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Solution of optimal reactive power dispatch of power systems using hybrid particle swarm optimization and imperialist competitive algorithms

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ABSTRACT

Management of reactive power resources is essential for secure and stable operation of power systems in the standpoint of voltage stability. In power systems, the purpose of optimal reactive power dispatch (ORPD) problem is to identify optimal values of control variables to minimize the objective function considering the constraints. The most popular objective functions in ORPD problem are the total transmission line loss and total voltage deviation (TVD). This paper proposes a hybrid approach based on imperialist competitive algorithm (ICA) and particle swarm optimization (PSO) to find the solution of optimal reactive power dispatch (ORPD) of power systems. The proposed hybrid method is implemented on standard IEEE 57-bus and IEEE 118-bus test systems. The obtained results show that the proposed hybrid approach is more effective and has higher capability in finding better solutions in comparison to ICA and PSO methods.

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Introduction

The optimal reactive power dispatch problem (ORPD) is impressive on safe and economical operation of power systems. In fact, it plays an important role for secure operation of power systems. It is a sub-problem of the optimal power flow (OPF) calculation, which adjusts all kinds of controllable variables, such as generator voltages, transformer taps, shunt capacitors/inductors, and handles a given set of physical and operating constraints to minimize transmission losses or other concerned objective functions [1–3]. The value of reactive compensators and transformer tap settings are discrete variables while reactive power outputs of generators and bus voltage magnitudes are continuous variables, which makes the ORPD problem mixed integer nonlinear programming problem. Many classical optimization techniques such as linear programming (LP) [4,5], gradient search (GS) [6], interior point methods (IP) [7], and quadratic programming (QP) [8], have been applied for solving ORPD problems in power systems.

Modified interior point (MIP) method has been proposed for determining the optimal values of reactive power sources to minimize the total system real power losses in [9]. In [10], Lagrangian decomposition based method has been proposed for solution of the ORPD problem in multi-area power systems. In this paper the cost of the reactive power exchanges among areas are also considered.

These classical methods have some drawbacks, such as converging to the closest local optima. These methods are also unable of handling nonlinear and non-convex constraints and discontinuous functions and problems having multiple local minimum points. In the past, computational intelligence-based techniques, such as improved GA [11], genetic algorithm (GA) [12], real parameter GA [13], evolutionary programming (EP) [14], adaptive GA [15], particle swarm optimization (PSO) [16], bacterial foraging optimization (BFO) [17], hybrid PSO [18], differential evolution (DE) [19–21], gravitational search algorithm (GSA) [22], seeker optimization algorithm (SOA) [1] have been applied for solving ORPD problem. These methods present extremely superiority in obtaining the near-global optimum and in handling non-convex and discontinuous objectives and have effectiveness in overcoming the disadvantages of classical algorithms. In [23], a new optimization algorithm has been proposed for solution of ORPD problem, which is based on the mass interactions and law of gravity.

Total loss minimization, voltage deviation reduction and voltage stability improvement are the main objective functions considered in solution of ORPD problem [24]. In [25], biogeography-based optimization (BBO) algorithm presented for solving multi-objective ORPD problems. In [26], harmony search algorithm (HSA) proposed to solve ORPD problem. In [27], an improved GA

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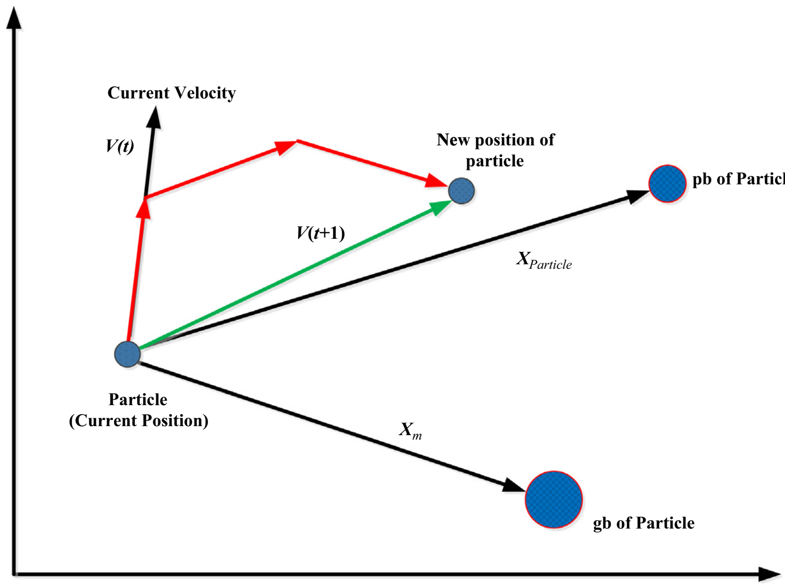

Fig. 1. Particle swarm optimization principle (PSO).

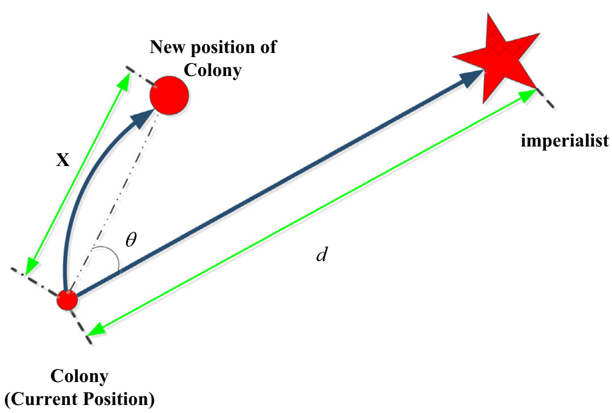

Fig. 2. Movement of colonies toward their relevant imperialist.

approach is presented to solve ORPD problem for enhancing voltage stability. Modified NSGA-II (MNSGA-II) is implemented in [28] to solve multi-objective ORPD problem by minimizing real power loss and maximizing the system voltage stability. In this paper, controlled elitism and dynamic crowding distance strategies are added to the conventional NSGA-II. The load uncertainty is modeled using Monte-Carlo simulations in solving multi objective ORPD problem [29]. In [30] a newly developed teaching learning based optimization (TLBO) algorithm has been proposed to solve multi-objective optimal reactive power dispatch (ORPD) problem by minimizing real power loss, voltage deviation and voltage stability index. A hybrid approach based on binary imperialist competitive algorithm (BICA) and binary particle swarm optimization (BPSO) has been proposed in [31] to find the optimal energy procurement for electricity retailer with multiple procurement options. In [32] hybrid invasive weed optimization (IWO) and modified imperialist competitive algorithm (MICA) has been proposed for solving the optimal reactive power dispatch problem. In this paper, hybrid PSO–ICA is applied for the solution of ORPD problem of power systems. Two IEEE standard power systems, i.e., IEEE 57-bus and 118-bus power systems, are used for solving ORPD problem with objectives of minimization of transmission loss and total voltage deviation (TVD). The simulation results show that hybrid PSO–ICA has better or comparable performance than the other algorithms.

The rest of the paper is organized as follows: In section 'Problem formulation', ORPD problem is formulated. In section 'Proposed methodology', a hybrid PSO–ICA algorithm is described. In section 'Simulation results and discussion', simulation results are presented and discussed. The conclusion is drawn in section 'Computation time'.

Problem formulation

Objective functions

Two different objective functions are considered in this work for ORPD problem. It should be mentioned that these two objectives are considered separately and is not solved as a multi-objective optimization problem.

