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Hybrid optimization algorithm for parameter estimation of poly-phase induction motors with experimental verification

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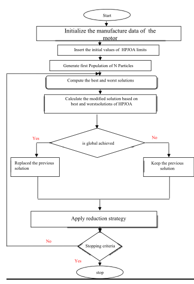
HIGHLIGHTS

- A novel HPJOA for the parameter estimation of poly-phase IMs is presented.
- The proposed method is compared with previous competitive PSO and JOA algorithms.
- Experimental verifications are done on two poly-phase IMs.
- Assessment studies are presented to evaluate the competitive algorithms.
- The robustness of the proposed HPJOA is proved.

GRAPHICAL ABSTRACT



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ABSTRACT

The estimated parameters accuracy of poly-phase induction motors is crucial for effective performance prediction and/or control in various manufacturing applications. This study investigates hybrid algorithm between particle swarm optimization and Jaya optimization algorithms for finding the optimal parameters estimation of poly-phase induction motors. It is carried out using the manufacturer's operation characteristics on two poly-phase induction motors. Numerical results show the capability of the proposed hybrid optimization algorithm. The proposed algorithm has competitive performance compared with conventional algorithms as well as with differential evolution and genetic algorithms. Experimental verifications are carried out on three-phase and six-phase induction motors. Also, it emulates the closeness between experimental and estimated parameters with fast convergence compared to other algorithms. Also, the results reflect the high robustness of the proposed algorithm compared with other algorithms for varied iteration numbers, population size and convergence.

1. Introduction

The Poly-phase Induction Motors (PIMs) are the most used electrical machines [1]. They contribute around 60% of electric power converted to mechanical energy [2]. PIM are favored due to their ruggedness and simplicity in the industry section as 90% of industrial motors are IMs [3]. Examples of induction motors applications involve motor tools equipped with induction motors, adjustable speed motors and pumps [4]. To achieve the target performance of induction machines, the accurate modelling is considered as crucial issue for PIMs [5]. These issues involve the transient and steady-state behavior. The model expresses the stator and rotor windings voltage balance, flux linkages and currents, the air-gap power, and the electromagnetic torques. Therefore, finding the unknown parameters of these machines is a complicated nonlinear non-smooth optimization problem [6]. It aims at achieving the highest closeness degree between the estimated parameters and those of the actual ones. Therefore, the objective function of the considered parameter estimation problem is the minimum deviation between estimated and actual parameters with preserving these parameters within their permissible operating boundaries. To satisfy the parameter identification process, several optimization algorithms have been developed to guarantee the accurate PIM models. In this regard, this paper proposes the hybrid

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Nomenclature

R_s	Per phase stator resistance, Ω
R_2	Per phase rotor resistance, Ω
X_s	Per phase stator reactance, Ω.
X_2	Per phase rotor reactance, Ω.
X_m	Per phase magnetizing reactance, Ω.
V_{ph}	Per phase stator voltage, V
p	number of pole pairs
T_d	electromagnetic torque of the motor, N.m
s	Induction motor slip
I_2	Per phase rotor current, A.
I_s	Per phase stator current, A.
I_{st}	starting current, A.
T_{st}	starting torque of the motor, N.m
T_{max}	maximum torque of the motor, N.m
T_{FL}	rated torque of the motor, N.m
ΔT_d	Normalized power factor
v	velocity of the control variables
F_k^{best}	personal best of control variables
gF_k^{best}	global best of control variables
ΔF_k^{worst}	worst suggested of possible solution
eT_d	Estimated developed torques
mT_{max}	Measured maximum developed torques
eT_{max}	Estimated maximum developed torques
mT_{st}	Measured starting developed torques
eT_{st}	Estimated starting developed torques
s_{mT}	Slip at maximum torque
ΔF	objective function
Δpf	Normalized power factor
ΔT_{st}	Normalized power factor
ΔT_{max}	Normalized power factor
pf	Rated power factor
m	Number of phases
epf	Estimated power factors
mpf	Measured power factors
mT_d	Measured developed torques
k	Iteration number
c_1, c_2, c_3	The learning coefficients
r1, r2, r3	random numbers
$Iter^{max}$	maximum number of iterations

algorithm between particle swarm optimization and Jaya optimization algorithms HPJOA form finding the optimal unknown PIM parameters.

The modelling of induction motors is considered as vital issue in ac drive systems. Accurate parameters identification of induction motor is an urgent work in the viewpoint of control drives and operation aspects [7,8]. It is necessary to find the IMs' parameters at low implementation costs at high degree of accuracy. The traditional methods applied for finding the equivalent circuit parameters are dependent on no-load and locked rotor tests as in IEEE Std 112-1991 and its modifications IEEE Std 112-2004 [9]. Added to that, the high cost of hardware that is needed to implement. So, Due to these restrictions, many optimization methods developers provide number of advanced methods to meet the target of finding satisfactory level of the estimated parameters [10]. For achieving this target, several optimization methods are exploited to optimally estimating the parameter of PIMs equivalent circuits [11–13]. In the literature, several methods have been carried out for finding the unknown parameters of PIMs. References [14] review the various methods that were developed for estimating the unknown parameters of PIMs. In this line, the previous efforts are summarised as follows:

- Reference [15] developed the artificial immune system for extracting the IM parameters to optimize the parameters of IMs from experimental tests and manufacturer data.
- Reference [16] presented the neural network as training mechanism for finding the solution of parameter estimation problem.
- References [17,18] presented the shuffled frog-leaping for extract the equivalent circuit parameters of IMs from the manufacturer data.
- Reference [19] presented a simplified model for parameter estimation of the PIMs.
- Reference [20] estimated the 6-phase IM parameters using modified standard tests. This zero-sequence test is proceed using an improved equivalent circuit to enhance the estimated parameter accuracy.
- Reference [21] developed multi-objective PSO algorithm to minimize the deviation between the manufacturer and estimated data.
- Reference [22] developed differential evolution for finding the parameter estimation of three phase IMs.

The previous survey shows the application of various optimization techniques for solving the parameter estimation problem. The field of optimization is continuous and worth of interest. Many optimization algorithms were developed for many real engineering problems as: moth-flame [23], fruit fly [24], cat swarm [25], sunflower [26], wind driven [27], and water cycle [28] optimization algorithms. Among the optimization algorithm, PSO algorithm that mimics the main idea of fish or birds looking for food was introduced in by Eberhart and Kennedy [29] . Several real-world works are reported based on PSO algorithm and its variants in the literature. Reference[30] presented an intelligent diagnosis method using, design of synchronous motor [30], optimization of PID controller parameters adjustment [31], optimal costs of generation production [32]. The main drawback of PSO is the need to adjust learning and inertia coefficients.

An efficient metaheuristic technique called PSO it was started by Kennedy and Eberhart was presented in Ref.[33]. This algorithm was taken from swarm attitude such as bird flow and education in nature [30]. Particles that move inside the problem are used at high speeds [34]. In every repetition, the velocities of the self-particles are randomly preset related to the best position of the same particle and the best position of the near particle. The best particles and the best close ones are selected according to the conditions set by the user. The transition of all particles occurs normally to the best solution. The word "swarm" originates from the unequal movement of particles in the problem area, and now very much resembles a group of fish or birds [35]. The Jaya algorithm [36] is one of the recent metaheuristic techniques which is quickly finding many applications in different fields of engineering and science. The JOA directed the solution towards the best value with the progress of the optimization algorithm [37]. The main merits of JOA are its simplicity and the benefits of no need for adopting and selecting the specific control parameters that avoid the demerits of PSO algorithm. JOA is very promising optimizer which is developed for many real-world applications as: optimal sizing of capacitor-bank types in the low voltage distribution networks [38], control of online load frequency in wind power systems [39], solving economic/emission unit commitment [40]. Added to the previous applications, JOAs is applied for harmonic mitigation and employing reactive power compensation of three phase induction motor that drives by photo-voltaic-based DSTATCOM [41], automatic generation control of multi-area interconnected power system [42], for optimal power flow [43], environment based allocation of distributed energy resources in a micro-grid [44] for optimizing the thermal performance of the underground power cable system [45], for reactive power dispatch problem [46], and for design the digital FIR filters in [47].

As mentioned, the problem is formulated as non-linear optimization problem because the conventional optimization techniques fail to deal exactly with the need of linearization that reduces the solution quality and high dependency on the initial point of linearization. So, it must seek other methods to solve the non-linear optimization problem avoiding the previous drawbacks. The features of this paper are concluded as follows:

- The steady state model of multi-phase induction motor is derived.

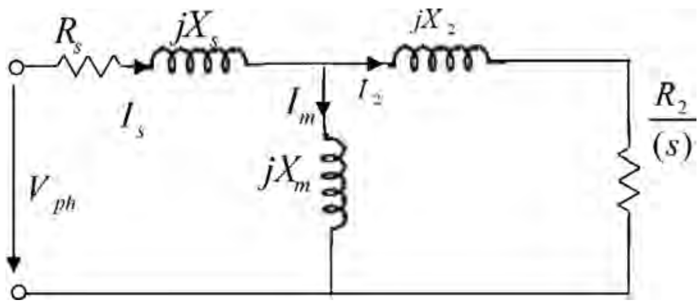


Fig. 1. Multi-phase induction motor equivalent circuit.

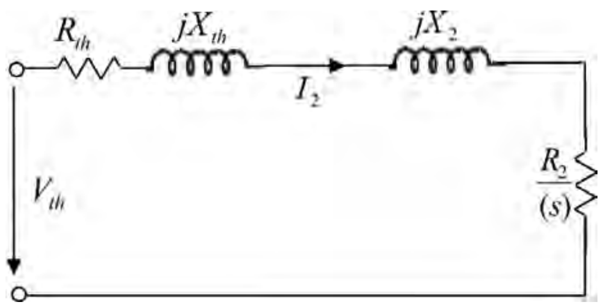


Fig. 2. Thevenin equivalent circuit.

