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ORIGINAL RESEARCH

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Impact of the penetration of distributed generation on optimal reactive power dispatch

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Abstract

Optimal reactive power dispatch (ORPD) is a complex and non-linear problem, and is one of the sub-problems of optimal power flow (OPF) in a power system. ORPD is formulated as a single-objective problem to minimize the active power loss in a transmission system. In this work, power from distributed generation (DG) is integrated into a conventional power system and the ORPD problem is solved to minimize transmission line power loss. It proves that the application of DG not only contributes to power loss minimization and improvement of system stability but also reduces energy consumption from the conventional sources. A recently proposed meta-heuristic algorithm known as the JAYA algorithm is applied to the standard IEEE 14, 30, 57 and 118 bus systems to solve the newly developed ORPD problem with the incorporation of DG. The simulation results prove the superiority of the JAYA algorithm over others. The respective optimal values of DG power that should be injected into the four IEEE test systems to obtain the minimum transmission line power losses are also provided.

Keywords: Active power loss, Distributed generation, DG penetration, JAYA algorithm, Optimization problem, ORPD, Particle swarm optimization, Variants of PSO, Transmission line losses

1 Introduction

Minimizing power loss in transmission systems is a major area of research in power system engineering. Voltage collapse, as another major issue, is also attracting much research worldwide to find solutions to improve voltage stability and thus improve the security of the power system and make power transmission more economic. Optimal reactive power dispatch (ORPD) deals with not only the problem of increasing power loss with the expansion of power networks but also the increasing voltage instability problem. The ORPD problem is a sub-problem of optimal power flow (OPF) whose solution helps determine the optimal values to the control variables such as the generator voltage, setting of the tap-changing transformer, and the optimal value of reactive power to be injected to compensate for the VAR demand, in order to simultaneously reduce the active power loss and improve voltage stability. Thus, the solution to the ORPD problem helps enhance the security of the power system and improve its economics. However, the ORPD problem is a complex, non-continuous and non-linear problem, and many conventional optimization techniques such as the Newton method, quadratic programming, linear programming, and interior-point methods, have failed to solve it since these methods have low accuracy, high complexity, and inability to find the local and global optima and thus result in insecure convergence [1–6].

Many modern stochastic and meta-heuristic techniques have been applied to overcome these disadvantages, such as the genetic algorithm (GA) [7], improved GA [8], particle swarm optimization (PSO) [9], evolutionary programming (EP) [10], hybrid evolutionary

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strategy [11], the seeker optimization algorithm (SOA) [12], bacterial-foraging optimization (BFO) [13], the gravitational search algorithm (GSA) [14], differential evolution (DE) [15], and the artificial bee colony algorithm (ABC) [16]. K. Medani et al. in [17] applied the whale optimization algorithm which was inspired by the bubble-net hunting technique of the humpback whales to solve the ORPD problem, while A. M. Shaheen et al. in [18] proposed a backtracking search optimizer (BSO) where five diversified generation strategies of mutation factor were applied. In [19], K. Lenin proposed an algorithm named Enhanced Red Wolf Optimization which is a hybrid of the wolf optimization (WO) and particle swarm optimization (PSO) algorithm, to solve the ORPD problem. In [20], an improved social spider optimization (ISSO) was used for determining the optimal solution of power loss in the ORPD problem. Zelan Li et al. [21] proposed an Antlion optimization algorithm (IALO) for a three-bus system, whereas R. N. S Mei et al. [22] used two different algorithms, namely the Moth-Flame Optimizer and Ant Lion Optimizer, to optimize the ORPD problem.

This paper uses a novel algorithm, namely the JAYA algorithm developed by Rao [23], to solve the ORPD problem. Many other algorithms such as PSO and different variants of PSO, e.g., R-PSO, L-PSO, PSO-CFA, Improved PSO Based on Success Rate (IPSO-SR) [24], Fruit Fly optimization algorithm (FOA), and modified Fruit Fly optimization algorithm (MFOA) are also tested along with the JAYA algorithm. The results are compared to determine the best algorithm in terms of convergence, the ability to determine the optimal solution, and robustness.

The main contributions of the paper are as follows:

i) Minimizing transmission line power loss by obtaining the optimal setting of the control variables within the system without violating the equality and inequality constraints.
ii) Incorporating the concept of distributed generation (DG) into the ORPD problem to study its effect and analyze its contribution towards minimizing power loss and increasing system efficiency in the problem.

