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EFFICIENT PARAMETER ESTIMATION PROCEDURE USING SUNFLOWER OPTIMIZATION ALGORITHM FOR SIX-PHASE INDUCTION MOTOR

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The accuracy of studying the performance of the six-phase induction motors (SPIMs) depends on the accurate estimation of the motor parameters. This article examines the performance evaluation of SPIMs among several optimization algorithms using parameter optimization. The competitive algorithms are differential evolution (DE), genetic algorithm (GA), Jaya optimization algorithm (JOA), particle swarm optimization (PSO), and sunflower optimization (SFO) algorithms. Parameter estimation is extracted from the performance curves based on manufacturer data. Laboratory verifications are performed on a SPIM modified from a three-phase induction motor. It also shows that using SFO gives convergence between measured and estimated parameters with small errors and fast response compared to many optimization algorithms. The statistical analysis of the results shows the effectiveness of the proposed SFO algorithm compared to other methods at different values of iterations.

1. INTRODUCTION

The most widely used electrical machines in industrial applications are multi-phase induction motors (MPIMs) [1]. To study the target performance of poly phase induction machines, real modeling is an important issue for this type of machine. The problem of parameter estimation for the MPIMs is modeled as nonlinear mathematical equations. The optimization programs aim to achieve the best degree of convergence between the actual parameters and the estimated parameters. Therefore, the main function of the studied parameters evaluation problem is to maintain the minimum distance between the actual and estimated parameters.

Parameter's estimation of the MPIMs models aims at finding their unknown variables. Exact determination of the induction motor parameters is one of the important things for the operation and control of the MPIM [2, 3]. It is important to know all MPIMs parameters with very high accuracy and costs as low as possible. The old methods for calculating equivalent circuit parameters depend on a set of experimental tests as in IEEE Std 112-1991 and updated in IEEE Std 112-2004[4] . The accuracy of the experimentally based methods estimated parameters is dependent on the accuracy degree of the monitoring and implementation procedures. Added to the difficulty of the tests needed to calculate the parameters is the large cost of implementing the tests required for implementation. Therefore, due to these limitations, many designers of optimization tools provide a number of methods aimed to getting acceptable solutions to estimate the MPIMs parameters [5]. To achieve this objective of the modernization process, many types of optimization methods used in the SPIMs equivalent circuit parameter estimation process have been improved [6].

In this part, the topics studied for estimating parameters by optimization methods are summarized:

- Reference [7] presented the parameters estimation of induction motor from manufacturing data by using artificial immune methods.
- Reference [8] presented the induction motor parameter estimation using shuffled frog-leaping form data on nameplate.
- Reference [9] presented a measurement of mechanical Power by using simplified Indirect Technique for the PIMs.
- References [10] developed a particle swarm optimization using data taken from tests to minimize the error data.
- Reference [11] presented a differential evolution to estimate the induction motor parameters.
- Reference [12] presented a six-phase IM parameters estimation by using zero-sequence test to improve the accuracy of parameter estimation.
- In [13], the poly-phase IM parameters were estimated using a hybrid optimizer motor with experimental verification.
- Reference [14], which discusses the detection of induction motors using a new genetic approach..

The previously studied survey demonstrates the use of various optimization methods to solve the parameter estimation problem of induction motors. The area of improvement is ongoing and deserves attention. Several optimization methods have been developed for several engineering applications such as: fruit fly [15], moth-flame optimization algorithm[16], cat swarm optimizer [17], sunflower optimization algorithm [18], water cycle used in Distributed Generation [19], and wind driven algorithm [20]. One of the methods used for optimization, PSO optimization method is designed by Eberhart and Kennedy to emulate the movement of birds to move around or the movement of fish [21, 22]. There are many engineering applications that depend on the process of optimization on PSO, such as: method of intelligent diagnosis using optimal LS-SVM presented in [23, 24], optimal design of onshore wind farm, and for the optimal parameters of PID controller [25], optimal cylindrical rotor synchronous motor design [22], one of the main drawbacks of PSO is the good knowledge of the parameters that need to be tuned for the inertia and learning coefficients.