- The Hybrid PSO-Jaya optimization algorithm is proposed to extract the optimal unknown parameters of PIM from the nameplate data.
- The performance of HPJOA is assessed compared with Jaya, GA, DE and PSO optimization algorithms for three and six-phase induction motors.
- The assessment study proves that the HPJOA has the fast response compared with other competitive algorithms with actual parameters.
- Also, the results reflect the high robustness of the proposed HPJOA compared with others.

The rest sections are organized as follows: In section 2, the steady state characteristics of poly-phase IM is presented based on equivalent circuit. In Section 3, the parameter estimation problem is formulated as an optimization problem that defines the objective and constraints. The previous optimization algorithms are added to section 4. The design procedure of HPJOA is presented in Section 5. In Section 6, the parameter estimation problem and its operation characteristic are applied on two poly-phase IMs. Section 7 concludes the paper findings.

2. Steady state characteristics ofpoly-phase induction motor

The steady state operating characteristics are identified based on the steady state equivalent circuit shown in Fig. 1. The equivalent circuit shows the per phase steady state equivalent circuit of poly-phase induction motor without separate mutual leakage inductance of stator winding [20]. The stator and magnetizing impedance in poly-phase induction motor can be reduced to the Thevenin equivalent circuit as shown in Fig. 2.The Thevenin voltage is computed through:

$$V_{th} = \frac{jX_m}{R_s + jX_s + jX_m} V_{ph} \tag{1}$$

The Thevenin equivalent circuit of poly phase induction motor(PIM)is shown in Fig. 2 as:

$$Z_{th} = R_{th} + jX_{th} = \frac{jX_m(R_s + jX_s)}{R_s + jX_s + jX_m} = \frac{R_s X_m}{X_s + X_m} + j\frac{X_m X_s}{X_s + X_m} \tag{2}$$

The current flow in the IM rotor circuit of induction motor can be calculated as:

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

The developed torque can be determined by Eq. (4) as:

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

From the above equation the slip at maximum torque s_{mT} can be calculate from

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

Substituting the slip at maximum torque from Eq. (5) into the electromagnetic torque in Eq. (4) the maximum torque can be calculated 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 Starting torque can be calculated from

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

The input current power factor can be obtained from

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

3. Problem formulation

The fitness function aims at finding the lowest deviation level for the starting, operating , maximum torques and the power factor. This fitness function assures the capability of estimated parameters at different operating conditions. Eq. (9) presents the combined fitness function for finding the optimal parameter estimation of the tested induction motors. It aims at minimizing the deviation between the estimated and experimental data. The combined objective function, in Eq. (9), has four normalized deviation components for the starting, rated and maximum torques, and the full load power factor as:

$$\Delta F = \Delta {T_d}^2 + \Delta {T_{\max}}^2 + \Delta {T_{st}}^2 + \Delta pf^2 \tag{9}$$

Computing the normalized components is carried out using Eqs. (10)–(13) as:

$$\Delta pf = \frac{epf - mpf}{mpf} \tag{10}$$

$$\Delta \mathrm{T_d} = \frac{\mathrm{eT_d} - \mathrm{mT_d}}{\mathrm{mT_d}} \tag{11}$$

$$\Delta T_{\max} = \frac{eT_{\max} - mT_{\max}}{mT_{\max}} \tag{12}$$

$$\Delta T_{st} = \frac{eT_{st} - mT_{st}}{mT_{st}} \tag{13}$$

where ΔF is assumed as the required objective square error function of full load, starting, and maximum torque, and rated power factor which is to be minimized.

Eq. (9) is solved subject to the minimum and maximum limitations of the stator and rotor sides' motor parameters.

4. The developed optimization algorithms

In the following section, the GA, DE, PSO, and JAYA are described in details as:

4.1. Differential evolution DE

Differential evolution DE is algorithm based on stochastic and population. The population is composed of pop individuals and every individual in the population represents a solution that possible to minimize the fitness function. DE operates in three sequential steps in all iteration [22]:

- Mutation: pop mutated individuals are generated using some individuals of the population. A vector for the mutated solution is called mutant vector. There are different strategies to create a mutant vector. Here only the three most common mutation methods are explained [48]. Other mutation strategies and their performance have been discussed in.
- Mutation strategy is random mutation strategy, in which three randomly selected individuals from the population are used to generate the mutant vector.
- Mutation strategy uses the best individual from the population to create the mutant vectors.
- The mutation strategy moves the current individual towards the best individual in the population before being disturbed with a scaled difference of two randomly selected individuals.

Crossover: we recombine the set of mutant vectors created in mutation with the original population members to generate progeny solutions.

Selection: In this last step, the progeny is compared with its origin, and the best one will but the population for the next generation

4.2. Genetic algorithm GA

GA is an evolutionary optimizer that takes a sample of possible solutions and employs mutation, crossover, and selection as the primary operators for optimization. For the case of multi-phase induction motor parameters estimation, there are five parameters being optimized for the multi-phase induction motor parameters estimation [34].

The workability of GAs is based on Darwinian's theory of survival of the fittest. Genetic algorithms may contain a chromosome, a gene, and set of population, fitness, fitness function, breeding, mutation and selection. Genetic algorithms begin with a set of solutions represented by chromosomes, called population [49]. Solutions from one population are taken and used to form a new population, which is motivated by the possibility that the new population will be better than the old one. Further, solutions are selected according to their fitness to form new solutions, that is, offspring's.

The solution procedure of the parameters estimation problem can be carried out using the proposed GA optimization algorithm as follows:

1 Start: Generate random population of chromosomes, that is, suitable solutions for the problem.
2 Fitness: Evaluate the fitness of each chromosome in the population.
3 New population: Create a new population by repeating following steps until the new population is complete.
i Selection: Select two parent chromosomes from a population according to their fitness. Better the fitness, the bigger chance to be selected to be the parent.
ii Crossover: With a crossover probability, cross over the parents to form new offspring, that is, children. If no crossover was performed, offspring is the exact copy of parents.
iii Mutation: With a mutation probability, mutate new offspring at each locus.
iv Apply: Place new offspring in the new population.
4 Update: Use new generated population for a further run of the algorithm.
5 Check: If the end condition is satisfied, stop, and return the best solution in current population.

4.3. PSO algorithm

The Particle Swarm Optimization is configured with a set of random results and seeks to improve by updating generations. In PSO, the possible solutions, called particles, flythrough the problem space by following the current optimum particles [30]. In PSO, a set of randomly initial swarm propagates in the design space towards the optimal solution over a number of iterations based on large amount of information about the design space that is assimilated and shared by all members of the swarm. Modification of the swarm agent positions is realized by the position and transition information. Each agent transition can be simulated by two dimensional referred to the available information's about self and group experiences. The basic PSO version is based on the collected information of self and group experiences according to the positions of agents.

The basic PSO is presented as in [33] as:

$$\Delta \mathrm{x}_{k+1} = \mathrm{v}_k.\Delta \mathrm{x}_k + \mathrm{c}_1 \times \mathrm{r}_1 \times \left(\mathrm{x}_k^{\mathrm{best}} - \mathrm{x}_k\right) + \mathrm{c}_2 \times \mathrm{r}_2 \times \left(\mathrm{xg}_k^{\mathrm{best}} - \mathrm{x}_k\right) \tag{14}$$

$$\mathrm{x}_{k+1} = \mathrm{x}_k + \Delta \mathrm{x}_{k+1}$$

where, X_k, $x_k^{best}$is the vector of control variables and personal best of control variables at iteration k. $xg_k^{best}$is the vector of global best of control variables at iteration k, $x_{k+1}$is the vector of control variables at iteration k+1.

The velocity of the control variables updated at iteration k is:

$$v_k = v_k^{\max} - (v_k^{\max} - v_k^{\min}) \times k / Iter^{\max} \tag{15}$$

Where $v_k{}^{max}$ and $v_k{}^{min}$ is a function of search space length in each dimension, $Iter^{max}$ is the maximum number of iterations. The learning coefficients c_1 and c_2 are the factors which PSO technique optimizes different objective functions on the basis of personal and group experiences and each agent tries to modify its position the updating formula (14).

The minimum and maximum transition of the updating formula in (14) for agent position as:

$$\Delta x^{\min} \le \Delta x_k \le \Delta x^{\max} \tag{16}$$

where:

$$\begin{cases} \Delta x^{\max} = k_m (x_k^{\max} - x_k^{\min}) \\ \Delta x^{\min} = -k_m (x_k^{\max} - x_k^{\min}) \end{cases} \tag{17}$$

4.4. JAYA optimization algorithm

The Jaya optimization algorithm (JOA) replaces the updating formula in PSO algorithm by the following equation as [50,51]. The main advantage of JOA is characterized with the high ability of movement in the direction of the best solution and avoiding the possibility of trapping into worst solutions. The combination of these two terms concentrates on the best solution region [52]. Two global solutions, reflected in the updating equation terms, the best and worst solution for the overall