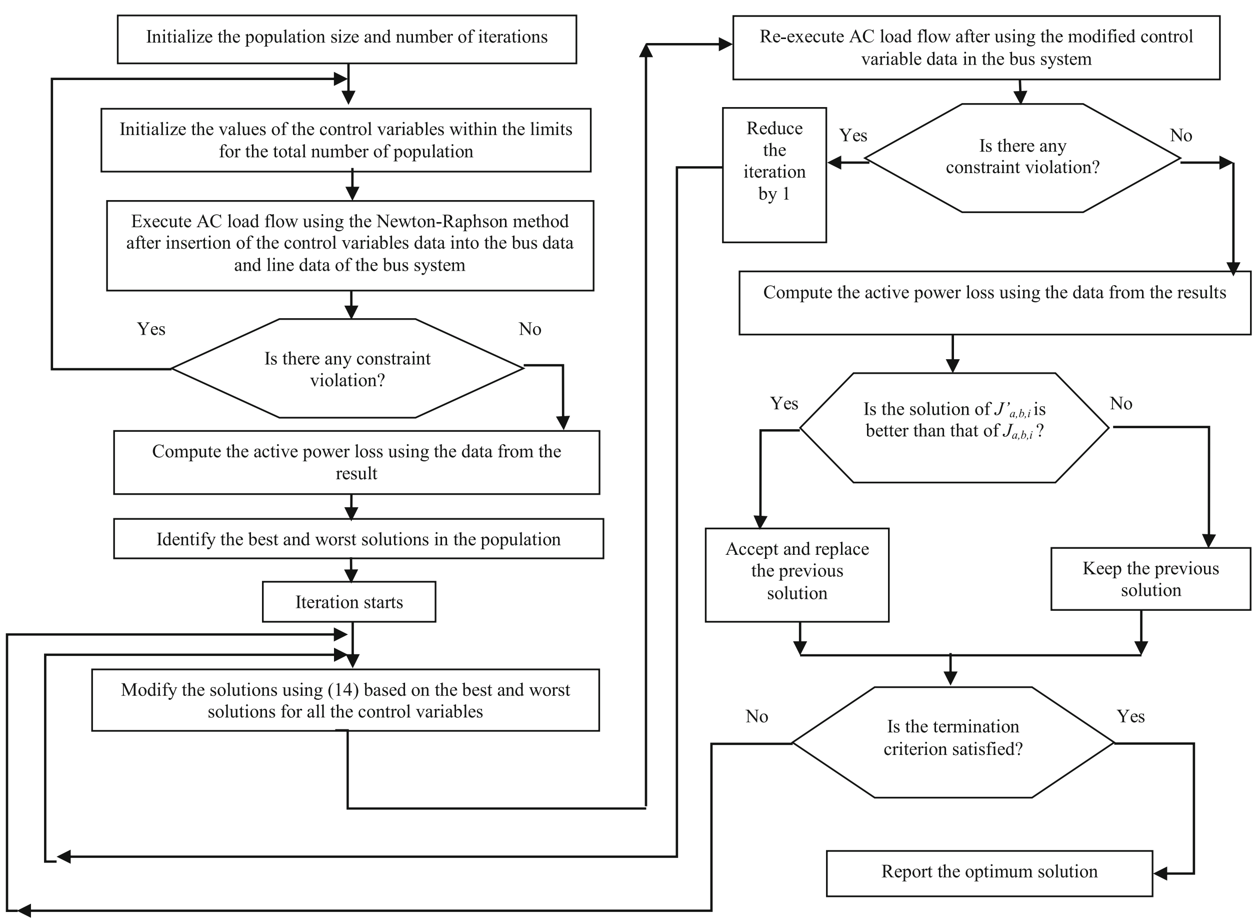

Fig. 1 Flow chart of the JAYA algorithm implemented on the ORPD problem

Table 1 The comparative results of G01-G24 benchmark functions using different algorithms