Minimization of active power loss

One of the main objectives of the reactive power dispatch is to minimize the active power losses in the transmission network, which can be defined as follows:

$$f_1 = \min(P_{Loss}) = \min\left[\sum_{k=1}^{N_{TL}} G_k(V_i^2 + V_j^2 - 2V_iV_j\cos\alpha_{ij})\right] \tag{1}$$

Improvement of voltage profile

The voltage of the system buses are generally considered as constraint. But considering them as constraint results in a system, where all the voltages are at their maximum limits after optimization, which means the power system lacks the required reserves to provide reactive power during contingencies. One of the effective ways to avoid this situation is to choose the minimization of the absolute deviations of all the actual bus voltages from their desired voltages as an objective function. Minimization of TVD of load buses can allow the improvement of voltage profile [33]. This objective function may be formulated as follows:

$$\mathrm{TVD} = \sum_{i \in N_L} \left|V_i - V_i^{ref}\right| \tag{2}$$

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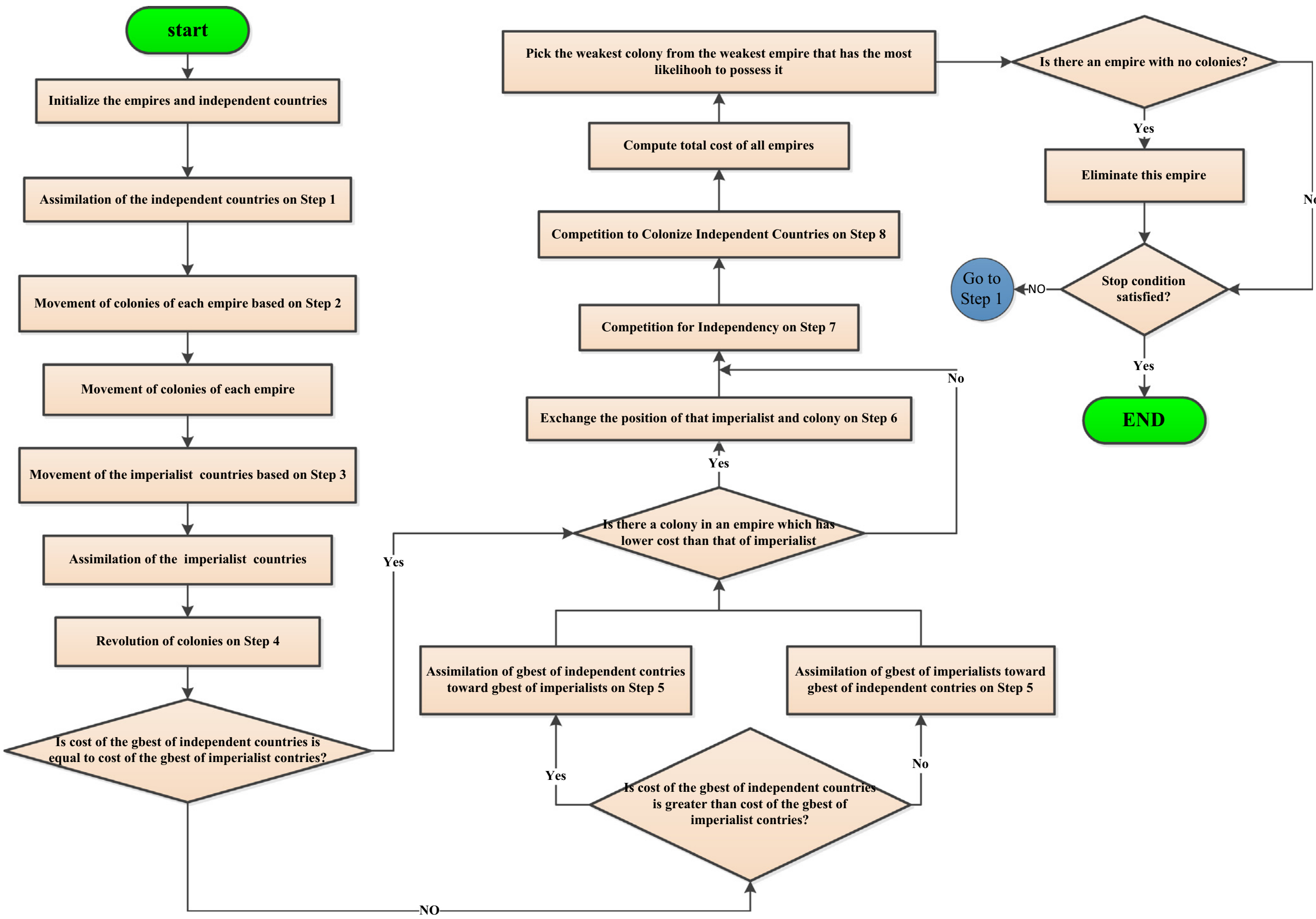

Fig. 3. Flowchart of the proposed hybrid methodology.

where V_i^{ref} the desired is value of the voltage magnitude at bus i which is usually set to 1.0 p.u.

System constraints

Equality constraint

The equality constraints of optimal reactive power dispatch problem can be expressed as follows:

$$P_{G_i} - P_{D_i} - V_i \sum_{j-1}^{N_B} V_j [G_{ij} \cos(\theta_i - \theta_j) + B_{ij} \sin(\theta_i - \theta_j)] = 0; \quad i = 1, \ldots, N_B \tag{3}$$

$$Q_{G_i} - Q_{D_i} - V_i \sum_{j-1}^{N_B} V_j [G_{ij} \sin(\theta_i - \theta_j) - B_{ij} \cos(\theta_i - \theta_j)] = 0; \quad i = 1, \ldots, N_B \tag{4}$$

where B_{ij} is the imaginary part of the bus admittance matrix of the (i,j)-th entry; G_{ij} is the real part of the bus admittance matrix of the (i,j)-th entry. P_{D_i} and Q_{D_i} are the active and reactive load demand of the ith bus. P_{G_i} and Q_{G_i} are the active and reactive power generation of the ith bus, respectively.

Inequality constraints

There are several inequality constraints such as capacity limits of reactive power sources, tap changer limits of transformers, reactive power generation limit, bus voltage deviation limit, and transmission line capacity limits that should be considered in ORPD formulation. In ORPD problem, the tap position of transformers, generator bus voltages and the amount of the reactive power source installations are the independent variables and these inequality constraints are mathematically expressed as [30]:

$$V_{G_i}^{\min} \leqslant V_{G_i} \leqslant V_{G_i}^{\max}; \quad i = 1, \ldots, N_G \tag{5}$$

$$Q_{C_i}^{\min} \leqslant Q_{C_i} \leqslant Q_{C_i}^{\max}; \quad i = 1, \ldots, N_C \tag{6}$$

$$T_i^{\min} \leqslant T_i \leqslant T_i^{\max}; \quad i = 1, \ldots, N_T \tag{7}$$

where $V_{G_i}^{\max}$, $V_{G_i}^{\max}$ are the maximum and minimum generator voltage of the ith bus, respectively. $Q_{C_i}^{\max}$, $Q_{C_i}^{\min}$ are the maximum and minimum reactive power injection of the ith shunt compensator, respectively. $T_i^{\max}$, $T_i^{\min}$ are the maximum and minimum tap setting of the ith transmission line, respectively. N_T is the number of tap changing transformers and N_C is the number of shunt compensators. The reactive power output of generators, load voltages and transmission line loading are the dependent variables and they are restricted by their upper and lower limits as follows:

$$V_{L_i}^{\min} \leqslant V_{L_i} \leqslant V_{L_i}^{\max}; \quad i = 1, \ldots, N_L \tag{8}$$

$$Q_{G_i}^{\min} \leqslant Q_{G_i} \leqslant Q_{G_i}^{\max}; \quad i = 1, \ldots, N_G \tag{9}$$

$$|S_{L_i}| \leqslant S_{L_i}^{\max}; \quad i = 1, \ldots, N_{TL} \tag{10}$$

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Table 1
Effect of the parameters (β and β_1) on optimization of benchmark function ($f_5(x)$).