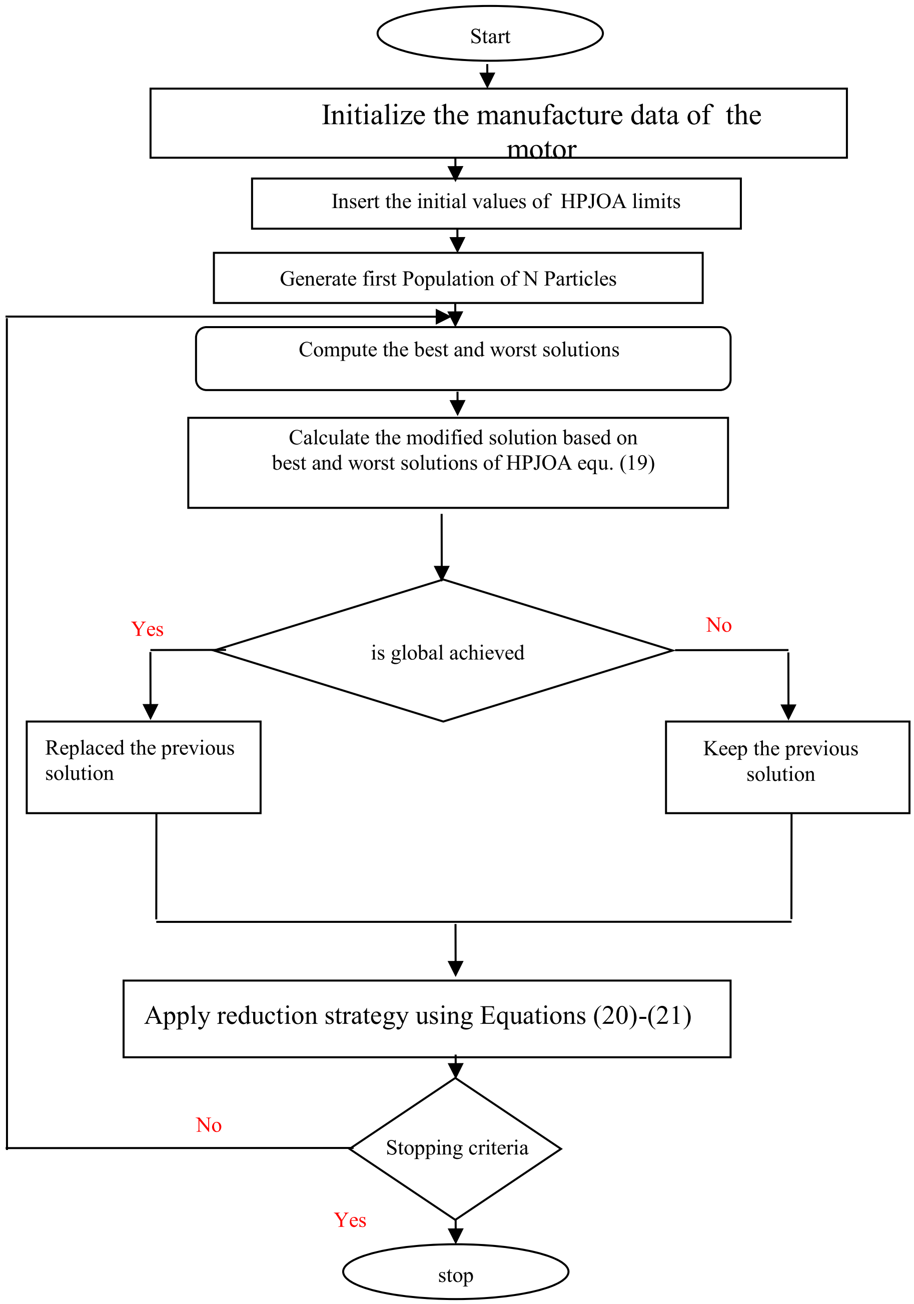


Fig. 3. Flowchart for hybrid PSO-Jaya based optimization process.

particles. But, JOA is not dependent on the self-experience of particle as in PSO algorithm [53]. Then, the updating equation has two terms the first enhances the closeness between the best solutions while the second terms avoid the closeness to worst solution.

The updating equation is expressed as:

$$x_{k+1} = x_k + r_1 \times \left(x_k^{best} - \Delta x_k\right) - r_2 \times \left(x_k^{worst} - x_k\right) \quad (18)$$

where, x_k^{best}, x_k^{worst} are the value of the variable k for the best and worst suggested member of a set of possible solution. r_1 and r_2 are two random numbers in the range (0,1).

5. The proposed hybrid PSO -JAYA optimization algorithm

The proposed hybrid optimization algorithm combines the merits of PSO and Jaya algorithms. It enhances the search space, forces the solution to the global best solution and away from the worst solutions. Eq. (19) presents the updating formula for the proposed HPJOA. It is dependent on the global best, worst solution and taken into consideration the impact of self-experience of the associated particles.

The proposed updating equation can be expressed as:

$$x_{k+1} = v_k x_k + c_1 \times r_1 \times \left(x_k^{best} - x_k\right) - c_2 \times r_2 \times \left(x_k^{worst} - x_k\right) + c_3 \times r_3 \times (x_k^{gbest} - x_k) \quad (19)$$

where, x_k^{gbest} is the value of the variable k for the global member of a set of possible solution. For the *k*th iteration in the range of (0, 1), r_1, r_2 and r_3 are the three random numbers for the *k*th variable. c_1, c_2 and c_3 are learning coefficients, the first term shows the affinity of solution to move nearer to the personal best solution, The second term shows the affinity of solution to move nearer to the global best solution and the last term is the tendency of the solution to avoid the worst solution.

Fig. 4. Experimental setup at Faculty of Engineering, Kafrelsheikh University.

5.1. Proposed procedure steps

The proposed procedure of HPJOA can be carried out as follows:

1 Defining the motor manufacture data, parameters limits, constraints and the HPJOA coefficients.
2 Initialize the control variables (estimation variables) within the predefined boundaries.
3 Evaluate each particle of the initialized matrix by determining the fitness function through solving the steady state equivalent circuit.
4 Identify the global, personal and worst solutions.
5 Update the control variables using Eq. (19).
6 Check the upper and lower boundaries and transition constraints given in Eqs. (16) and (17).
7 The reduction strategy to concentrate the search space and there for enhance the solution quality. The factor α refers to the coefficient applied for reduction strategy. In this strategy, the search space is managed through adaptive variation of the upper and lower limits according to the following two equations:

$$\min \upsilon = \min \upsilon + \alpha \times (\max \upsilon - \min \upsilon) \tag{20}$$

$$\max \upsilon = \max \upsilon - \alpha \times (\max \upsilon - \min \upsilon) \tag{21}$$

In this paper the factor α equals 0.08.

Repeat steps 3 to 4 until the maximum iteration as stopping criteria are achieved. Fig. 3 shows the flow chart of HPJOA.

6. Applications

6.1. Experimental setup

The experimental tests- open, short circuit and DC tests- are carried out on two poly-phase IM to obtain the equivalent circuit parameters. Photograph of the experimental implementation located at Faculty of Engineering; Kafrelshiekh University is provided in Fig. 4. The tests are carried out according to the specifications of the IEEE Std 112^{TM}-2004 for tests procedure for PIM [6]. Table 1 represents the recorded measurements for three-phase and six-phase IMs. By using the data recorded for voltage, current, input power and the dc resistances from no load, short circuit and short circuit tests in Table 1. These records are used to determine the three and six phase induction motor parameters by using the proposed hybrid HPJOA and the competitive algorithms.

Table 1
Experimental tests of 1/3 HP three-phase and 3 HP six-phase IMs.

Variables	Three phase IM (1/3 HP)		Six phase IM (3 HP)	
	No load test	Short-circuit test	No load test	Short-circuit test
Voltage, V	220	89.7	220	96.9
Current, A	0.22	0.65	0.95	2.67
Input power, W	9.5	25.6	104	159.37
R_{dc} Ω	21.25		12	

6.2. Settings of competitive optimization algorithms' parameters

The parameters setting for the competitive algorithms are described as follows:

Maximum iteration number is 100 and the population size is 60.

For GA [34], the parameters were set crossover length = 0.5, resolution = 3, and mutation probability = 0.12. For DE [22,48], the parameters were set crossover probability = 0.7 and scaling factor =0.5, mutation probability = 0.5. Finally, for HPJOA, the parameters are c_1=1, c_2=2, c_3=1.5 and search space length were set $\upsilon_k^{\max} = 0.8,\ and\ \upsilon_k^{\min} = 0.8$.

Case 1: three phase induction motor parameter estimation

The competitive algorithms are integrated to obtain the parameter estimations of 1/3 HP three-phase induction motor. The experimental parameters of the steady state equivalent circuit of the 3 phase induction motor are shown in the second column of Table 2. The estimated parameters of steady-state equivalent circuit of three phase induction motor using PSO, JOA, GA, DE and HPJOA methods are reported in the rest of columns of the Table 2. The obtained results show that the parameters by using the proposed HPJOA are closer to actual value of motor than PSO and JOA, GA and DE. In the viewpoint of operational indices, a comparison is carried out between the estimated and the experimental values of the starting, maximum, full load torques, and full load power factor. The HPJOA has the lower fitness function (1.71×10^{-6}) compared with Jaya method which equals (2.9×10^{-5}), with PSO method which equals (9.25×10^{-5}), with GA method which equals (4.84×10^{-5}) and with DE method which equals (1.98×10^{-4}). It is cleared that, the pro-