Function	PSO		BBO	DE	ABC	HTS	TLBO	JAYA
G01	**Best**	**– 15**	**–14.977**	**– 15**	**– 15**	**– 15**	**– 15**	**– 15**
(– 15.00)	Mean	– 14.71	– 14.7698	– 14.555	–15	– 15	– 10.782	**– 15**
G02	Best	–0.669158	– 0.7821	– 0.472	– 0.803598	- 0 .7517	– 0.7835	**–0.803605**
(–0.803619)	Mean	–0.41996	– 0.7642	–0.665	– 0.792412	–0.6437	– 0.6705	**–0.7968**
G03	Best	1	– 1.0005	–0.99393	–1	– 1.0005	–1.0005	**– 1.005**
(– 1.0005)	Mean	0.764813	–0.3957	–1	– 1	–0.9004	– 0.8	**–1**
G04	Best	– 30,665.539	– 30,665.539	– 30,665.539	–30,665.539	– 30,665.539	–30,665.539	**– 30,665.539**
(– 30,665.539)	Mean	– 30,665.539	–30,411.865	– 30,665.539	–30,665.539	– 30,665.539	–30,665.539	**– 30,665.539**
G05	Best	5126.484	5134.2749	5126.484	5126.484	5126.486	5126.486	**5126.486**
– 5126.486	Mean	5135.973	6130.5289	5264.27	5185.714	5126.5152	5126.6184	**5126.5061**
G06	Best	– 6961.814	–6961.8139	– 6954.434	– 6961.814	– 6961.814	–6961.814	**– 6961.814**
(– 6961.814)	Mean	– 6961.814	– 6181.7461	–6954.434	–6961.813	– 6961.814	–6961.814	**– 6961.814**
G07	Best	24.37	25.6645	24.306	24.33	24.3104	24.3101	**24.3062**
–24.3062	Mean	32.407	29.829	24.31	24.473	24.4945	24.837	**24.3092**
G08	Best	–0.095825	– 0.095825	–0.095825	– 0.095825	– 0.095825	– 0.095825	**– 0.095825**
(– 0.095825)	Mean	– 0.095825	–0.95824	– 0.095825	–0.095825	– 0.095825	–0.095825	**– 0.095825**
G09	Best	680.63	680.6301	680.63	680.634	680.6301	680.6301	**680.6301**
– 680.6301	Mean	680.63	692.7162	680.63	680.634	680.6329	680.6336	**680.6301**
G10	Best	7049.481	7679.0681	7049.548	7053.904	7049.4836	7250.9704	**7049.312**
– 7049.28	Mean	7205.5	8764.9864	7147.334	7224.407	7119.7015	7257.0927	**7052.7841**
G11	Best	0.749	0.7499	0.752	0.75	0.7499	0.7499	**0.7499**
–0.7499	Mean	0.749	0.83057	0.901	0.75	0.7499	0.7499	**0.7499**
G12	Best	–1	–1	–1	–1	–1	–1	**–1**
(–1)	Mean	–0.998875	–1	– 1	– 1	– 1	– 1	**– 1**
G13	Best	0.085655	0.62825	0.385	0.76	0.37319	0.44015	**0.003625**
(–0.05394)	Mean	0.569358	1.09289	0.872	0.968	0.66948	0.69055	**0.003627**
G14	Best	–44.9343	54.6679	–45.7372	–44.6431	–47.7278	–46.5903	**–47.7322**
(–47.764)	Mean	–40.871	175.9832	–29.2187	–40.1071	–46.4076	–39.9725	**– 46.6912**
G15	Best	961.715	962.664	961.715	961.7568	961.715	961.715	**961.715**
–961.715	Mean	965.5154	1001.4367	961.7537	966.2868	961.75	962.8641	**961.715**
G16	Best	–1.9052	–1.9052	–1.9052	–1.9052	– 1.9052	– 1.9052	**– 1.9052**
(– 1.9052)	Mean	– 1.9052	– 1.6121	–1.9052	– 1.9052	–1.9052	– 1.9052	**–1.9052**
G17	Best	8857.514	9008.5594	8854.6501	8859.713	8853.5396	8853.5396	**8853.5396**

Table 1 The comparative results of G01-G24 benchmark functions using different algorithms *(Continued)*

Function	PSO		BBO	DE	ABC	HTS	TLBO	JAYA
G01	**Best**	**– 15**	**–14.977**	**– 15**	**– 15**	**– 15**	**– 15**	**– 15**
– 8853.5396	Mean	8899.4721	9384.268	8932.0444	8941.9245	8877.9175	8876.5071	**8872.5402**
G18	Best	–0.86603	–0.65734	– 0.86531	– 0.86603	– 0.86603	– 0.86603	**– 0.86603**
(– 0.86603)	Mean	– 0.8276	– 0.56817	–0.86165	– 0.86587	–0.77036	– 0.86569	**–0.86602**
G19	Best	33.5358	39.1471	32.6851	33.3325	32.7132	32.7916	**32.6803**
–32.6555	Mean	36.6172	51.8769	32.768	36.0078	32.7903	34.0792	**32.7512**
G20	Best	0.24743	1.26181	0.24743	0.24743	0.24743	0.24743	**0.24139**
–0.204979	Mean	0.97234	1.43488	0.26165	0.80536	0.25519	1.22037	**0.24385**
G21	Best	193.7311	198.8151	193.7346	193.7343	193.7264	193.7246	**193.5841**
– 193.274	Mean	345.6595	367.2513	366.9193	275.5436	256.6091	264.6092	**193.7219**
G22	Best	– 258.74	– 267.15	– 249.12	–243.43	– 272.78	– 248.78	**– 242.45**
– 236.4309	Mean	–255.55	– 254.44	–249.46	– 251.33	– 265.66	– 252.56	**– 239.05**
G23	Best	– 105.9826	2.3163	–72.642	–43.2541	– 390.6472	–385.0043	**– 391.5192**
(– 400.055)	Mean	–25.9179	22.1401	–7.2642	–4.3254	– 131.2522	–83.7728	**– 381.2312**
G24	Best	– 5.508	– 5.508	– 5.508	– 5.508	– 5.508	– 5.508	**– 5.508**
(– 5.5080)	Mean	– 5.508	–5.4982	– 5.508	–5.508	– 5.508	–5.508	**– 5.508**