In recent years, the Jaya optimization algorithm (JOA) is one of the latest optimization methods used in many engineering applications [26, 27]. JOA is an optimizer that has been used in many engineering applications as follows:

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The optimal size for a capacitor used in low voltage applications is unknown [28], unit commitment economic application [29], Reducing the reactive power in photovoltaics' used to power an induction motor was discussed in [30], multi-area control of power system automatic generation [31], optimization of power system current flow [32], Environmental distribution of energy sources in a small network[33] for the thermal performance optimizing of the system using underground power cable[34], for the optimization of reactive power solution[35], and by using digital FIR filters design presented in [36]. The SFO is used in many application such as the electrical parameters for three-diode photovoltaic model [37], for optimal estimation of the circuit-based PEMFCs [38], for placement distributed generation in distribution system [39], and for Solving the Security Constrained Optimal Power Flow Problem [40]. In [41], the SFO was developed for finding the parameters of Lithium ion battery. In [42], an improved SFO was developed for efficient distribution systems operation taking into account the impact of the uncertain output power of wind turbines. The SFO algorithm benefited over PSO, JOA, GA, and DE for solving the optimal power flow problem as presented in [43].

This paper derives the equivalent circuit of 6-phase IM. The estimated parameters are carried out using the SFO algorithm. The assessment of simulation results obtained by SFO is compared with four computing paradigms called JOA, GA, DE, and PSO methods. The performance of the competitive algorithms is assessed. The results proved the efficiency of the proposed SFO method by comparing the results obtained with this method with the results obtained from other optimization methods.

The remaining parts are divided as follows: In part 2, the electrical steady-state performance of SPIM is presented depending on the electrical circuit of SPIM. In part 3, the estimated problem of SPIM parameter computation is described as an optimization problem that defines the goal and limitations. The proposed procedure of SFO is explained in section 4. In section 5, the experimental work and comparative analysis of simulation results for all optimization methods are presented. Section 6 concludes the main results of this article.

2. STEADY STATE CHARACTERISTICS OF 6-PHASE INDUCTION MOTOR

Figure 1 shows the steady state equivalent circuit of 6-phase induction motor that is used to study the performance of motor operation at different modes of operation. The equivalent circuit shows the electrical circuit of SPIM without a separate stator winding mutual leakage inductance [12].

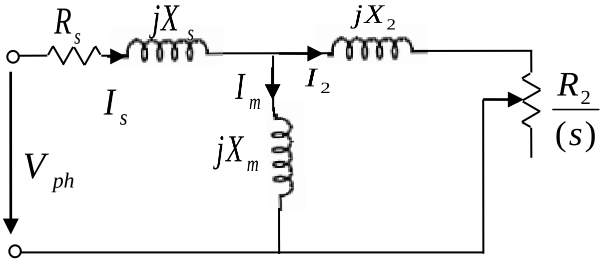

Fig. 1 – Six-phase electrical equivalent circuit of IM.

The stator impedance and magnetizing reactance in SPIM can be written using the Thevenin electrical circuit in Fig. 2.

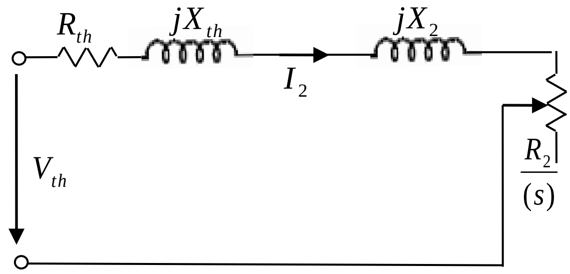

Fig. 2 – Thevenin equivalent circuit.

$$V_{th} = \frac{\mathrm{j}X_m}{R_s + \mathrm{j}X_s + \mathrm{j}X_m} V_{ph} \ , \tag{1}$$

$$Z_{th} = R_{th} + \mathrm{j}X_{th} = \frac{\mathrm{j}X_m(R_s + \mathrm{j}X_s)}{R_s + \mathrm{j}X_s + \mathrm{j}X_m} = \frac{R_s X_m}{X_s + X_m} + \mathrm{j}\frac{X_m X_s}{X_s + X_m} \ . \tag{2}$$

where X_m is magnetizing reactance, R_s and X_s are the stator resistance and reactance, respectively. R_{th} and X_{th} are the equivalent Thevenin resistance and reactance, respectively.