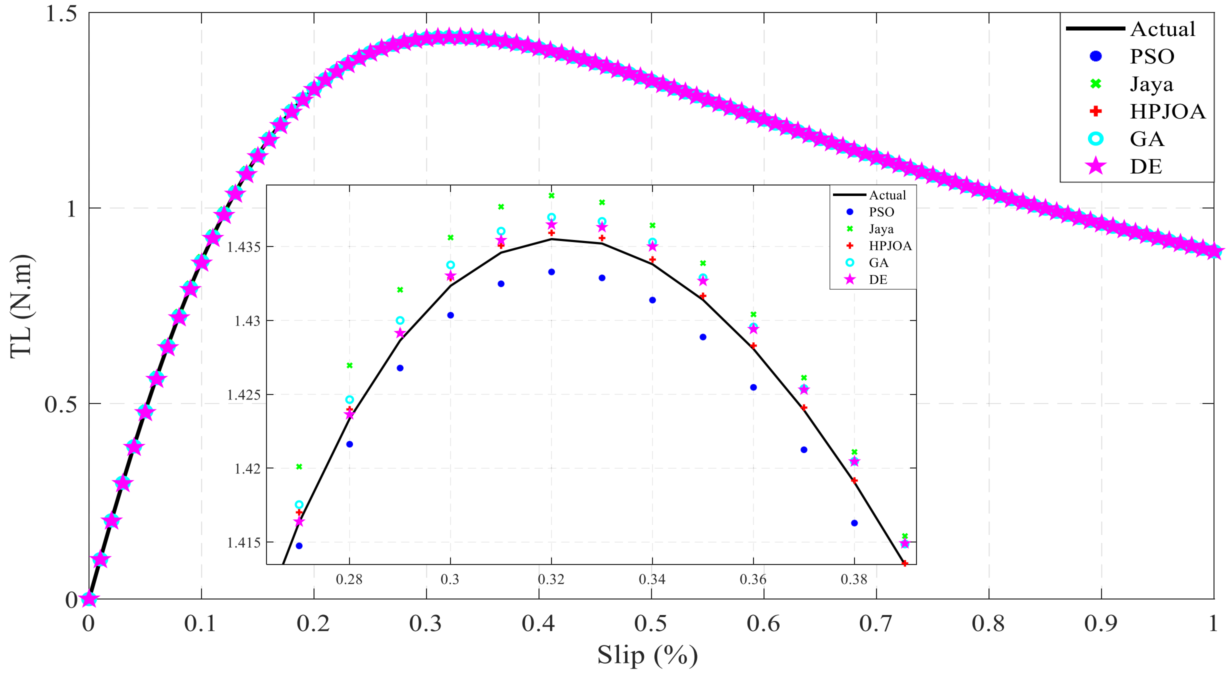


Fig. 5. Electromagnetic torque - slip characteristics of three phase IM (-measurement,* PSO, × Jaya, o GA, DE, +HPJOA).

Table 2
Assessment of competitive algorithms for 3-phase induction motor.

Parameters	Experimental	DE	PSO	GA	Jaya	HPJOA
R_s	21.25	19.46	21.53	20.21	21.33	21.177
X_s	61.95	63.42	60.40	60.62	61.87	61.01
R_r	39.32	40.08	39.379	39.93	39.42	39.352
X_r	61.95	62.74	63.78	64.99	62.03	63.07
X_m	999.52	1049.5	1012.1	1045	1005.3	1000.1
T_{st}	0.89	0.889	0.89	0.889	0.89	0.89
T_{FL}	0.987	0.981	0.988	0.985	0.992	0.988
T_{max}	1.435	1.44	1.433	1.43	1.439	1.436
Pf	0.807	0.810	0.808	0.811	0.807	0.806
$\Delta F \times 10^{-4}$		1.98	0.924	0.484	0.29	0.0171
% reduction		-	53.33%	25.56%	85.35%	91.36%

Table 3
Assessment of competitive algorithms for six-phase induction motor.

Parameters	Experimental	PSO	DE	Jaya	GA	HPJOA
R_s	12	11.63	11.38	11.65	12.4	11.898
X_s	12.8426	13.86	12.74	13.78	12.65	13.095
R_r	8.0978	8.12	8.26	8.105	8.04	8.092
X_r	12.8426	12.14	13.69	12.13	12.65	12.66
X_m	266.68	273.55	268.41	274.29	268.27	263.66
T_{st}	3.34	3.348	3.35	3.36	3.348	3.34
T_{FL}	3.1785	3.17	3.16	3.18	3.183	3.18
T_{max}	5.36	5.377	5.38	5.386	5.339	5.36
Pf	0.844	0.846	0.84	0.847	0.847	0.842
$\Delta F \times 10^{-4}$		0.963	0.791	0.788	0.329	0.0208
% reduction		-	17.86%	18.18%	65.84%	97.84%

posed HPJOA achieves the hoiesht reduction of 91.36% improvement is occurred with the largest fitness function obtained with DE.

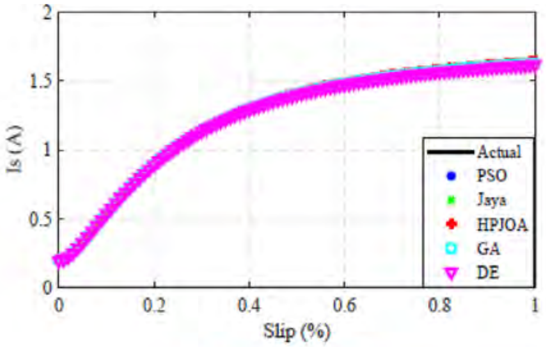
Case 2: Six phase induction motor parameter estimation

Table 3 shows the experimental tests are recorded for the 3 HP modified six-phase induction motor. To confirm the proposed HP JOA algorithm is performed for parameter estimation. While the estimated parameters of steady-state equivalent circuit of six phase induction motor using PSO, Jaya and Hybrid PSO-Jaya methods are recorded in Table 4, receptively. The comparison between the experimental and estimated parameters concludes that the investigated estimation algorithms can accurately estimate the equivalent circuit parameter at acceptable levels of closeness. The estimated parameters obtained by using HPJOA are closer to actual value of motor and it has smaller error than Jaya, and PSO. The Hybrid PSO-Jaya optimization algorithm has lower fitness function (2.08×10^{-6}) compared with Jaya method which equals (7.88×10^{-5}), with PSO method which equals (9.63×10^{-5}), with GA method which equals (3.29×10^{-5})and with DE method which equals (7.91×10^{-5}). It is cleared that, the proposed HPJOA achieves the highest reduction of 97.84% improvement is occurred with the largest fitness function obtained with PSO.

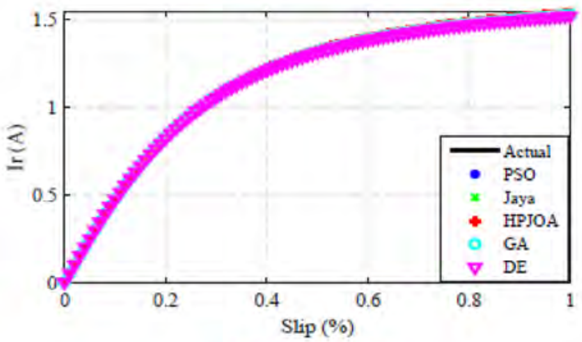
Performance of operating characteristic with estimated parameters

Fig. 5 shows the three-phase induction motor torque-slip characteristic using parameters that was recorded from the measurements clearly, that the parameters estimated from optimization PSO, that the parameters estimated from optimization Jaya, that the parameters estimated from optimization GA, that the parameters estimated from optimization DE, and that the parameters estimated from the proposed HPJOA. Estimated torque-slip characteristic, using parameters calculated by DE, has a little difference compared to the measured torque-slip characteristic, while estimated curve using parameters obtained by the HPJOA is very close to real characteristic.

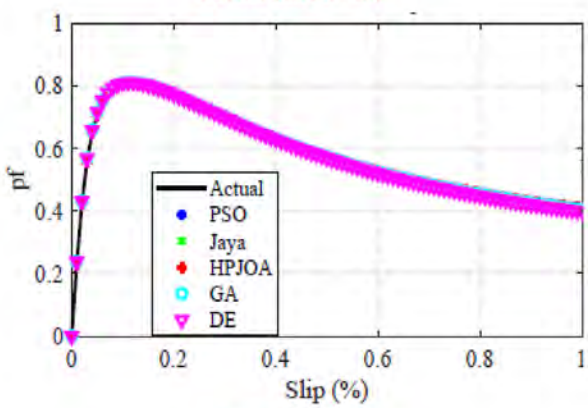
The stator-slip and rotor current-slip characteristics using parameters estimated by the five algorithms are shown in Fig. 6a, b. Estimated stator and rotor current characteristics using parameters calculated by PSO has large difference compared to the measured characteristics, while estimated characteristics using parameters calculated by the HPJOA is very close to the real characteristics. The magnetizing current-slip and power factor-slip characteristics of three-phase induction motor using parameters calculated by the PSO, Jaya, GA, DE and HPJOA are shown in Fig. 6 c, d. Estimated magnetizing current and power factor characteristics using parameters calculated by PSO, Jaya, GA and DE have big difference compared to the measured characteristics, while



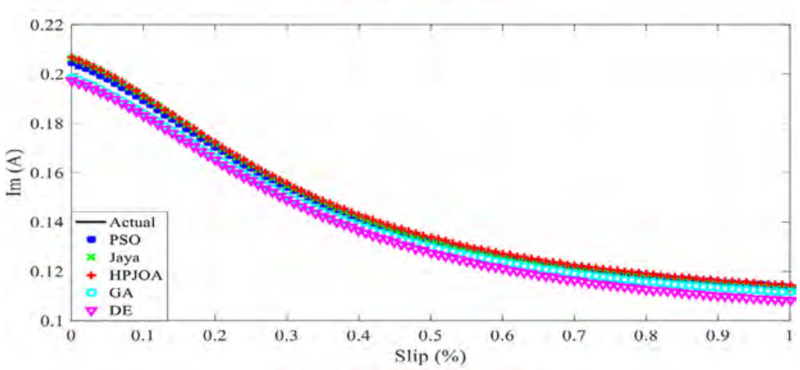
a Stator current - slip



b Rotor current - slip



c Power factor - slip



d Magnetizing current - slip

Fig. 6. Performance characteristics of three phase IM (-measurement,* PSO, × Jaya, o GA, Δ DE, +HPJOA).

