115 (N m s/rad)
Moment of inertia J	0.008 (kg m2)

In each generation of MFOA, number of moths and constant for announcing the shape of the logarithmic spiral there are set 100 and 1, respectively. The optimization process of the fitness function by MFOA and PSO is shown in Figure 3 and the final value of fitness function for both optimization techniques is provided in Table 2.

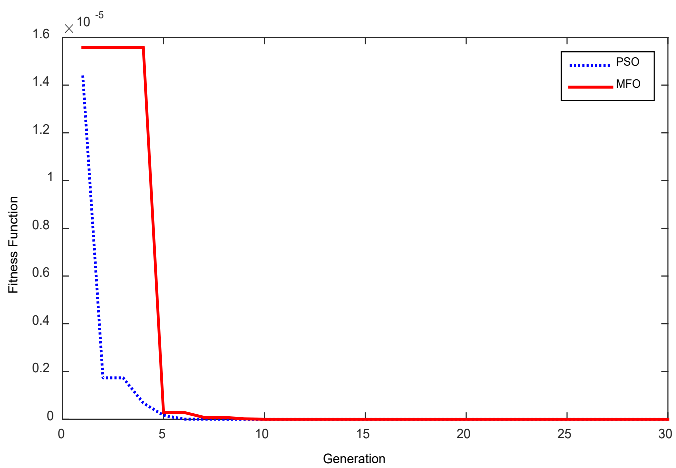

Fig. 3.Fitness function optimization process

TABLE II
Final value of fitness function

Algorithm	PSO	MFO
Final fitness value	0.2874e-9	0.0013e-9

The stator resistance estimation process is shown in Figure 4. MFOA based method converged after less than 25 iterations. The resulted value is 0.173 Ω, which has 1.76% deviation from actual value. Although PSO based method converges faster than MFO, but its calculated value for stator resistance is 0.33 Ω. Therefore, the MFOA based proposed method is more accurate than PSO ones. As demonstrated in Figure 5, disturbed load torque by the methods converges to 2.99 Nm. According to actual value of T_{Ld} i.e. 3 Nm, estimation error is 0.33%. According to these error values, these estimations can be adopted as high precision.

So far estimation has been conducted for one set of data. In other words, an offline or static estimation has been performed. If the number of iteration for both methods set 30, then meeting accurate results will be guaranteed. The same estimation strategy can be developed to online parameter identification. For online identification, the measured data are sent to the proposed estimator as input. When the algorithms finish searching for 30 iterations, the identification process will be terminated. For each round of the applying algorithms, the previously obtained optimum parameters are used as the initial values for next round. This will result in faster convergence in the case of online application of the method. The entire optimization process of MFO and PSO algorithms during online optimization are shown in Figure 6. According to this demonstration, it is obvious that the algorithms converge within 10 to 15 iterations whether starts with a good or bad guess. The main reason of different starting fitness value is that when system parameter changes, i.e. the system operating point changes, the fitness will have different sensitivity. So, there might be a large change in fitness while there is a small change in parameters.