β	β_1	Average	β	β_1	Average	β	β_1	Average
0.5	0.5	51.44	2	2.5	20.2	3.5	4.5	3610.92
0.5	1	41.46	2	3	12.04	3.5	5	3930.7
0.5	1.5	13.32	2	3.5	8.38	4	0.5	1504.14
0.5	2	6.36	2	4	442.38	4	1	969.38
0.5	2.5	9	2	4.5	750.4	4	1.5	87.8
0.5	3	4.92	2	5	763.38	4	2	35.56
0.5	3.5	21.86	2.5	0.5	577.5	4	2.5	52.5
0.5	4	30.9	2.5	1	436.88	4	3	34.04
0.5	4.5	34.18	2.5	1.5	51.18	4	3.5	2.98
0.5	5	33.4	2.5	2	16.32	4	4	639.94
1	0.5	5.22	2.5	2.5	16.78	4	4.5	5731.82
1	1	5.1	2.5	3	11.06	4	5	7334.38
1	1.5	2.78	2.5	3.5	5.2	4.5	0.5	1637.34
1	2	2.5	2.5	4	879.84	4.5	1	958.42
1	2.5	1.86	2.5	4.5	1819.82	4.5	1.5	86.44
1	3	0.52	2.5	5	1854.66	4.5	2	34.34
1	3.5	0.82	3	0.5	865	4.5	2.5	67.18
1	4	1.5	3	1	510.36	4.5	3	38.12
1	4.5	2.04	3	1.5	55.06	4.5	3.5	4.22
1	5	1.38	3	2	21.92	4.5	4	643.36
1.5	0.5	39.68	3	2.5	30.14	4.5	4.5	6272.5
1.5	1	37.84	3	3	12.12	4.5	5	14229.86
1.5	1.5	13.62	3	3.5	4.96	5	0.5	1721.36
1.5	2	6.48	3	4	1043.24	5	1	1038.34
1.5	2.5	5.16	3	4.5	2549.12	5	1.5	94.62
1.5	3	2.9	3	5	2870.66	5	2	35.14
1.5	3.5	20.58	3.5	0.5	1205.54	5	2.5	39.7
1.5	4	41.86	3.5	1	761.26	5	3	273.72
1.5	4.5	41.8	3.5	1.5	62.84	5	3.5	4.96
1.5	5	44.52	3.5	2	24.92	5	4	709.22
2	0.5	328.38	3.5	2.5	47.04	5	4.5	7430.6
2	1	228.1	3.5	3	12.24	5	5	18375.54
2	1.5	42	3.5	3.5	5.22			
2	2	11.78	3.5	4	664.56			

where $V_{L_i}^{max}$ and $V_{L_i}^{min}$ are the maximum and minimum voltage of the ith load bus, respectively. $Q_{G_i}^{max}$ and $Q_{G_i}^{min}$ are the maximum and minimum reactive power generation of the ith generator bus, respectively. $S_{L_i}^{max}$ is the maximum apparent power flow in the ith line. N_L is the number of load buses.

Table 4
Description of test systems [41].

Description	IEEE 57-bus	IEEE 118-bus
Buses	57	118
Generators	7	54
Transformers	15	9
Shunts	3	14
Branches	80	186
Equality constraints	114	236
Inequality constraints	245	572
Control variables	27	77
Discrete variables	20	21
Base case for P_{Loss} (MW)	27.8637	132.4500
Base case for TVD (p.u.)	1.23358	1.439337

Table 5
Comparison of simulation results for 57-bus test system in first case.

Method	P_{Loss} (reported)	P_{Loss} (calculated)
BBO [43]	24.544	30.252
AGA [1]	24.56484	32.882
CGA [1]	25.24411	42.657
NLP [1]	25.90231	26.163
SPSO [1]	24.43043	24.414
L-DE [1]	27.81264	35.94
LSACP-DE [1]	27.91553	39.487
GSA[22]	23.461194	29.405
OGSA [41]	23.43	26.4211
ICA	23.5471	23.5471
PSO	23.6266	23.6266
Proposed	23.3535	23.3535

Proposed methodology

In this section, the background of PSO, ICA, and proposed hybrid approach based on PSO–ICA methods are presented.

Table 2
Benchmark functions [39].

Benchmark functions	n	Search space	Global minimum
$f_1(x) = \sum_{i=1}^{n}(100(x_{i+1} - x_i^2))^2 + (x_i - 1)^2$	30	$[-30, 30]^n$	0
$f_2(x) = \sum_{i=1}^{n}(x_i^2 - 10\cos(2\pi x_i) + 10)^2$	30	$[-5.2, 5.2]^n$	0
$f_3(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$	30	$[-32, 32]^n$	0
$f_4(x) = \sum_{i=1}^{n}\left(\sum_{j=1}^{i}x_j\right)^2$	30	$[-100, 100]^n$	0
$f_5(x) = \sum_{i=1}^{n}(\lfloor x_i + 5\rfloor)^2$	30	$[-100, 100]^n$	0

Table 3
Comparison of different algorithm mean and standard deviation for benchmark functions.

Method	Functions	F1	F2	F3	F4	F5
GA [39]	Mean	338.5516	0.6509	1.0038	9749.9145	3.697
	Std.	361.497	0.3594	6.7545E−2	2594.9593	1.9517
PSO [39]	Mean	37.3582	20.7863	0.2323	1.1979E−3	0.146
	Std.	32.1436	5.94	0.4434	2.1109E−3	0.4182
GSO [39]	Mean	49.8359	1.0179	3.0792E−2	5.7829	1.6000E−2
	Std.	30.1771	0.9009	3.0867E−2	3.6813	0.1333
QGSO [36]	Mean	34.4281	3.3666E−3	1.2926E−4	0.0404	0.0040
	Std.	24.5366	2.6140E−3	1.8995E−4	0.0291	0.0015
Proposed PSO–ICA	Mean	1.336	1.22E−24	4.39E−14	0	0
	Std.	1.9068	6.70E−24	2.30E−14	0	0

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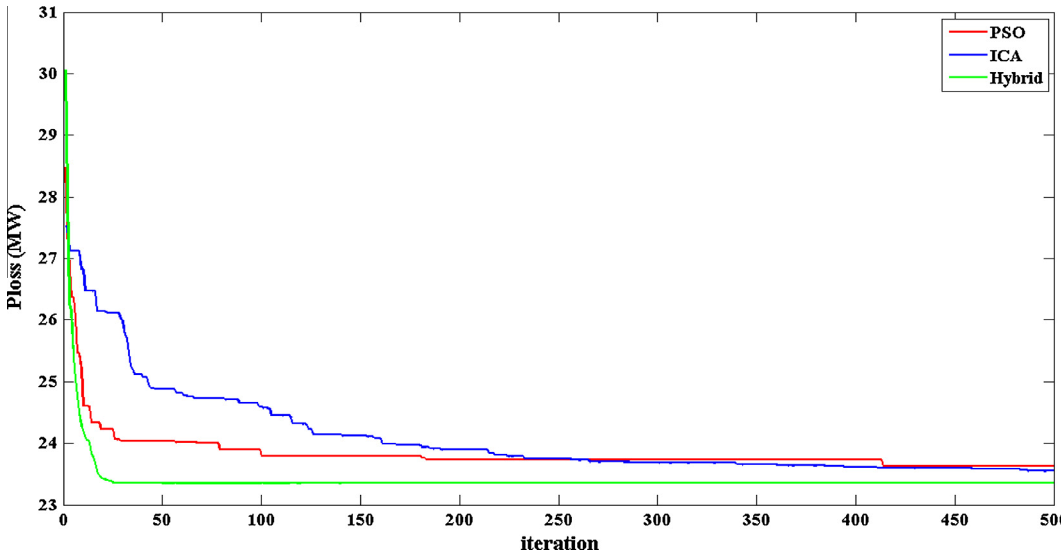

Fig. 4. Loss convergence characteristics using hybrid, ICA and PSO algorithms for first case of test system 1.