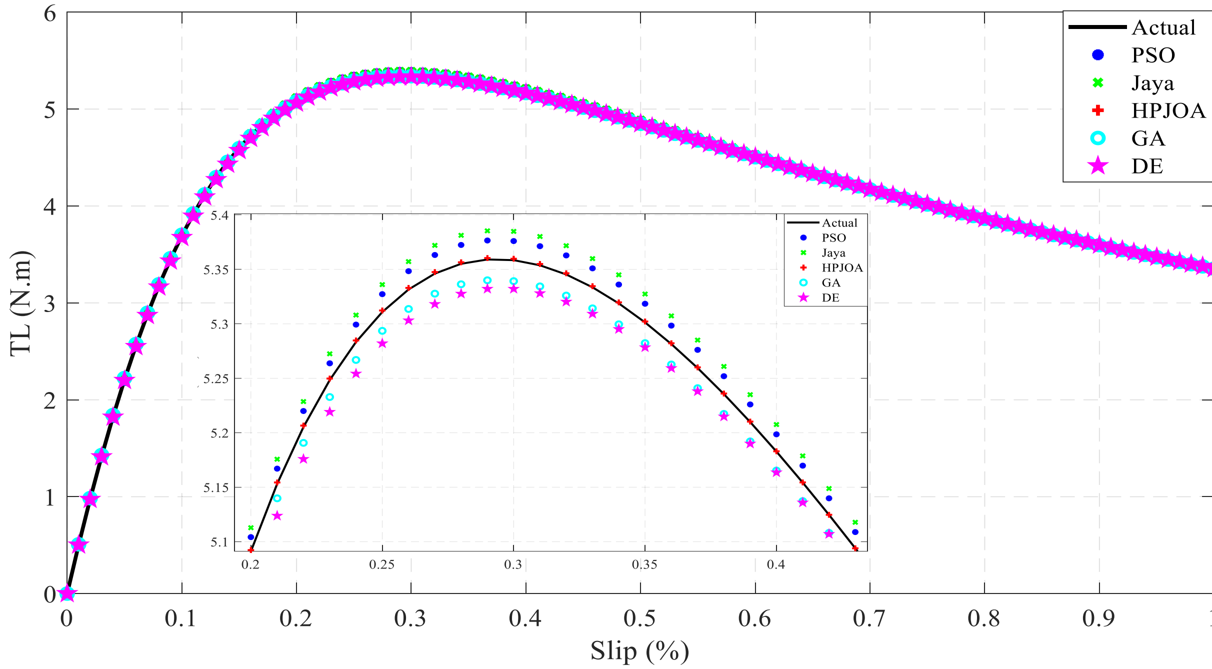


Fig. 7. Torque - slip characteristics of six phase (-measurement,* PSO, × Jaya, o GA, Δ DE, +HPJOA).

estimated characteristics using parameters calculated by the HPJOA is very close to the real characteristics.

Fig. 7 shows the six-phase induction motor parameters estimated from the measurements clearly, that the parameters estimated from optimization PSO, that the parameters estimated from optimization Jaya, GA, DE and that the parameters estimated from the proposed hybrid algorithm. Estimated torque-speed characteristic using parameters calculated by PSO, Jaya, GA and DE have little differences compared to the measured torque speed characteristic, while estimated curve using parameters obtained by the proposed algorithm is very close to real characteristic.

The stator and rotor current -slip characteristics of six-phase induction motor that are based on the parameters calculated by the PSO, Jaya and Hybrid PSO-Jaya are shown in Fig. 8a and b. Estimated stator and rotor current characteristics using parameters, which are calculated by PSO and Jaya are compared to the measured characteristics, while estimated characteristics using parameters calculated by the Hybrid PSO-Jaya is very close to the real characteristics. The magnetizing current and power factor-slip characteristics of six-phase induction motor using parameters calculated by the PSO, Jaya and HPJOA algorithm are shown in Fig. 8 c, d. Estimated magnetizing current and power factor characteristics using parameters calculated by PSO and Jaya has difference compared to the measured characteristics, while estimated characteristics using parameters calculated by the HPJOA is very close to the real characteristics.

6.3. *Competitive tools assessment*

6.3.1. *Statistical analysis*

Tables 4 and 5 present the statistical indices, mean, median, best, worst, standard deviation and variance, of the competitive algorithms that are carried for 100 iterations and 60 populations, respectively. It is concluded that the proposed HPJOA leads to the best values of the indices compared with PSO, GA, DE and JOA.

6.3.2. *Convergence rates*

The convergence rate of the fitness function of the competitive optimization algorithms are shown in Fig. 9 a and b, respectively. It can be seen that from this figure that the proposed HPJOA has better converges rates as the early reaching to final solution provides a proof for fast response compared with other optimization algorithms

6.3.3. *Robustness*

To verify the robustness of the competitive algorithms, 100 separate runs are applied on the tested motors. Fig. 10 a and b illustrate the robustness of the five algorithms. It is clear that, the proposed HPJOA has the highest robustness compared with PSO, GA, DE and Jaya algorithms. To confirm the fair comparison between the competitive algorithms, we consider the effects of population and maximum iteration variation. Figs. 11 and 12 clear that, the proposed HPJOA has the highest robustness, compared with PSO, GA, DE and Jaya algorithm.

Table 4
Statistical analysis of the competitive methods for the three-phase IM.

index	Competitive algorithms				
	GA	DE	PSO	Jaya	HPJOA
Mean	3.77×10^{-5}	6.33×10^{-5}	3.2×10^{-5}	4.23×10^{-5}	3.09×10^{-6}
Median	3.43×10^{-5}	4.92×10^{-5}	2.82×10^{-5}	3.74×10^{-5}	2.20×10^{-6}
Best	4.34×10^{-6}	6.86×10^{-6}	1.47×10^{-6}	2.07×10^{-6}	3.59×10^{-7}
Standard deviation	2.27×10^{-5}	4.49×10^{-5}	2.28×10^{-5}	2.85×10^{-5}	2.43×10^{-6}
Variance	5.13×10^{-10}	2.01×10^{-9}	5.19×10^{-10}	8.15×10^{-10}	5.91×10^{-12}
worst	1.26×10^{-4}	2.43×10^{-4}	1.22×10^{-4}	1.73×10^{-4}	1.16×10^{-5}

Table 5
Statistical analysis of the competitive methods for the six-phase IM.

index	Competitive algorithms				
	GA	DE	PSO	Jaya	HPJOA
Mean	3.44×10^{-5}	7.57×10^{-6}	1.87×10^{-5}	1.52×10^{-4}	5.21×10^{-6}
Median	3.04×10^{-5}	6.49×10^{-9}	8.93×10^{-6}	1.22×10^{-4}	2.57×10^{-6}
Best	5.82×10^{-6}	4.07×10^{-7}	4.89×10^{-7}	9.74×10^{-6}	2.30×10^{-7}
Standard deviation	1.96×10^{-5}	5.78×10^{-6}	3.73×10^{-5}	1.19×10^{-4}	8.18×10^{-6}
Variance	3.84×10^{-10}	3.34×10^{-11}	1.39×10^{-9}	1.42×10^{-8}	6.69×10^{-11}
worst	9.47×10^{-5}	2.79×10^{-5}	2.89×10^{-4}	5.77×10^{-4}	4.88×10^{-5}

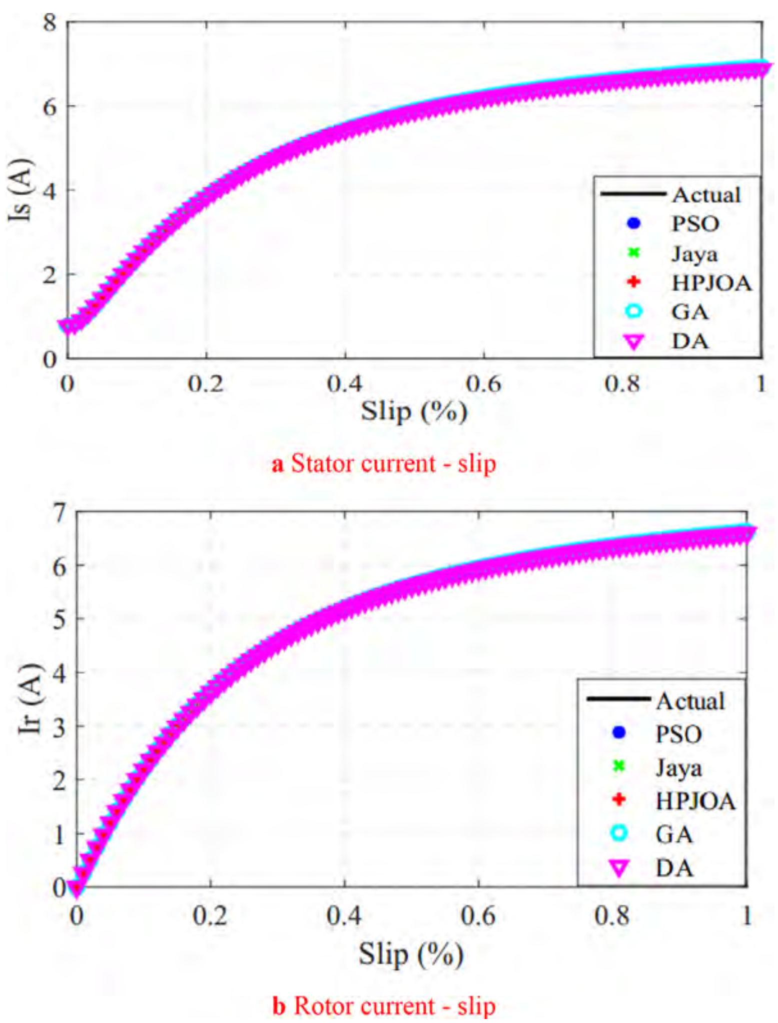
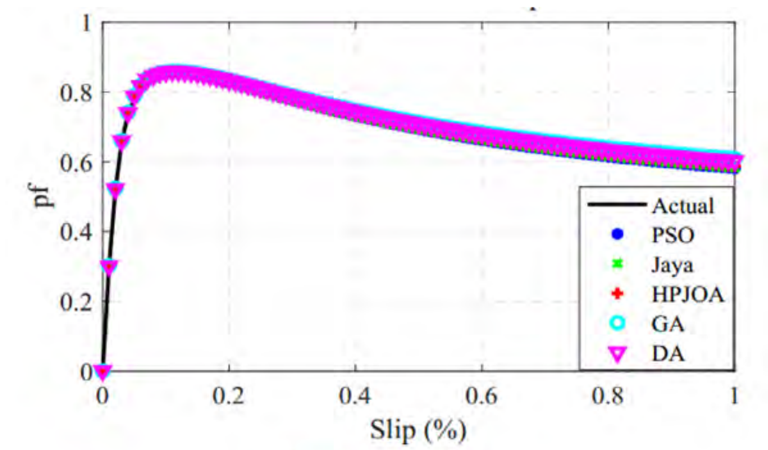
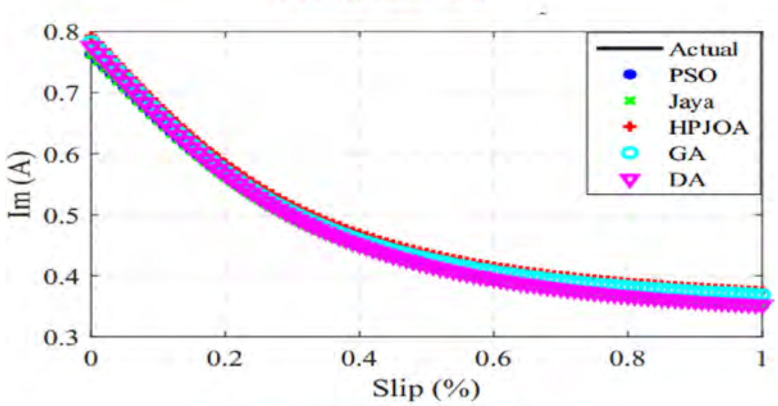