Table 2 Typical parameters of the bus systems

Control variables	IEEE 14 bus system	IEEE 30 bus system	IEEE 57 bus system	IEEE 118 bus system
Buses	14	30	57	118
Generators	5	6	7	54
Transformers	3	4	15	9
Shunt compensators	2	3	3	14
Transmission lines	20	41	80	186
Control variables	10	13	25	77
Base P_{loss} (MW)	13.49	5.66	27.8637	132.45

iii) The superiority of the JAYA algorithm is established over other algorithms reported in the literature.

1.1 Distributed generation

Alternative sources of energy such as wind, solar, etc. are being used currently. In many cases, such sources of energy are used to generate power on a small scale in areas close to the end users. The end users consume power and any excess power is sent back to the grid. This approach is called distributed generation (DG) and it helps reduce coal consumption, the cost of generation, and transmission line power loss. Furthermore, the demand of consumers in remote areas can be fulfilled from the local generation and the risk of voltage collapse is also reduced. Much research has been carried out to increase the utilization of DG to enhance the security and economic growth of power systems [25–30].

In this work, DG power is supplied to the buses along with power from conventional sources to study the transmission line loss characteristic by solving the ORPD problem. The DG power is injected individually at each bus (except for the slack bus) within a specified limit and the ORPD problem is solved to determine the optimal values of the control variables for minimizing transmission line losses. The control variables chosen for the ORPD problem are the

Table 3 Simulation results on the IEEE 14 bus system using different algorithms without DG injection

Control Variables (p.u.)	PSO	R-PSO	L-PSO	PSO-CFA	IPSO-SR	FOA	MFOA	JAYA
V_{G1}	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
V_{G2}	1.1	1.1	1.1	1.1	1.0863	1.1	1.1	1.0859
V_{G3}	1.0701	1.0696	1.0703	1.0702	1.0578	1.1	1.1	1.0568
V_{G6}	1.1	1.1	1.1	1.0605	1.0575	0.9	1.1	1.1
V_{G8}	1.1	1.1	1.1	1.1	1.0726	0.95	1.1	1.1
T_{4-7}	0.9285	0.9551	1.1	1.1	0.9685	1.1	1.1	0.9492
T_{4-9}	1.1	1.1	0.9	0.9	1.1	0.935	1.1	1.0766
T_{5-6}	1.1	1.0179	1.0047	1.1	1.1	1.1	1.1	1.0031
Q_{sc9}	0.2332	0.3	0.2643	0.015	0.2134	0.000328	0.0443	0.3
Q_{sc14}	0.0555	0.0604	0.0	0.0641	0.0634	0.000296	0.0443	0.0594
Total P_{loss} (MW)	12.4268	12.3585	12.4041	12.416	12.2957	12.5992	12.7531	**12.2270**
DE [32]	ABC [32]	ACO_R [32]	TLA [32]	DE [32]	MTLA [32]	MTLA-DDE [32]	LCA [32]	CSS [32]
13.1053	12.9333	13.1226	12.9229	13.1053	12.9106	12.8978	12.9891	12.9748
BRCFF [32]	BB–BC [32]	PBIL [32]	DDE [32]	TLBO [33]	BBPSO [33]	BBDE [33]	GBTLBO [33]	MGBTLBO [33]
12.9264	13.0039	13.0008	12.9286	12.9878	12.9919	12.9973	12.4152	12.3105
PSO [17]	PSO-TVAC [17]	WOA [17]	MDE [18]	SARGA [18]	RTS [18]	EP [18]	BSO 1 [18]	BSO 2 [18]
12.381	12.279	12.255	13.0532	13.21643	13.236	13.3462	12.4633	12.4672
BSO 3 [18]	BSO 4 [18]	BSO 4 [18]						
12.4651	12.4588	12.4699						