Table 6
Comparison of simulation results for 57-bus test system in second case.

Method	P_{Loss} (reported)	P_{Loss} (calculated)
BBO* [43]	24.2616	24.262
PSO-cf [1]	24.28022	24.28022
PSO-w [1]	24.27052	24.2705
CLPSO [1]	24.5152	24.891
LSaDE [1]	24.26739	24.303
SOA [1]	26.548	24.265
PSO	24.7742	24.7742
ICA	24.1607	24.1607
Proposed	24.1386	24.1386

BBO* means (after relaxing Q-limit of bus 2 and 9).

Table 7
Comparison of simulation results that in it's both constraint are satisfied.

Method	Hybrid	PSO	ICA
V_{g1}	1.0395	1.0284	1.06
V_{g2}	1.0259	1.0044	1.0388
V_{g3}	1.0077	0.9844	1.0078
V_{g6}	0.9982	0.9872	0.9688
V_{g8}	1.0158	1.0262	0.9715
V_{g9}	0.985	0.9834	0.9556
V_{g12}	0.9966	0.9844	0.9891
Q_{C-18}	9.9846	9	0
Q_{C-25}	10	7.0185	10
Q_{C-53}	10	5.0387	9.5956
T_{4-18}	0.9265	0.9743	0.9584
T_{4-18}	0.9532	0.9716	0.9309
T_{21-20}	1.0165	1.0286	1.0269
T_{24-26}	1.0071	1.0183	1.0085
T_{7-29}	0.9414	0.9401	0.9
T_{34-32}	0.9555	0.94	0.9872
T_{11-41}	0.9032	0.9761	0.9097
T_{15-45}	0.9356	0.9211	0.9377
T_{14-46}	0.9172	0.9165	0.9166
T_{10-51}	0.9337	0.9044	0.9057
T_{13-49}	0.9	0.9118	0.9
T_{11-43}	0.9206	0.92	0.9
T_{40-56}	1.0042	0.9891	0.9575
T_{39-57}	1.0297	0.9430	1.0476
T_{9-55}	0.9294	0.9998	0.9
P_{Loss}	25.5856	27.55434	26.99968
TVD	1.1548	1.1379	1.2846

Table 8
Comparison of simulation results for TVD minimization in case 1 and 2 of test system 1.

Method	Case 1	Case 2
ICA	0.6137	0.7759
PSO	0.6405	0.7593
Proposed	0.6031	0.6829

Table 9
Comparison of simulation results for TVD minimization in case 3 of test system 1.

Method	Hybrid	PSO	ICA
V_{g1}	1.0099	1.0290	1.06
V_{g2}	1.00301	1.0129	1.0414
V_{g3}	1.0073	1.0123	1.0169
V_{g6}	1.0044	1.0079	0.9956
V_{g8}	1.047	1.0366	0.9915
V_{g9}	1.0145	1.0059	0.9670
V_{g12}	1.0336	1.0285646	0.9935
Q_{C-18}	0	6.9827	0
Q_{C-25}	10	8.6683	10
Q_{C-53}	0	4.8687	10
T_{4-18}	1.0438	0.9743	0.9100
T_{4-18}	0.9338	0.9610	1.0291
T_{21-20}	0.9732	0.9963	0.9801
T_{24-26}	1.1	1.0251	1.0134
T_{7-29}	0.9490	0.9602	0.9622
T_{34-32}	0.9344	0.9149	0.9170
T_{11-41}	0.9	0.9155	0.9
T_{15-45}	0.9510	0.9633	0.9668
T_{14-46}	0.9910	0.9482	0.9
T_{10-51}	1.0164	0.9566	0.9748
T_{13-49}	0.9	0.9568	0.9
T_{11-43}	0.9606	0.9534	0.9
T_{40-56}	1.0211	0.9653	1.0262
T_{39-57}	0.9	1.0053	0.9
T_{9-55}	0.9808	0.9808	0.9266
P_{Loss} (MW)	29.3169	26.8937	26.9373
TVD	0.7130	0.8007	0.7952

PSO background

Particle swarm optimization is one of the population based stochastic search algorithms that was introduced by Eberhart and Kennedy (1995) [34]. In the PSO, population is consisted from candidate solutions which called particles. In PSO, each particle moves

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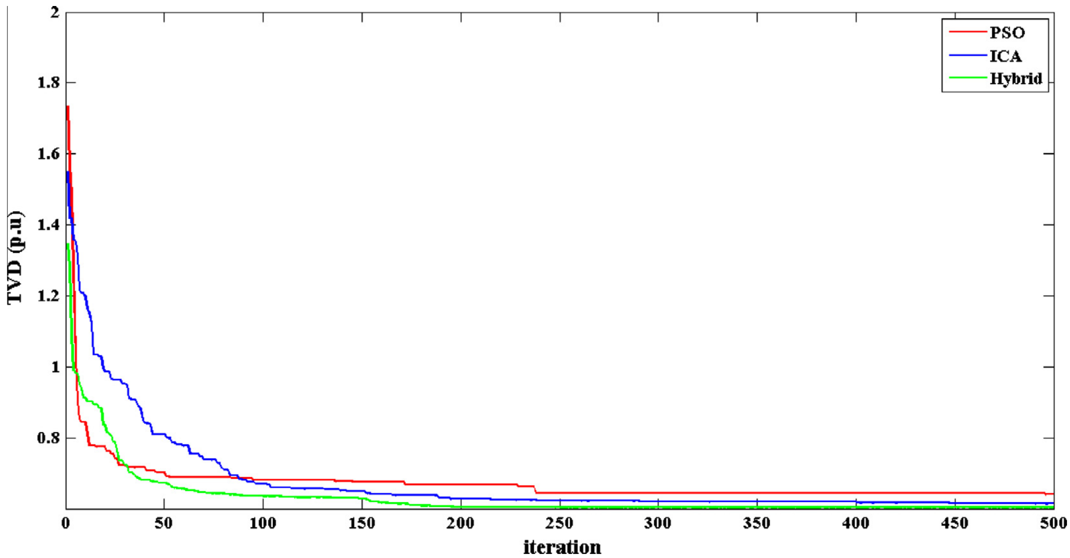

Fig. 5. Comparative convergence profiles for TVD minimization in first case for PSO–ICA, PSO and ICA for first case of test system 1.

Table 10
Comparison of simulation results that for case 1 of test system 2.

Method	P_{Loss} (reported)	P_{Loss} (calculated)
GSA [22]	127.7603	152.886
OGSA [41]	126.99	130.344
CLPSO [44]	130.96	236.174
ICA	123.0825	123.0825
PSO	117.3484	117.3484
Proposed	116.8550	116.8550

Table 11
Comparison of simulation results for case 2 of test system 2.