Fig. 8. Performance characteristics of six phase IM (-measurement,* PSO, × Jaya, o GA, Δ DE, +HPJOA).

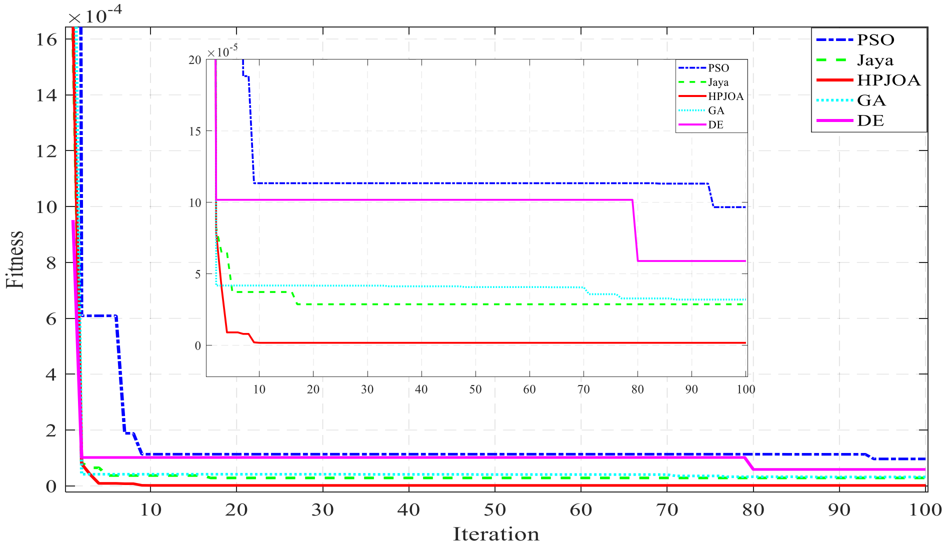
Fig. 8. Continued



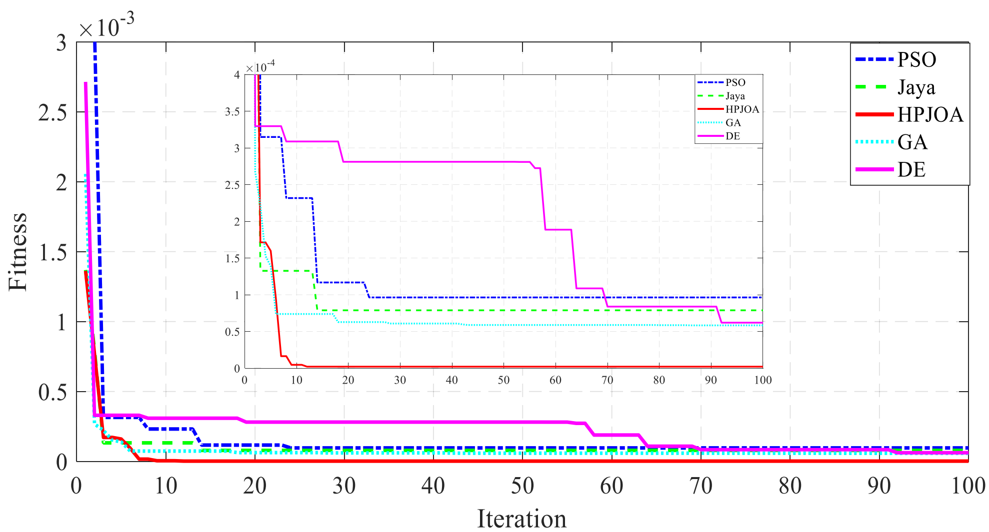
c Power factor - slip



d Magnetizing current - slip

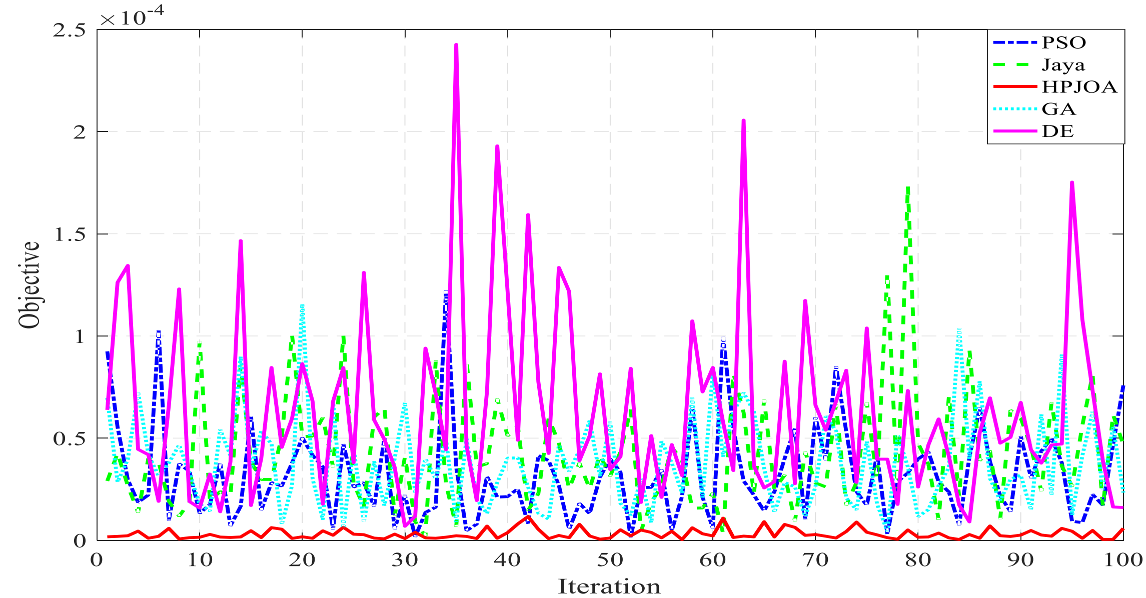


(a)*3 phase motor*

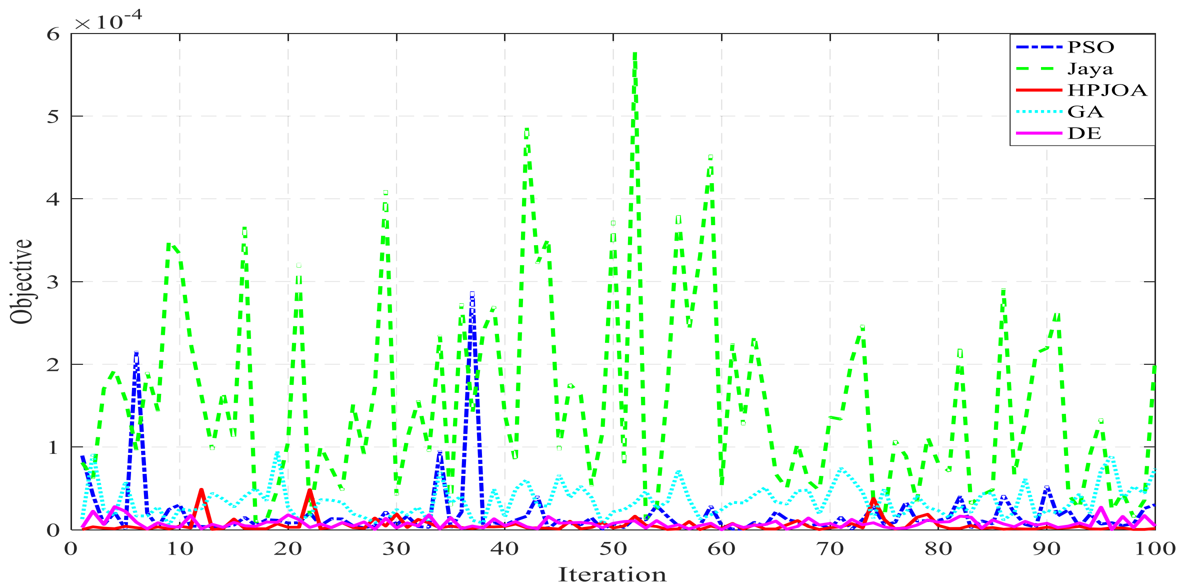


(b)*6-phase motor*

Fig. 9. Convergence rates of competitive algorithms (PSO, Jaya, GA, DE and HPJOA).