The rotor current I_2 in the Thevenin circuit can be computed as:

$$I_2 = \frac{V_{th}}{Z_{th} + Z_2} = \frac{V_{th}}{\left(R_{th} + \frac{R_2}{s}\right) + \mathrm{j}\left(X_{th} + X_2\right)}, \tag{3}$$

where X_2 is the per phase reactance of rotor and R_2 is the per phase resistance of rotor. The electrical torque is calculated from Eq. (4) as:

$$T_d = \frac{m}{\omega_s} I_2^2 \frac{R_2}{s} = \frac{m}{\omega_s} \frac{V_{th}^2}{\left(R_{th} + \frac{R_2}{s}\right)^2 + \left(X_{th} + X_2\right)^2} \frac{R_2}{s}, \tag{4}$$

where s is the slip of induction motor, m is no of motor phases, ω_s synchronous angular speed, the slip defined at the maximum torque is

$$s_{mT} = \frac{R_2}{\sqrt{\left(R_{th}\right)^2 + \left(X_{th} + X_2\right)^2}} . \tag{5}$$

The 6-phase induction motor maximum torque is computed from:

$$T_{\max} = \frac{m}{2\omega_s} \frac{V_{th}^2}{\left[R_{th} + \sqrt{\left(R_{th}\right)^2 + \left(X_{th} + X_2\right)^2}\right]} . \tag{6}$$

The 6-phase induction motor starting torque is computed as

$$T_{st} = \frac{m}{\omega_s} \frac{V_{th}^2}{\left(R_{th} + R_2\right)^2 + \left(X_{th} + X_2\right)^2} R_2 . \tag{7}$$

The stator current power factor is computed as

$$PF = \cos\left(\tan^{-1}\left(\frac{X_{th} + X_2}{R_{th} + \frac{R_2}{s}}\right)\right). \tag{8}$$

3. **PROBLEM FORMULATION**

Equation (9) presents the objective function of the optimal parameter estimation of the motor under study that aims to minimize the deviation between the experimental and estimated values as:

$$EF = ET_d^{\,2} + ET_{\max}^{\,2} + ET_{st}^{\,2} + Epf^{\,2} . \tag{9}$$

The objective function has four normalized error components representing the full load power factor, the starting torque, rated torque, and the maximum torques. Normalized components are computed as in Eqs. (10)-(13) as:

$$Epf = \frac{epf - mpf}{mpf} , \tag{10}$$

$$ET_d = \frac{eT_d - mT_d}{mT_d} , \tag{11}$$

$$ET_{\max} = \frac{eT_{\max} - mT_{\max}}{mT_{\max}} , \tag{12}$$

$$ET_{st} = \frac{eT_{st} - mT_{st}}{mT_{st}} , \tag{13}$$

where *EF* is objective function expressed as summation of square error that consists of rated power factor, starting torque, full load torque, and maximum torque, where the optimization process aims to reduce the error to the lowest possible value.

4. **SFO ALGORITHMS**

The proposed SFO method is designed to simulate the movement of a sunflower to track the movement of the sun through the pollination that occurs between sunflowers and each other. SFO can also be represented by the inverse square distance of the solar radiation [44]. The direction of sunflower S_k to the sun is written as:

$$S_k = \frac{X^* - X_k}{\left\| X^* - X_k \right\|} , \qquad k = 1, 2, 3, \ldots\ldots, n_p . \tag{14}$$

where X_k and X^* are the existing and best status of plants to the sun directions, n_p is the sunflowers number.

The sunflower step moves in the direction of the sun can be written as

$$d_k = \lambda \times P_k \left(\left\| X_k + X_{k-1} \right\| \right) \times \left\| X_k + X_{k-1} \right\| \tag{15}$$

where λ is the inertial displacement that occurs due to the movement of the sunflower plant and $P_k \left(\left\| X_k + X_{k-1} \right\| \right)$ is the probability of pollination of each flower of a sunflower plant *k* with nearby flowers is expressed as *k*–1. The maximum sunflower step moves in the direction of the sun can be written as

$$d_{\max} = \frac{\left(\left\| X_{\max} - X_{\min} \right\| \right)}{2 \times N_{pop}} , \tag{16}$$

where X_{max} is the higher constraints value, X_{min} is the lower value of constraints and N_{pop} is the sunflowers number of the population. The next updated population X_{k+1} is calculated as:

$$\overline{X}_{k+1} = \overline{X}_k + d_k \times \overline{S}_k . \tag{17}$$

The SFO steps are presented in the flowchart as shown in Fig. 3.