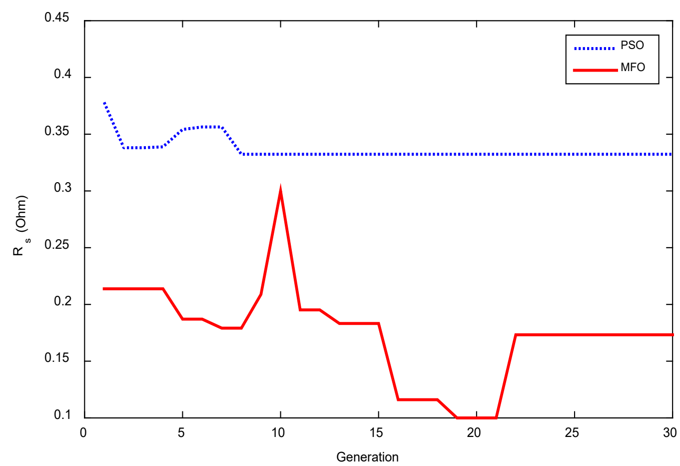

Fig. 4.Estimation of the stator resistance

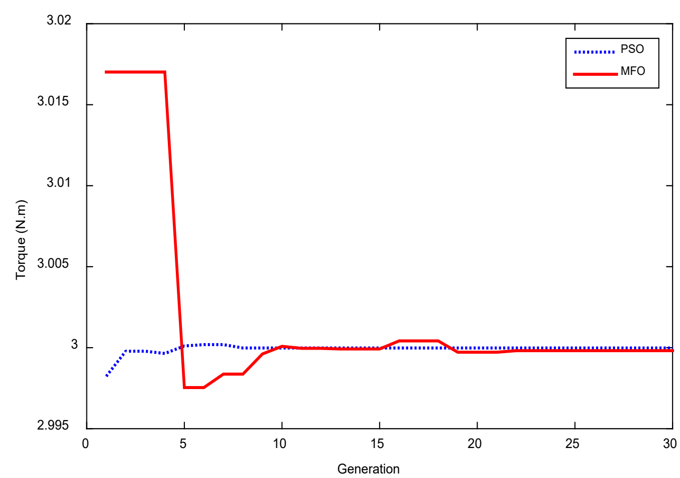

Fig. 5.Estimation of the torque

After comparing the actual and identified parameters, the performance of the main and estimated systems are compared. As mismatching the estimated parameters, may cause system dynamic response deviation, so, this investigation is essential.