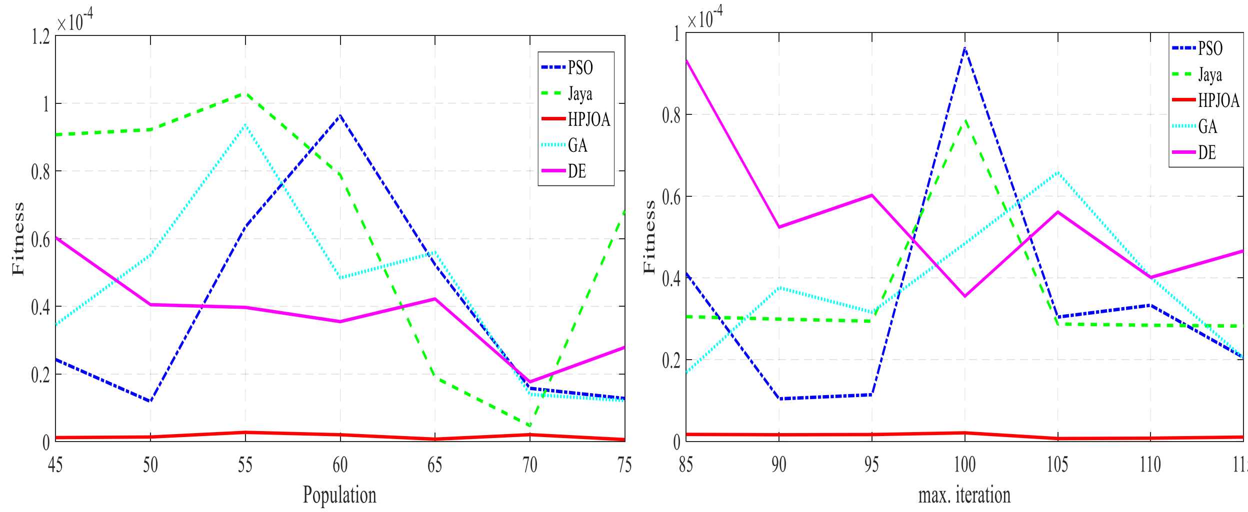


a *3 phase motor*



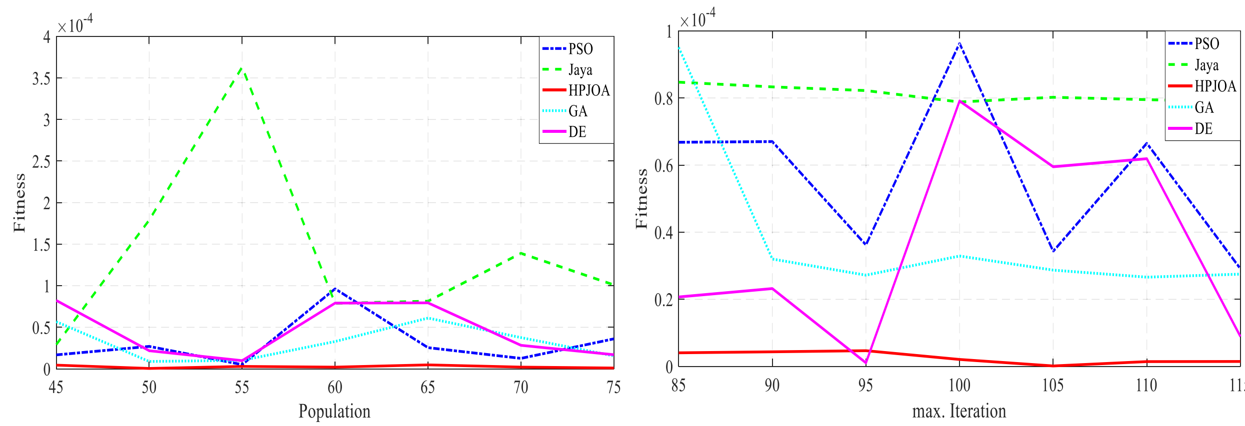
b *6 phase motor*

Fig. 10. Robustness of competitive algorithms (PSO, Jaya, DE, GA and HPJOA).



a. variable population at max. iteration =100 b. variable max. iteration at population =60

Fig. 11. Fitting of competitive algorithms of three phase induction motor.



a. variable population at max. iteration =100b. variable max. iteration at population =60

Fig. 12. Fitting of competitive algorithms of six phase induction motor.

7. Conclusions

This study has presented the parameters estimations of poly-phase induction motors. The HPJOA, Jaya, and PSO algorithm have been used to estimate the parameters of the electrical model of the poly-phase induction motors. The benefits of the proposed HPJOA algorithm have been compared with PSO, JOA, GA and DE for two poly-phase induction motors. The parameters estimation of the competitive algorithms is assessed together the performance of the poly-phase induction motors. Also, the estimated parameters have been compared with the experimental tests. The results indicate the validation and reliability of the suggested hybrid optimization algorithm for efficient extraction of the optimal parameters of three- and six poly phase induction machines. Statistical analyses are provided to assess the competitive algorithms. The robustness of the proposed HPJOA is proved against other competitive algorithms and for varied iteration numbers and population sizes. In addition, the proposed HPJOA realizes fast, stable, and smooth operation characteristic at acceptable convergence rates compared with PSO and Jaya. The proposed HPJOA achieves the highest reduction of 91.38% and 97.84% that are occurred with the largest fitness function obtained with the competitive algorithms, DE and PSO, for three and six phase motors, respectively. The statistical indices involve best agreements between the estimated and experimental values for the three optimization algorithms. It can be concluded that the HPJOA is most simple, stable, and global out performance optimization algorithm. The use of HPJOA leads to decrease the deviation of estimated parameters compared to PSO and Jaya. Also, the use of HPJOA also enhances the operating performances of the tested PIMs.

Declaration of Competing Interest

Authors have no conflict of interest.

References

[1] S JX, Fei GYW, Luk PCK, Ma J. A high-performance line-start permanent magnet synchronous motor amended from a small industrial three-phase induction motor. IEEE Trans Magn 2009;45(10):4724–7.

[2] Kahn M, Ayeleso AO. Plasma energy conversion system for electric power generation. In: 2015 International conference on the industrial and commercial use of energy (ICUE). South Africa: Cape Town; 2015. p. 206–11. doi:10.1109/ICUE.2015.7280270.