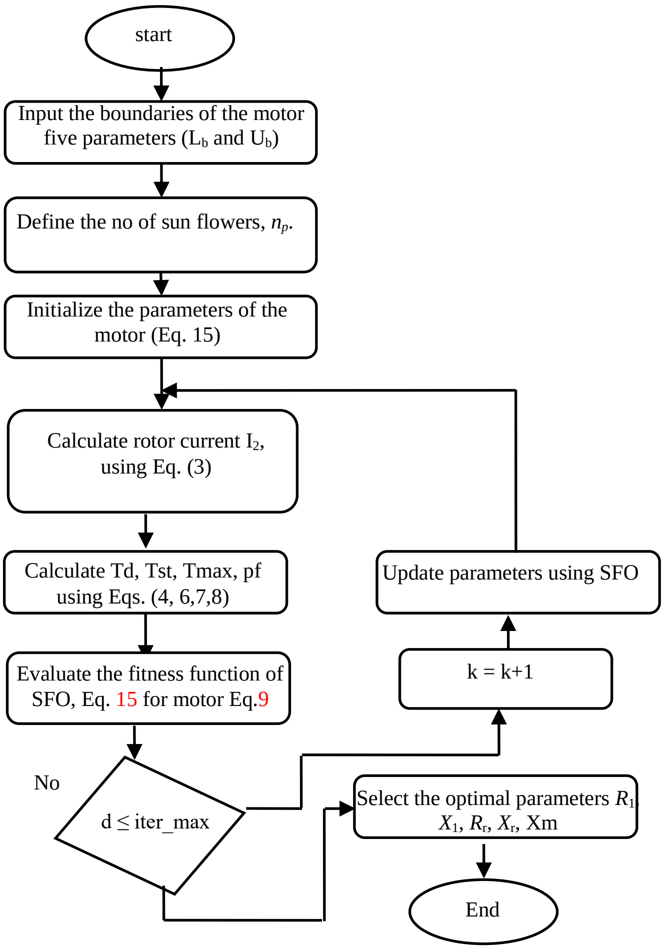

Fig. 3 – SFO flowchart of proposed six phase induction motor parameter estimation.

5. **APPLICATIONS**

5.1. EXPERIMENTAL SETUP

The experimental tests- dc, short circuit (S.C.), and open tests- are implemented on SPIM to calculate the parameters of the electrical circuit. Figure 4 shows an experimental photograph in the Faculty of Engineering, Kafrelsheikh University. The tests are implemented according to the IEEE specifications Std 112TM-2004 for SPIM [4]. Table 1 represents the test data taken for the six-phase IM.

Table 1

Experimental tests of 3 HP six-phase IMs

Variables	**3 HP six phase IM**	
	O.C. test	**S.C. test**
Voltage, V	220	96.9
Current, A	0.95	2.67
Power W	104	159.37
R_{dc} Ω	12	

5.2. SETTINGS PARAMETERS OF OPTIMIZATION ALGORITHMS'

The population size and maximum iteration are respectively 60 and 100 for all algorithms. The other parameters for optimization algorithms are set as follows:

1. For DE [45], [11], mutation probability is 0.5, the crossover probability is 0.7 and scaling factor is 0.5, and for GA [46], [47], resolution = 3, the crossover length = 0.5, and mutation probability = 0.12.

2. For PSO [48], [49], weighting factor c_1= 1, c_2= 2, and search length space are v_k^{max} = 0.8, and v_k^{min} = 0.3.
3. For SFO [44], number of sunflowers = 150, mortality rate = 0.01, pollination rate = 0.05

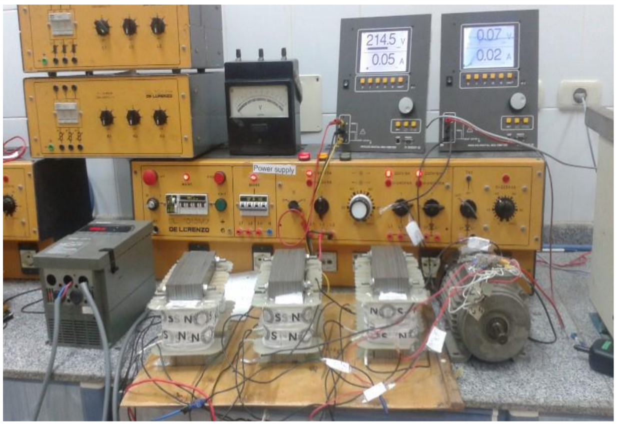

Fig. 4 – Photography of experimental setup of six phase induction motor.