Method	P_{Loss} (MW)
ICA	127.2459
PSO	119.2078
Proposed	117.0680

in the search space with a velocity according to its own previous best solution and its group's previous best solution. The position and velocity of each particle will be updated using the following equations:

$$X_i(t+1) = X_i(t) + CV_i(t+1) \tag{11}$$

where $X_i(t)$ and $V_i(t)$ are vectors representing the position and velocity of the ith particle, respectively and

$$V_{ij}(t+1) = wV_{ij}(t) + c_1 r_{1j}(pb_{ij} - X_{ij}(t)) + c_2 r_{2j}(gb_j - X_{ij}(t)) \tag{12}$$

where $j \in 1,2\ldots,d$ represents the dimension of the particle; $0 < w < 1$ is an inertia weight determining how much of particle's previous velocity is preserved; c_1 and c_2 are two positive acceleration constants; C is the constriction factor. r_{1j}, r_{2j} are two independently generated random numbers from [0, 1]. pb_i is the personal best position found by the ith particle; and gb is the best position found by the entire swarm so far. The performance of PSO has been proven in static and dynamic optimization problems but in some cases, it converges prematurely without finding even a local optimum [31]. The movement of particle is shown in Fig. 1. According this figure, each particle updates its location using three vectors $V(t)$, X_m, X_{particle}. This figure shows the full motion of a particle in the search space.

ICA background

Imperialist competitive algorithm (ICA) [35] is one of the recently proposed evolutionary algorithms, which is inspired by the imperialistic competition. In this algorithm, the countries are considered as initial population that the countries are like chromosomes of the genetic algorithm and particle in the PSO.

Countries are classified based on their power into two groups namely: imperialists and colonies. These colonies start moving toward their relevant imperialist country. With starting the imperialistic competition, any empire that is not able to succeed in this competition and cannot increase its power will be eliminated from the competition. The weak empires will lose their power and ultimately they will collapse. Imperialistic competition aims to suppress the weakest empire and strengthen the strongest empire [36].

In an N dimensional optimization problem a country is defined as below:

$$\text{Country} = [P1, P2, P3, \ldots, PN] \tag{13}$$

The cost of each country is evaluated with the cost function f at variables ($P1$, $P2$, $P3$, ..., PN) as the following:

$$C_i = f(\text{Country}_i) = f(P1, P2, P3, \ldots, PN) \tag{14}$$

The imperialist countries using the absorption policy absorb their colonies toward themselves. The absorption policy shown in Fig. 2 makes the main core of this algorithm and causes the countries to move toward their minimum optima. In ICA algorithm, to search different points around the imperialist, a random amount of deviation is added to the direction of colony movement toward the imperialist [37]. In Fig. 2, this deflection angle is shown as θ, which is selected randomly and with a uniform distribution. In our implementation γ is $\pi/8$ radian.

$$\theta \sim U(-\gamma, \gamma) \tag{15}$$

In the absorption policy, the colony moves toward the imperialist by x unit. In Fig. 2 the distance between the colony and imperialist shown by x and d is a random variable with uniform distribution. β is greater than 1 and is close to 2. Therefore, a proper choice can be $\beta = 2$

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Table 12
Comparison of simulation results for loss minimization of case 3 of test system 2.

Variable	Proposed	PSO	ICA
Generator voltage			
V_1, pu	0.9787	0.9875	0.9859
V_4, pu	0.9987	1.0286	1.0247
V_6, pu	0.9954	1.0111	1.0158
V_8, pu	1.0214	1.0101	1.0481
V_{10}, pu	1.06	1.0015	1.0490
V_{12}, pu	1.0026	1.0133	1.0049
V_{15}, pu	0.9956	0.9922	0.9792
V_{18}, pu	1.0033	0.9948	0.9768
V_{19}, pu	0.9922	0.9868	0.9744
V_{24}, pu	1.0154	1.0025	1.0079
V_{25}, pu	1.0366	1.0175	1.0396
V_{26}, pu	1.06	1.0105	1.06
V_{27}, pu	1.0206	1.0442	0.9948
V_{31}, pu	1.0076	1.0185	0.9812
V_{32}, pu	1.0147	1.0216	0.9903
V_{34}, pu	1.0141	0.9983	0.9823
V_{36}, pu	1.010	0.9962	0.9754
V_{40}, pu	0.9943	1.0196	0.9685
V_{42}, pu	0.9947	1.0093	0.9802
V_{46}, pu	1.0056	0.9892	1.0148
V_{49}, pu	1.0169	0.9976	1.0260
V_{54}, pu	0.9951	0.9870	1.0044
V_{55}, pu	0.9873	0.9788	1.0010
V_{56}, pu	0.9897	0.9811	1.0019
V_{59}, pu	1.0019	0.9974	1.0151
V_{61}, pu	1.0008	0.9888	1.0075
V_{62}, pu	0.9978	0.9785	1.0005
V_{65}, pu	1.008	1.0271	1.0110
V_{66}, pu	1.0118	0.9932	1.0277
V_{69}, pu	1.0375	1.0308	1.0328
V_{70}, pu	1.0179	0.9981	0.983
V_{72}, pu	0.9896	1.0086	0.988
V_{73}, pu	1.060	1.0014	0.98427
V_{74}, pu	0.9785	0.9695	0.9578
V_{76}, pu	0.9572	0.9521	0.9469
V_{77}, pu	0.9905	0.9950	0.9900
V_{80}, pu	0.9994	1.0147	1.0078
V_{85}, pu	1.0051	0.9986	0.9963
V_{87}, pu	1.0126	0.9908	0.9991
V_{89}, pu	1.0309	1.0231	1.02271
V_{90}, pu	1.0106	0.9917	0.9994
V_{91}, pu	1.0145	0.9967	0.9969
V_{92}, pu	1.0108	1.002	0.9962
V_{99}, pu	0.9700	0.9951	0.9783
V_{100}, pu	1.0095	1.0089	0.9795
V_{103}, pu	0.9948	0.9999	0.9599
V_{104}, pu	0.9756	0.9874	0.94
V_{105}, pu	0.9785	0.9864	0.9447
V_{107}, pu	0.9886	1.0014	0.9531
V_{110}, pu	0.9828	0.9896	0.9732
V_{111}, pu	0.9975	1.0178	1.0212
V_{112}, pu	0.9701	0.9744	0.9546
V_{113}, pu	1.0269	1.0131	0.9820
V_{116}, pu	0.9967	1.0163	0.9845
Capacitor banks			
$Q_{C\text{-}5}$	0	1.8675	0.1
$Q_{C\text{-}34}$	5.9799	3.5622	0.0132
$Q_{C\text{-}37}$	3.4564	6.0115	0
$Q_{C\text{-}44}$	0.0084	6.0068	0.0930
$Q_{C\text{-}45}$	3.1795	5.2212	0.0886
$Q_{C\text{-}46}$	0.0014	4.4975	0.0334
$Q_{C\text{-}48}$	6.1447	3.9845	0
$Q_{C\text{-}74}$	3.6680	6.8448	0.0390
$Q_{C\text{-}79}$	4.4375	5.3023	0.0630
$Q_{C\text{-}82}$	0.0024	5.0808	0.0758
$Q_{C\text{-}83}$	5.4761	5.2515	0.0227
$Q_{C\text{-}105}$	4.8875	4.0520	0
$Q_{C\text{-}107}$	6.9231	5.8284	0
$Q_{C\text{-}110}$	6.7564	3.7223	0.0112
Transformer tap ratio			
T_8	0.9733	0.9619	1.0137
T_{32}	1.0794	0.9961	1.0628

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Table 12 (*continued*)