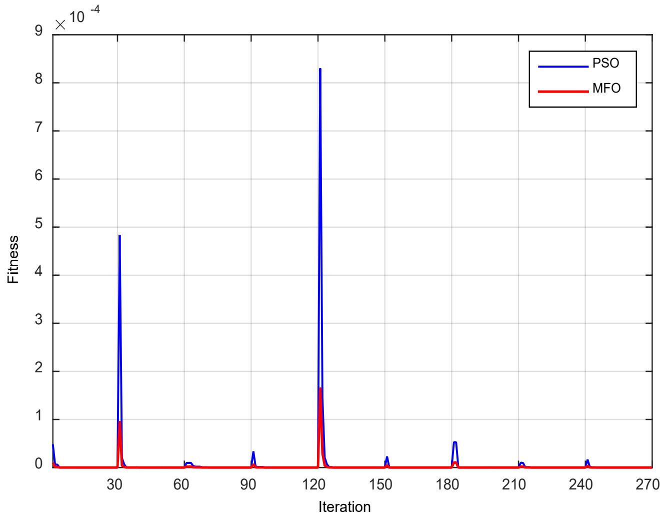

Fig. 6.Fitness function optimization process during online estimation

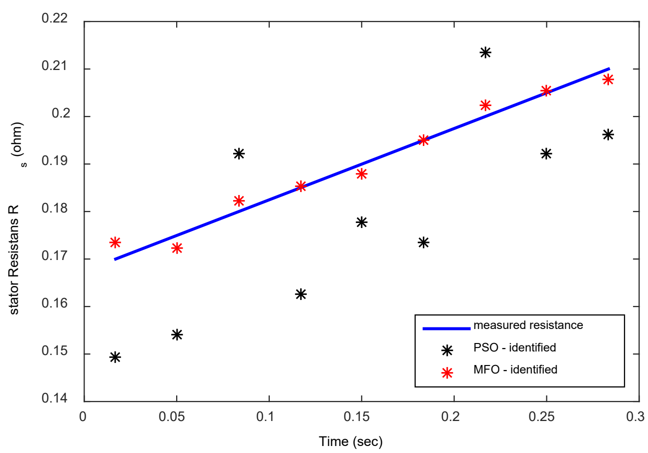

Fig. 7.Online estimation of stator resistance

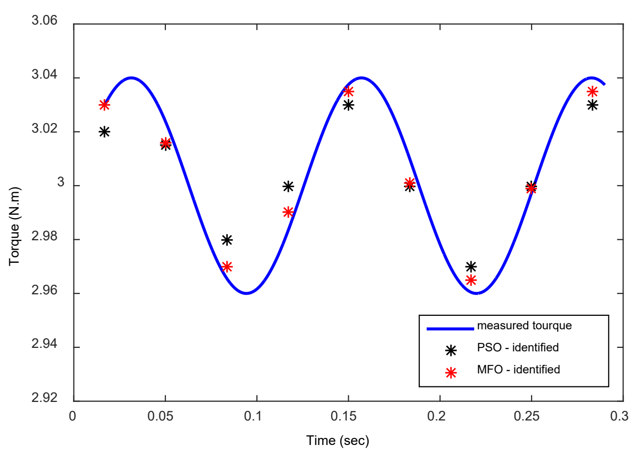

Fig. 8.Online estimation of load torque

The results are illustrated in Figure 9 and 10. First plot shows the stator phase current i_a and the next one is the rotor angular speed. Since the performances of the two models match each other quite well.

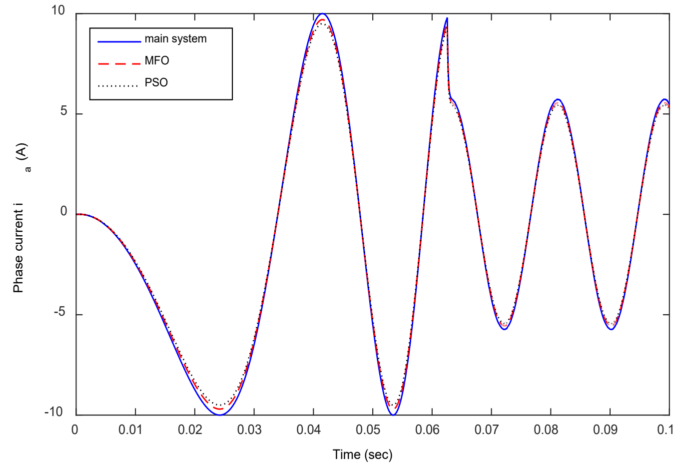

Fig. 9.Phase current (i_a) as performance index of the models

In this paper, the convergence has been presented in term of iteration number for the algorithms. The simulations continue for 30 iterations.

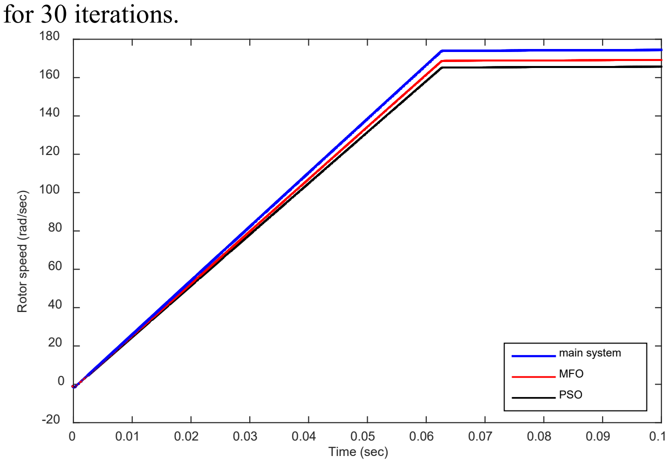

Fig. 10.Rotor speed (ω_r) as performance index of the models

The simulations for present period will continue until the 30 iterations complete and after that the next period of simulation will start. In other words, time has been not used for analyzing the algorithm performances. It worth noting that, the speed of computations is highly impacted by factors such as applied hardware, the sampling frequency, and other computer properties. As mentioned before, if we apply previous optimum results for the next period, we can save lots of time in continuous online applications.

V. CONCLUSION

In this paper, to estimate PMSM nonlinear model parameters, a method based on MFOA has been proposed. Simulation results show that the proposed estimator can approximate the parameters in both online and offline modes high precisely. The estimation error values have been resulted around 1%, which confirms the method performance. Also, the estimated system can track the actual one successfully. Since the presented method show a high performance potential in identifying when the parameters are subjected to an uncertainties or a fault. Therefore, it can be applied as fault diagnosis system using the parameter variations as fault symptoms. This optimization based identification method, although applied to PMSM, but is generally applicable to other systems with complicated nonlinear model structure.

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