5.3. SIMULATION RESULTS

Table 2 shows the recorded experimental parameters from the experimental tests on a 3 hp modified MPIMs. Also, this table shows the estimated parameters for SFO and four competitive algorithms Jaya and PSO, DE, GA. The fitness function with JOA is (2.99×10^{-5}), PSO algorithm equals (5.13×10^{-5}), with GA equals (1.21×10^{-4}) and DE algorithm equals (5.82 ×10^{-5}), while with the proposed SFO is (6.04×10^{-13}). By comparing the calculated results from the experimental parameters and the parameters estimated by optimization methods, the estimation algorithms can estimate the parameters with great accuracy at the smallest error limits.

Table 2

Evaluation of comparative algorithms for 6-phase IM

Parameters	***Exp.***	***GA***	***DE***	***PSO***	***Jaya***	***SFO***
R_s [Ω]	12	12.281	11.699	12.843	12.202	11.967
X_s [Ω]	12.843	13.687	13.38	11.78	12.428	13.719
R_2 [Ω]	8.098	8.025	8.078	7.98	8.091	8.042
X_2 [Ω]	12.843	11.611	12.11	13.057	13.1035	11.875
X_m [Ω]	266.68	273.141	266.29	260.46	270.769	265.637
T_{st} [N·m]	3.34	3.358	3.36	3.193	3.35	3.348
T_{FL} [N·m]	3.179	3.179	3.187	3.349	3.18	3.1785
T_{max} [N·m]	5.36	5.347	5.392	5.32	5.35	5.359
PF	0.844	0.85	0.843	0.845	0.844	0.844
ΔF		**1.21×10^{-4}**	**5.82×10^{-5}**	**5.13×10^{-5}**	**2.99×10^{-5}**	**6.04×10^{-13}**

Figure 5 clearly shows that the performance curve of 6-phase IM depends on the parameters that are calculated from estimation and the associated experimental tests, the parameters estimated is employed by the PSO optimization, Jaya, DE, GA optimization and proposed SFO algorithm. The estimated torque-slip characteristic by using proposed SFO has minimum differences compared with that calculated from parameters taken from experimental tests, whereas the torque-slip characteristics calculated using the parameters estimated by the suggested algorithms is very near to the real case when compared with other optimization methods. The inner graphic in Figure 5 shows a zooming of the torque speed curve of the region defined by the slip axis in the period from 0.22 to 0.35 and the torque axis in the period from 5.25 to 5.36 N·m., as the torque curve drawn by using SFO is the closest approach to the actual curve.

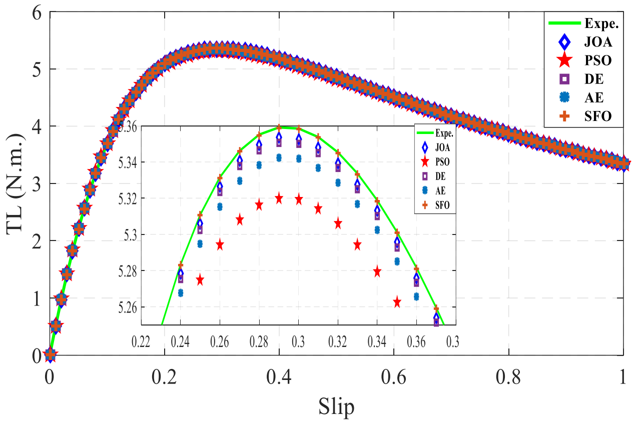

Fig. 5 – Six phase IM torque – slip characteristics.

The stator current characteristics versus slip of 6-phase IM that are dependent on the values computed using the PSO, DE, GA, Jaya, SFO and compared with that computed from experimental tests are shown in Figure 6. Estimated stator current based on parameters that are computed by DE, GA, PSO, JOA, are compared with the characteristics based on tests, while stator current calculated using parameters computed by the SFO is very near to stator current based on the tests.

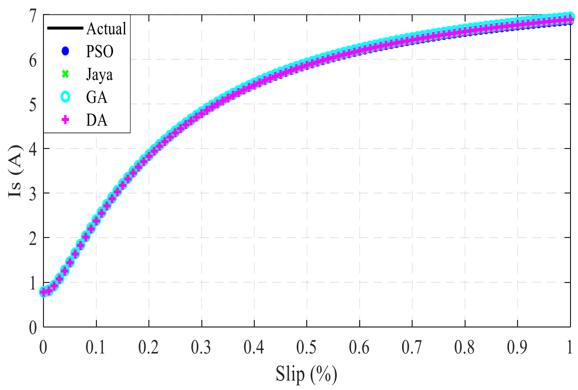

Fig. 6 – stator current curves of six phase IM.