[3] S. Tillner, “Operation and application of polyphase induction motors,” in Small electric motors, the institution of engineering and technology, Michael Faraday House, Six Hills Way, Stevenage SG1 2AY, UK: IET, pp. 45–64.
[4] Mirzaeva G, Sazdanoff L. The effect of flux optimization on energy efficiency of induction motors in fan and pump applications. In: 2015 Australasian universities power engineering conference (AUPEC). NSW, Australia: Wollongong; 2015. p. 1–6. doi:10.1109/AUPEC.2015.7324867.
[5] Vukosavic SN. Modeling of induction machines. In: Electrical Machines. New York, NY: Springer New York; 2013. p. 379–425.
[6] Al-Jufout SA, Al-Rousan WH, Wang C. Optimization of induction motor equivalent circuit parameter estimation based on manufacturer’s data. Energies 2018;11(7):1–13. doi:10.3390/en11071792.
[7] Bhowmick D, Manna M, Chowdhury SK. Estimation of equivalent circuit parameters of transformer and induction motor from load data. IEEE Trans Ind Appl 2018;5(3):2784–91. doi:10.1109/TIA.2018.2790378.
[8] Abdelwanis MI, El-Sehiemy RA. A fuzzy-based controller of a modified six-phase induction motor driving a pumping system. Iran J Sci Technol - Trans Electr Eng 2019. doi:10.1007/s40998-018-0066-4.
[9] Committee EM. IEEE standard test procedure for polyphase induction motors having liquid in the magnetic gap; 2004. November.
[10] Singh GK. Multi-phase induction machine drive research - a survey. Electr Power Syst Res 2002;61(2):139–47 X. doi:10.1016/S0378-7796(02)00007.
[11] Hannan MA, Ali JA, Mohamed A, Hussain A. Optimization techniques to enhance the performance of induction motor drives: a review. Renew Sustain Energy Rev 2018. doi:10.1016/j.rser.2017.05.240.
[12] Y. K. Damak, N., S. Kamoun, “Estimation of asynchronous machine parameters and state variables,” vol. 4, no. 3, pp. 1112–1120, 2011.
[13] Lindenmeyer D, Dommel HW, Moshref A, Kundur P. An induction motor parameter estimation method. Int J Electr Power Energy Syst 2001;23(4):251–62. doi:10.1016/S0142-0615(00)00060-0.
[14] L E, Toliyat MRHA. A review of RFO induction motor parameter estimation techniques. IEEE Power Eng. Rev. 2002;22(7):52 –52.
[15] Sakthivel VP, Bhuvaneswari R, Subramanian S. Artificial immune system for parameter estimation of induction motor. Expert Syst Appl 2010;37(8):6109–15. doi:10.1016/j.eswa.2010.02.034.
[16] K Z, Wlas HATM. Neural-network-based parameter estimations of induction motors. IEEE Trans Ind Electron 2008;55(4):1783–94. doi:10.1109/TIE.2008.918615.
[17] Perez I, Gomez-Gonzalez M, Jurado F. Estimation of induction motor parameters using shuffled frog-leaping algorithm. Electr Eng 2013;95(3):267–75. doi:10.1007/s00202-012-0261-7.
[18] Gomez-Gonzalez M PI, Jurado F. Shuffled frog-leaping algorithm for parameter estimation of a double-cage asynchronous machine. IET Electr Power Appl 2012;6(8):484–90.
[19] Bucci G SM, Ciancetta F, Fiorucci E, Ometto A. A simplified indirect technique for the measurement of mechanical power in three-phase asynchronous motors. Int J Emerg Electr Power Syst 2019;20(2).
[20] D O, Che ELHS, Abdel-Khalik AS. Parameter estimation of asymmetrical six-phase induction machines using modified standard tests. IEEE Trans Ind Electron 2017;64(8):6075–85.
[21] Ã Sakthivel VP, Bhuvaneswari R, Subramanian S. Engineering applications of artificial intelligence multi-objective parameter estimation of induction motor using particle swarm optimization. Eng Appl Artif Intell 2010;23(3):302–12. doi:10.1016/j.engappai.2009.06.004.
[22] Guedes JJ, Castoldi MF, Goedtel A, Agulhari CM, Sanches DS. Parameters estimation of three-phase induction motors using differential evolution. Electr Power Syst Res 2018;154:204–12. doi:10.1016/j.epsr.2017.08.033.
[23] Elsakaan AA, El-sehiemy RA, Kaddah SS, Elsaid MI. An enhanced moth-flame optimizer for solving non-smooth economic dispatch problems with emissions. Energy 2018;157:1063–78. doi:10.1016/j.energy.2018.06.088.
[24] R-A RM, Abou El-Ela DAFAA, Abdelaziz El-Sehiemy R. Solving multiobjective economical power dispatch problem using MO-FOA. In: Twentieth international middle east power systems conference (MEPCON). Egypt: Cairo; 2018. p. 19–24. doi:10.1109/MEPCON.2018.8635119.
[25] Abou El-Ela AA, El-Sehiemy RA, Ali ES, Kinawy AM. Minimisation of voltage fluctuation resulted from renewable energy sources uncertainty in distribution systems. IET Gener Transm Distrib Jun. 2019;13(12):2339–51. doi:10.1049/iet-gtd.2018.5136.
[26] Gomes GF, da Cunha SS, Ancelotti AC. A sunflower optimization (SFO) algorithm applied to damage identification on laminated composite plates. Eng Comput 2019;35(2):619–26. doi:10.1007/s00366-018-0620-8.
[27] Shaheen AM, El-Sehiemy RA, Farrag SM. A novel framework for power loss minimization by modified wind driven optimization algorithm. In: Others of 2018 international conference on innovative trends in computer engineering. ITCE; 2018. p. 344–9. 2018-March. doi:10.1109/ITCE.2018.8316648.
[28] El-Ela AAA, El-Sehiemy RA, Abbas AS. Optimal placement and sizing of distributed generation and capacitor banks in distribution systems using water cycle algorithm. IEEE Syst J 2018. doi:10.1109/JSYST.2018.2796847.
[29] Eberhart R KJ. A new optimizer using particle swarm theory. In: Proceedings of the sixth international symposium on micro machine and human science; 1995. p. 39–43. doi:10.1109/MHS.1995.494215.
[30] El-Sehiemy RA EM, Abd-Elwanis MI, Kotb AB. Synchronous motor design using particle swarm optimization technique. In: Proceedings of the 14th international Middle East power systems conference (MEPCON’10). Cairo University; 2010. p. 795–800.
[31] Jia L, Zhao X. An improved particle swarm optimization (PSO) optimized integral separation PID and its application on central position control system. IEEE Sens J 2019;19(16):7064–71. doi:10.1109/JSEN.2019.2912849.
[32] Abou-El-Ela AA, El-Sehiemy RA. Optimized generation costs using a modified particle swarm optimization version. In: 2008 12th international Middle East power system conference, MEPCON, 2008; 2008. p. 420–4. doi:10.1109/MEPCON.2008.4562392.
[33] Bijan MG, Pillay P. Efficiency estimation of the induction machine by particle swarm optimization using rapid test data with range constraints. IEEE Trans Ind Electron 2019;66(8):5883–94. doi:10.1109/TIE.2018.2873121.
[34] Hasanova N. A comparative study of particle swarm optimization and genetic algorithm. Qubahan Acad J 2020;1(1):33–45. doi:10.48161/qaj.v1n1a7.
[35] H J, del Valle RGHY, Venayagamoorthy GK, Mohagheghi S. Particle swarm optimization: basic concepts, variants and applications in power systems. IEEE Trans Evol Comput 2008;12(2):171–95. doi:10.1109/TEVC.2007.896686.
[36] Rao RVenkata. Jaya: a simple and new optimization algorithm for solving constrained and unconstrained optimization problems. Int J Ind Eng Comput 2016;7(1):19–34. doi:10.5267/j.ijiec.2015.8.004.
[37] Raut U, Mishra S. An improved Elitist–Jaya algorithm for simultaneous network reconfiguration and DG allocation in power distribution systems. Renew Energy Focus 2019. doi:10.1016/j.ref.2019.04.001.
[38] H W, Abbas MAE. Optimal sizing of capacitor-bank types in the low voltage distribution networks using JAYA optimization. In: 2018 9th international renewable energy congress (IREC). Tunisia: Hammamet; 2018. p. 1–5. doi:10.1109/IREC.2018.8362449.
[39] Pradhan C, Bhende CN. Online load frequency control in wind integrated power systems using modified Jaya optimization. Eng Appl Artif Intell 2017;77:212–28 no. December2019. doi:10.1016/j.engappai.2018.10.003.
[40] Yang Z, Guo Y, Niu Q, Ma H, Zhou Y, Zhang L. A novel binary jaya optimization for economic/emission unit commitment. In: 2018 IEEE Congr. Evol. Comput. CEC 2018 - Proc.; 2018. noJanuary 2019.
[41] Mishra S, Ray PK. Power quality improvement using photovoltaic Fed DSTATCOM based on JAYA optimization. IEEE Trans Sustain Energy 2016;7(4):1672–80. doi:10.1109/TSTE.2016.2570256.
[42] Singh SP, Prakash T, Singh VP, Babu MG. Analytic hierarchy process based automatic generation control of multi-area interconnected power system using Jaya algorithm. Eng Appl Artif Intell 2017;60:35–44 September 2016. doi:10.1016/j.engappai.2017.01.008.
[43] Warid W, Hizam H, Mariun N, Abdul-Wahab NI. Optimal power flow using the Jaya algorithm. Energies 2016;9(9). doi:10.3390/en9090678.
[44] J P, Trivedi MTBIN, Purohit SN. Environment dispatch of distributed energy resources in a microgrid using JAYA algorithm. In: 2016 2nd International conference on advances in electrical, electronics, information, communication and bio-informatics (AEEICB). India: Chennai; 2016. p. 224–8. doi:10.1109/AEEICB.2016.7538278.
[45] Ocłoń P, et al. Thermal performance optimization of the underground power cable system by using a modified Jaya algorithm. Int J Therm Sci 2018;123:162–80. doi:10.1016/j.ijthermalsci.2017.09.015.
[46] Barakat AF, El-Sehiemy RA, Elsayd MI, Osman E. Solving reactive power dispatch problem by using JAYA optimization algorithm. Int J Eng Res Africa 2018;36:12–24. doi:10.4028/www.scientific.net/JERA.36.12.
[47] Chilamkurthi DPVSVS, Tirupatipati GC, Sulochanarani J, Pamula VK. Design of optimal digital FIR filters using TLBO and Jaya algorithms. In: 2017 International conference on communication and signal processing (ICCSP). Chennai; 2017. p. 0538–41. doi:10.1109/ICCSP.2017.8286416.
[48] Wang C, Liu Y, Liang X, Guo H, Chen Y, Zhao Y. Self-adaptive differential evolution algorithm with hybrid mutation operator for parameters identification of PMSM. Soft Comput 2018;22(4):1263–85. doi:10.1007/s00500-016-2413-6.
[49] Bijan MG, Al-Badri M, Pillay P, Angers P. Induction machine parameter range constraints in genetic algorithm based efficiency estimation techniques. IEEE Trans Ind Appl 2018;54(5):4186–97. doi:10.1109/TIA.2018.2836344.
[50] Azizipanah-Abarghooee R, Dehghanian P, Terzija V. Practical multi-area bi-objective environmental economic dispatch equipped with a hybrid gradient search method and improved Jaya algorithm. IET Gener Transm Distrib 2016;10(14):3580–96. doi:10.1049/iet-gtd.2016.0333.
[51] Huang C, Wang L, Yeung RSC, Zhang Z, Chung HSH, Bensoussan A. A prediction model-guided Jaya algorithm for the PV system maximum power point tracking. IEEE Trans Sustain Energy 2018;9(1):45–55. doi:10.1109/TSTE.2017.2714705.
[52] Rao RV, More KC. Design optimization and analysis of selected thermal devices using self-adaptive Jaya algorithm. Energy Convers Manag 2017;140:24–35. doi:10.1016/j.enconman.2017.02.068.
[53] El-Sattar SA, Kamel S, El Sehiemy RA, Jurado F, Yu J. Single- and multi-objective optimal power flow frameworks using Jaya optimization technique. Neural Comput Appl 2019;31(12):8787–806. doi:10.1007/s00521-019-04194-w.