Variable	Proposed	PSO	ICA
T_{36}	0.9758	0.9791	1.02714
T_{51}	0.9411	1.0216	1.0021
T_{93}	0.9760	0.9906	0.9664
T_{95}	1.0384	1.0313	1.0014
T_{102}	0.9989	1.0435	1.0304
T_{107}	0.9203	0.9976	0.9018
T_{127}	0.9848	0.9400	0.9411
P_{Loos} MW	127.8247	130.4973	128.6945
TVD, pu	0.797892	0.851813	2.455719

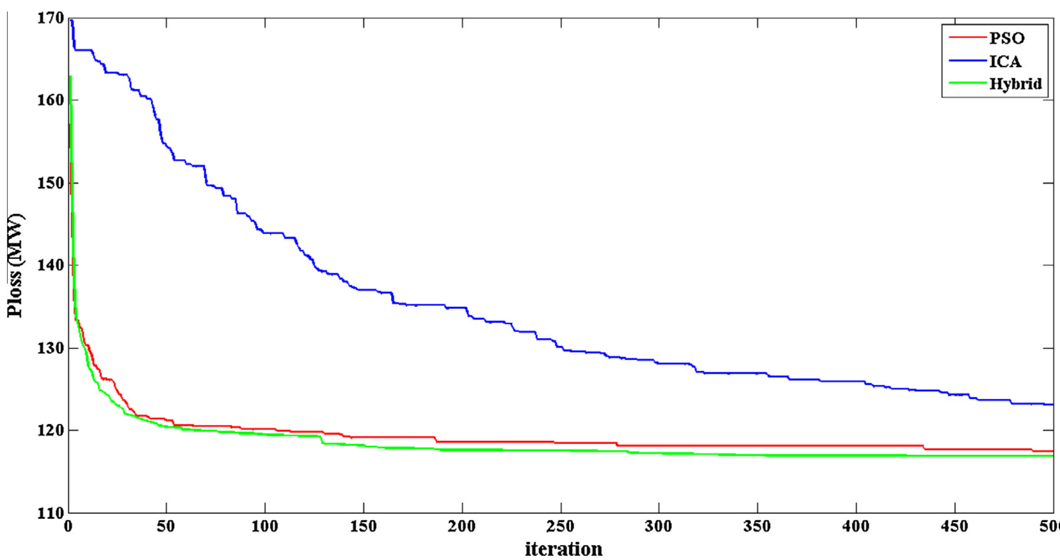

Fig. 6. Loss convergence characteristics using hybrid and ICA and PSO algorithms for case 1 of test system 2.

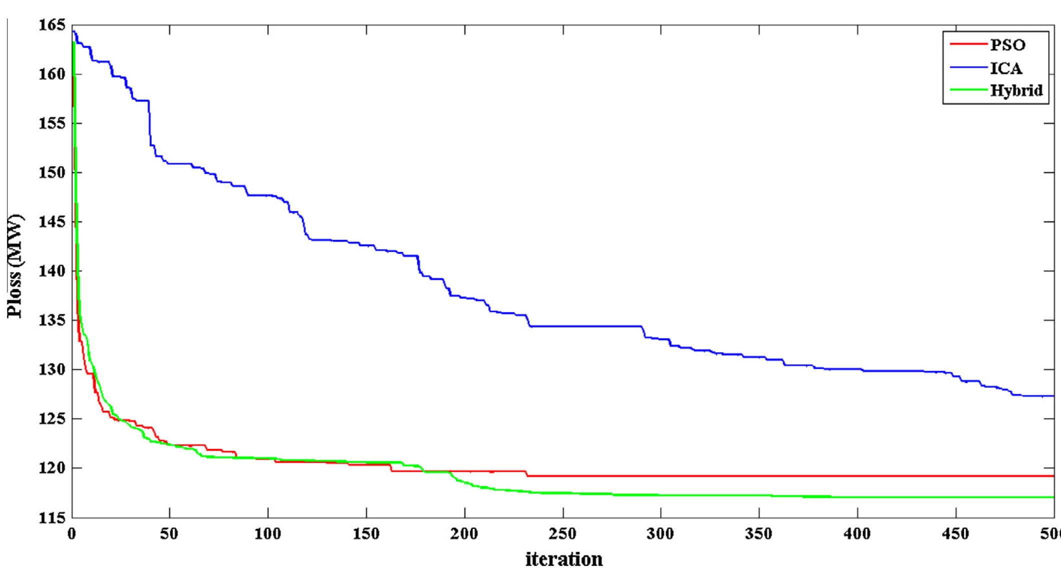

Fig. 7. Loss convergence characteristics using hybrid and ICA and PSO algorithms for case 2 of test system 2.

$$x \sim U(0, \beta \times d) \tag{16}$$

We will have the revolution operator, after absorption process. It is a known fact that revolution occur in some countries, so in ICA, revolution occurs with a probability and makes a sudden change in one or more parameters of the problem. After absorption and revolution, a colony may reach a better position, which the colony position changes according to the position of the imperialist. The total cost of each empire is calculated as below:

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Table 13
Comparison of simulation results for IEEE 118-bus test system for TVD minimization.

Method	Case 1	Case 2
ICA	0.2643	0.2824
PSO	0.3335	0.3670
Proposed	0.1747	0.1755

$$\mathrm{TN}_n = \mathrm{cost}(\mathrm{imperialist}_n) + \xi \ \mathrm{mean}\{\mathrm{cost}(\mathrm{colony\ of\ empire}_n)\} \tag{17}$$

TN_n is total cost of nth empire and ξ is positive number between [0, 1]. For more information, the interested reader can refer to [38].

This paper applied the hybrid approach of imperialist competitive algorithm (ICA) and particle swarm optimization (PSO) for

Table 14
Comparison of simulation results for IEEE 118-bus test system for TVD minimization in case 3.