Table 3 presents the statistical components, standard deviation, median, variance, best, worst, and mean of all algorithms adjusted to the same values of 60 populations and 100 iterations, respectively. The results extracted from Table 3 ensure that the proposed SFO gives the best results compared to JOA, PSO, GA, and DE.

Table 3

Statistical components for the different algorithms

index	***Comparative Algorithms***				
	GA	**DE**	***PSO***	***Jaya***	***SFO***
Mean	3.44×10^{-5}	7.57×10^{-6}	1.87×10^{-5}	1.52×10^{-4}	4.03×10^{-9}
Median	3.04×10^{-5}	6.49×10^{-9}	8.93×10^{-6}	1.22×10^{-4}	1.61×10^{-12}
Best	5.82×10^{-6}	4.07×10^{-7}	4.89×10^{-7}	9.74×10^{-6}	4.69×10^{-14}
Standard deviation	1.96×10^{-5}	5.78×10^{-6}	3.73×10^{-5}	1.19×10^{-4}	3.69×10^{-8}
Variance	3.84×10^{-10}	3.34×10^{-11}	1.39×10^{-9}	1.42×10^{-8}	1.37×10^{-15}
worst	9.47×10^{-5}	2.79×10^{-5}	2.89×10^{-4}	5.77×10^{-4}	3.69×10^{-4}

Figure 7 shows the convergence rate of the best solution for all optimization methods. Fig. 7 proves that the SFO method achieves the best convergence if compared to other optimization methods, as it is faster and more stable.

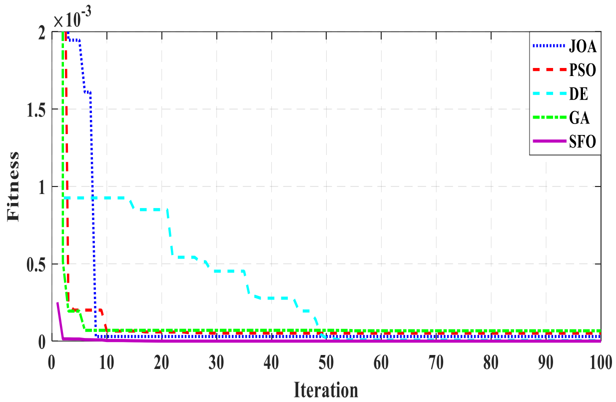

Fig. 7 – Convergence of competitive optimization tool of 6- phase IM.

5.4. ROBUSTNESS

Figure 8 shows the robustness of the competitive five optimization methods. The suggested SFO has a lower error than JOA, GA, PSO, and DE algorithms. Table 3 reports the statistical data of the proposed method. A fair comparison between all algorithms is assured at the same population and maximum iteration

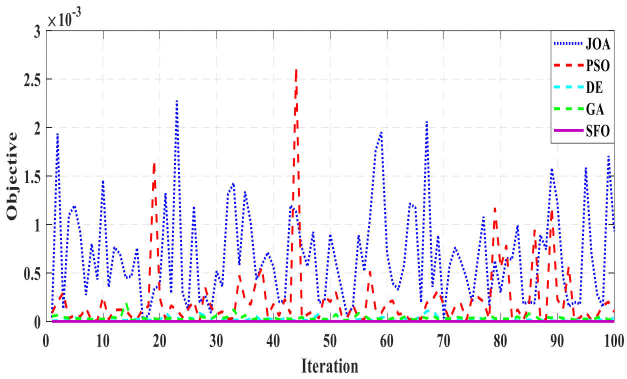

Fig. 8 – Robustness of different optimization algorithms of 6- phase IM.

6. **CONCLUSIONS**

The current paper presented the optimal parameters estimations of SPIM using the sunflower optimization algorithm compared with four optimization algorithms called Jaya, PSO, GA, and DE. The parameters estimated by experimental tests were also evaluated. The output values give an indication of the validity and reliability of all the proposed algorithms for the optimization of the specific parameters of the SPIM.

The statistical analyzes are done to assess the competitive algorithms, which proved that SFO is the best method, as it gave the least possible error with a greater convergence rate.

The resulting indicators from the statistical analysis give the best approximations between the calculated values of the parameters estimated by the optimization algorithms and the experimental parameters. The analytical analysis shows that the SFO algorithm provides a better solution for SPIM parameter estimation.

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