Variable	Proposed	PSO	ICA
Generator voltage			
V_1, pu	0.9997	0.9785	0.9907
V_4, pu	1.0148	1.0234	1.0387
V_6, pu	0.9841	0.9983	1.0114
V_8, pu	1.0055	1.0073	0.978
V_{10}, pu	0.9793	0.9896	1.0086
V_{12}, pu	1.0068	1.0050	1.0131
V_{15}, pu	1.0061	0.9850	1.006
V_{18}, pu	0.9779	0.9911	1.0104
V_{19}, pu	1.0285	0.9862	1.004
V_{24}, pu	1.0260	1.0085	1.027
V_{25}, pu	0.9901	1.0067	1.0505
V_{26}, pu	1.0241	0.9944	1.0299
V_{27}, pu	1.0012	1.0052	1.0064
V_{31}, pu	1.0111	0.9939	1.00115
V_{32}, pu	1.0096	1.0029	1.0015
V_{34}, pu	1.0071	1.0198	1.014
V_{36}, pu	0.9922	1.0164	1.0071
V_{40}, pu	0.994	0.9773	0.9994
V_{42}, pu	1.0294	0.9776	1.0255
V_{46}, pu	1.0432	0.9982	1.0536
V_{49}, pu	1.0121	0.9935	1.0149
V_{54}, pu	1.0261	0.9945	1.0463
V_{55}, pu	1.0281	0.99	1.0397
V_{56}, pu	1.0124	0.9901	1.0407
V_{59}, pu	1.0011	1.0086	1.06
V_{61}, pu	1.0002	1.0030	0.9871
V_{62}, pu	0.9912	0.9961	0.9856
V_{65}, pu	1.0101	1.0265	1.0348
V_{66}, pu	1.0146	1.0129	1.0208
V_{69}, pu	0.9664	1.06	1.06
V_{70}, pu	1.0007	1.0043	0.9996
V_{72}, pu	0.9951	0.9733	0.9420
V_{73}, pu	1.0029	1.003	1.005
V_{74}, pu	1.0321	0.9777	0.9671
V_{76}, pu	1.0077	0.9631	0.955
V_{77}, pu	1.0069	1.0033	0.9992
V_{80}, pu	1.0252	1.0201	1.0156
V_{85}, pu	1.0093	0.9985	1.0131
V_{87}, pu	1.0039	1.0324	1.0034
V_{89}, pu	1.0037	1.0174	1.06
V_{90}, pu	1.0236	1.0022	0.9774
V_{91}, pu	0.9877	1.0277	0.9954
V_{92}, pu	1.0047	1.0074	1.0291
V_{99}, pu	1.007	0.9782	0.977
V_{100}, pu	1.0274	1.0188	1.0339
V_{103}, pu	0.9856	1.0094	1.0297
V_{104}, pu	0.9923	0.9959	1.0147
V_{105}, pu	0.9936	0.9951	1.0194
V_{107}, pu	1.0168	1.016	1.0517
V_{110}, pu	1.0098	1.0149	1.0345
V_{111}, pu	1.0069	1.0372	1.0492
V_{112}, pu	1.0141	1.0164	1.0494
V_{113}, pu	0.9852	1.0130	1.0272
V_{116}, pu	1.001155	0.985321	0.991899
Capacitor banks			
$Q_{C\text{-}5}$	5.5338	8.3649	0.1
$Q_{C\text{-}34}$	7.5695	6.6130	0.0268
$Q_{C\text{-}37}$	6.0239	7.3458	0.0528
$Q_{C\text{-}44}$	5.0408	1.1125	0.0370
$Q_{C\text{-}45}$	7.754	5.294	0.0900
$Q_{C\text{-}46}$	5.956	8.1801	0.0245
$Q_{C\text{-}48}$	4.9398	8.236	0.0093

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Table 14 (*continued*)

Variable	Proposed	PSO	ICA
$Q_{C\text{-}74}$	5.2465	3.7390	0.1
$Q_{C\text{-}79}$	5.5913	6.1524	0.1
$Q_{C\text{-}82}$	6.4964	7.674	0.0462
$Q_{C\text{-}83}$	6.2727	7.3022	0.0601
$Q_{C\text{-}105}$	6.1335	5.2062	0.0728
$Q_{C\text{-}107}$	3.7238	1.4605	0.0292
$Q_{C\text{-}110}$	5.1057	0.805	0.0702
Transformer tap ratio			
T_8	1.0379	1.0511	0.9991
T_{32}	1.0152	1.0100	1.0145
T_{36}	0.9643	1.008	0.9697
T_{51}	1.0032	0.928	0.9669
T_{93}	0.9875	1.0383	0.9127
T_{95}	0.9928	1.0909	1.0493
T_{102}	0.9789	1.0068	1.0383
T_{107}	0.9776	0.9566	0.9261
T_{127}	0.9398	0.9686	0.9784
P_{Loos} MW	146.7116	133.2907	136.3446
TVD, pu	0.2993	0.7711	0.6789

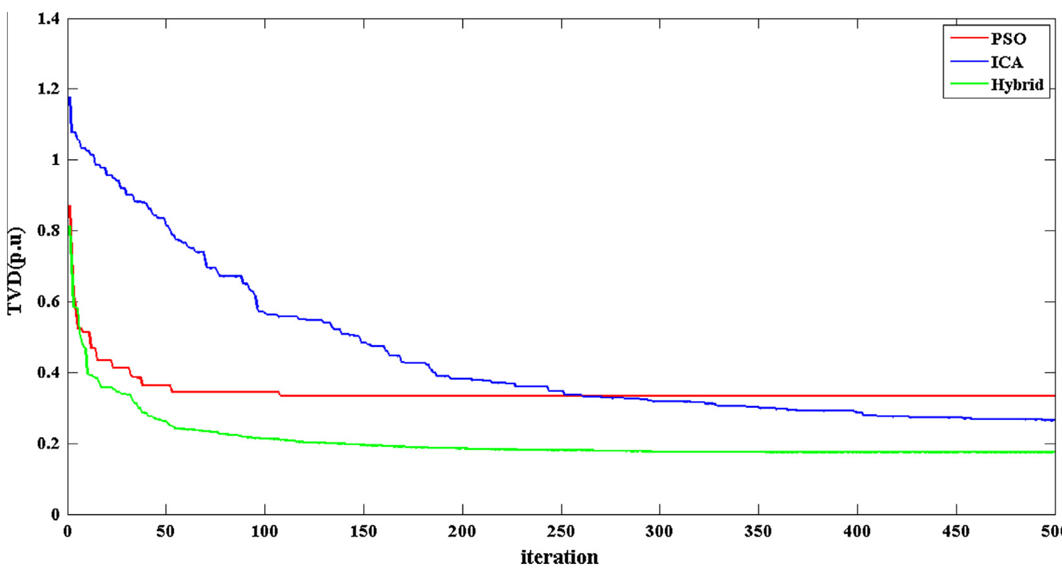

Fig. 8. Convergence profiles for TVD minimization in case 1 of test system 2.

better optimizer. In the standard ICA, there are only two types of countries: imperialists and colonies. In the proposed hybrid algorithm (PSO–ICA) we added another type of country called 'independent' country. Independent countries do not fall into the category of empires, and are anti-imperialism. In addition, they are united and their shared goal is to get stronger in order to rescue colonies and help them join independent countries. These independent countries are aware of each other positions and make use of swarm intelligence in PSO for their own progress.

With these definitions, steps of the proposed algorithm can be summarized as presented in the following:

Table 15
Comparison of the absolute and relative CPU time for all cases for loss minimization.

Case	Method	CPU speed (GHz)	Solution time (s)
IEEE 57-bus system	PSO	2.2	927
	ICA	2.2	1018
	PSO–ICA	2.2	1450
	GSA [22]	NA	321.4872
	OGSA [41]	NA	307.39
	AGA [1]	NA	321.4872
IEEE 118-bus system	PSO	2.2	1152
	ICA	2.2	1263
	PSO–ICA	2.2	1631
	GSA [22]	NA	1198.6583
	OGSA [41]	NA	1152.32
	AGA [1]	NA	NA

Proposed algorithm
1: Initialize and evaluate the empires and independent countries
2: **while** Stop condition is not satisfied steps do
Step 1: Assimilation of the independent countries similar to ICA background;
Step 2: Movement of colonies of every emperor similar to PSO background;
Step 3: Movement of imperialists of every emperor

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similar to PSO background;
Step 4: Revolution similar to ICA background;
Step 5: Assimilation between imperialists and independent countries similar to ICA background;
Step 6: Comparison of imperialist with the best colony similar to ICA;
Step 7: Competition for independency [38];
Step 8: Competition to colonize independent countries [38];
3: **if** there is a colony in an empire which has a lower cost than the imperialist then
4: Switch the positions of that colony and of the imperialist
5: **end if**
6: Compute the total cost of all empires
7: Imperialistic competition
8: **if** there is an empire with no colony then
9: Eliminate this empire
10: **end if**
11: **end while**

The flowchart of the proposed hybrid PSO–ICA is presented in Fig. 3. The proposed algorithm is sensitive to the parameters β and β_1. The proposed algorithm will have different convergence speed and optimal point in the different values of β and β_1. For more information about this algorithm, the interested reader can refer to [31].

How to choose the proper values of β and β_1 is mentioned in parameter selection section. For evaluating the performance of the proposed hybrid PSO–ICA algorithm, benchmark functions are studied in benchmark section.

Parameter selection

The maximum number of iterations is set to 300 for all benchmarks and 500 for all test systems. It should be mentioned that, these values are selected in a way to insure that the further convergence is not possible. Similar to [39], the population size for benchmark functions is set to 100 and for ORPD problems the population size of 200 is used. Using larger population size results in a better exploration of the search space with the cost of increasing computational time. In order to determine the parameters of the proposed PSO–ICA algorithm, a number of simulations are done using benchmark function $f_5(x) = \sum_{i=1}^{n}(\lfloor x_i + 5 \rfloor)^2$. Table 1 shows the average value of function for each combination of β and β_1 over 50 trial runs. It can be observed from this table that the $\beta = 1$ and $\beta_1 = 3$ result in better solution.

Benchmark functions

Five benchmark functions are studied in this section in order to evaluate the performance of the proposed hybrid PSO–ICA algorithm. Definitions of the benchmark functions [39] are presented in Table 2. Proposed hybrid PSO–ICA is applied to mentioned benchmark functions for 1000 times and minimum, mean, maximum, and standard deviation of the results is presented in Table 3. The obtained results are compared with GA, PSO, GSO and CQGSO [40] in Table 3. Default parameters are used for PSO and GA in [39]. The results of PSO and GA are directly quoted from [39]. It can be observed from this table that the proposed algorithm converges to better results in comparison with GA, PSO, GSO and CQGSO algorithms.

Simulation results and discussion

In this paper, hybrid PSO–ICA is applied to IEEE 57-and 118-bus standard test systems for the solution of ORPD problem. The proposed algorithm is implemented using the MATLAB 7.0 software and run on a PC with Intel(R) Core(TM) i3-2330M CPU 2.20 GHz 2 GB RAM. Description of these studied test systems is presented in Table 4.

IEEE 57-bus system

The standard IEEE 57-bus system [42], consists of seven generators (at the buses 1, 2, 3, 6, 8, 9, 12), eighty transmission lines and fifteen branches under load tap setting transformer branches is considered as test system 1. The candidate reactive power compensation buses are 18, 25 and 53. The search space of this case system has twenty-five dimensions, including seven generator voltages, fifteen transformer taps and three reactive power sources [41].

Minimization of system P_{Loss}

The proposed approach is applied for minimization of P_{Loss} as one of the objective function. The optimal values of the control variables are obtained using the hybrid PSO–ICA algorithm.

In previous articles, one or both of voltage and reactive power constraints are relaxed (or violated) that can be determined by applying the output of generator voltage magnitudes, transformer tap settings and switchable VAR sources in the power flow. The results of the available methods can be divided into three groups that in the first group, both constraints are violated and in the second groups, voltage constraint is satisfied but reactive power constraint is violated and in the third group, both constraints are satisfied.

For sake of comparison, the hybrid PSO–ICA algorithm is applied to IEEE 57-bus test system considering above three groups.

(a) *First case:* In this case both voltage and reactive power constraints are relaxed (not considered) and the obtained simulation results using the proposed hybrid method are compared to other optimization techniques like as BBO, AGA, CGA, NLP in Table 5. In Table 5, the first column is the reported results in the papers and the second column is the calculated amount of losses using the reported control variables. For example in BBO method, if the reported results for controlling variables such as generator voltages, transformer taps, shunt capacitors/inductors are used as input parameters to the power flow, the losses of standard IEEE 57-bus system is equal 30.252. Convergence characteristics using hybrid method, ICA and PSO algorithms are shown in Fig. 4. This figure confirms the ability of the proposed algorithm in finding the more efficient solutions and faster convergence in comparison with PSO and ICA. It can be observed that the proposed hybrid algorithm is converged in less than 50 iterations.
(b) *Second case:* In this case voltage constraint is satisfied along with other constraints and only the reactive power constraint is relaxed. The simulation results are compared with other optimization technique, that in them reactive power constraint is violated, like as BBO*, PSO-cf, PSO-w, CLPSO in Table 6.
(c) *Third case:* In this case all of the constraints are considered and none of them is relaxed. Simulation results of the proposed hybrid method are compared to other optimization techniques in Table 7. According to Table 7, the obtained minimum P_{Loss} from the proposed approach is 25.5856 MW. The value of P_{Loss} obtained by hybrid algorithm is lower than PSO by 1.9678 MW.

Minimization of system TVD

The proposed hybrid PSO–ICA approach is applied for the minimization of total voltage deviation of this test power network. Comparison of simulation results for TVD minimization in case 1

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and 2 of test system 1 is provided in Table 8. The results obtained by the proposed hybrid PSO–ICA approach are presented in Table 9 for case 3. It can be observed that the TVD is 0.7130 for the hybrid PSO–ICA method which is lower than the original PSO (0.8007) and original ICA (0.7952). Comparative convergence profiles for TVD minimization in first case for PSO–ICA, PSO and ICA are demonstrated in Fig. 5. From this figure it may be observed that the convergence profile of TVD for the proposed hybrid PSO–ICA approach is the promising one.

IEEE 118-bus system

The standard IEEE 118-bus test system is considered as test system 2. The search space of this case system has seventy-seven dimensions, fifty-four generator buses, sixty-four load buses, one hundred eighty-six transmission lines, nine transformer taps and fourteen reactive power sources [42].

Minimization of system P_{Loss}

The proposed approach is applied for minimization of real power loss as one of the objective functions. Similar to cases of the previous test system, with considering first, second and third case, the simulation results are presented in Tables 10–12, respectively. The obtained results are compared to other optimization techniques in the corresponding tables. According to Table 12, the obtained minimum P_{Loss} using the proposed approach is 127.8247 MW, which is lower than the result of PSO algorithm, i.e., 130.4973 MW. The convergence characteristics of the hybrid PSO–ICA, PSO and ICA algorithms are depicted in Figs. 6 and 7 for case 1 and 2, respectively.

Minimization of system TVD

In this section the optimal reactive power dispatch is solved using the proposed hybrid PSO–ICA for TVD minimization. The obtained results for case-1 and case 2 are presented in Table 13. Table 14 shows the obtained results for case 3. It can be observed from Table 14 that for this case the TVD is 0.2993 using the hybrid PSO–ICA algorithm, while the TVD is 0.6789 for ICA and 0.7711 for PSO algorithm. Fig. 8 shows the convergence characteristics of hybrid PSO–ICA, ICA and PSO TVD minimization. This figure shows that the proposed hybrid PSO–ICA algorithm can achieve a more efficient solution in the iterations less than 50 compared to PSO and ICA. The obtained results show that with increasing the variables and system's size, the proposed algorithm can find the more optimal solution.

Computation time

In order to compare the computation time of the proposed algorithm, absolute CPU time and relative simulation times for all case study systems for loss minimization are provided in Table 15. Computation time has a direct relation with CPU speed. It should be mentioned that both CPU speed and simulation times for some methods were not available in literature.

Conclusions

The ORPD problem is formulated as a nonlinear optimization problem with inequality and equality constraints of the power network. In this study, minimization of active power loss and the absolute value of total voltage deviation considered. The proposed hybrid PSO–ICA is tested on IEEE 57-bus and 118-bus test power systems to show its effectiveness and robustness. Simulation results obviously demonstrate the proposed hybrid PSO–ICA algorithm is able to produce better transmission loss and voltage deviation compared to other recently developed optimization techniques for both test systems. Thus, the proposed hybrid PSO–ICA is capable of quickly and effectively solving reactive power dispatch problem and can be considered as a promising candidate for the future researches.

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