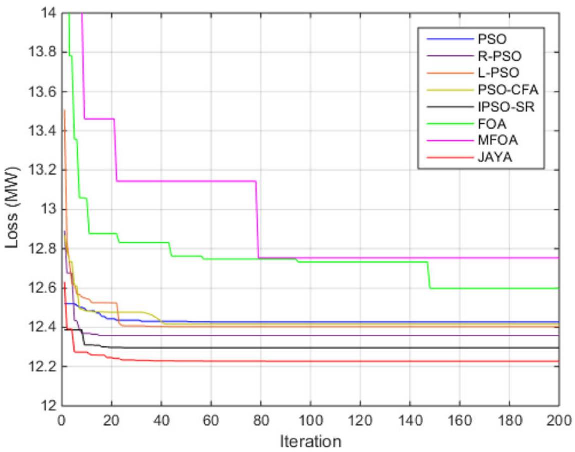

Fig. 2 Convergence characteristics of the algorithms for the IEEE 14 bus system without DG injection

generator bus voltages, tap position of the tap-changing transformer, the VAR output of the compensating devices, and the injected DG active power. Thus for an n-bus system, the ORPD problem is solved n-1 times. The proposed algorithm is used to determine the optimal value of DG power for each bus in order to reduce transmission line loss for the ORPD problem. The power losses for the n-1 buses are compared, and the bus with the minimum power loss and the corresponding injected DG power are selected.

2 Problem formulation

The objective of solving the ORPD problem is the minimization of power loss in transmission lines incorporating DG. The solution to this problem is to determine the optimal values of the control variables while simultaneously satisfying all the constraints in the system. First, the ORPD problem is solved without the incorporation of DG in the system, and power losses for the test cases are evaluated and compared using different optimization algorithms. The DG is then introduced and the algorithms again determine the power loss of the system with the penetration of DG. The objective function remains the same while the amount of DG power to be injected is considered as an additional control variable.

The objective function for the problem is expressed as [4]:

$$f_{\mathrm{n}} = \min\left(P_{\mathrm{loss}}\right) = \sum_{k=1}^{Nl} G_k\left(V_i^2 + V_j^2 - 2V_iV_j\cos\delta_{ij}\right) \tag{1}$$

where Nl represents the total number of transmission lines, and the conductance of the k^{th} branch is G_k. V_i and V_j represent the magnitudes of the bus voltage for buses i and j, respectively, and δ_{ij} is the phase difference between V_i and V_j. The different constraint

Table 4 Simulation results on the IEEE 30 bus system using different algorithms without DG injection

Control Variables (p.u.)	PSO	R-PSO	L-PSO	PSO-CFA	IPSO-SR	FOA	MFOA	JAYA
V_{G1}	1.1	1.1	1.1	1.1	1.1	0.9757	0.95	1.1
V_{G2}	1.1	1.1	1.1	1.1	1.1	0.95	0.95	1.0945
V_{G5}	1.1	1.1	1.1	1.0806	1.1	0.95	0.95	1.0752
V_{G8}	1.1	1.1	1.1	1.0821	1.0882	0.95	0.95	1.077
V_{G11}	1.1	1.1	1.1	1.1000	1.1	1.1	0.95	1.1
V_{G13}	1.1	1.1	1.1	1.1000	1.1	1.1	0.95	1.1
T_{6-9}	0.9981	1.1	1.1	0.9777	0.9758	0.9	0.9	1.073
T_{6-10}	1.1	0.9	1.1	1.1	1.1	0.9	0.9	0.9001
T_{4-12}	0.9726	0.9729	1.0063	1.1	0.9553	0.9	0.9	0.9411
T_{28-27}	0.9896	0.9746	0.998	1.0041	0.9644	0.9	0.9	0.9522
Q_{sc3}	0.0	0.0	0.0	0.0	0.094958	0.0003	0.2993	0.0915
Q_{sc10}	0.36	0.2362	0.36	0.0954	0.36	0.0005	0.2993	0.2824
Q_{sc24}	0.0949	10.056	0.1032	0.107	0.0994	0.0003	0.2993	0.0978
P_{loss} (MW)	4.7915	4.7392	4.8655	4.7282	4.7190	6.2775	5.0957	**4.5983**
ICA [34]	IWO [34]	MICA-IWO [34]	C-PSO [35]	CI-PSO [35]	LDI-PSO [35]	B-DE [35]	R-DE [35]	SFLA [35]
4.6155	4.6287	4.5984	4.6801	4.6124	4.6124	4.6124	4.6675	4.6148
NMSFLA [35]								
4.6118								

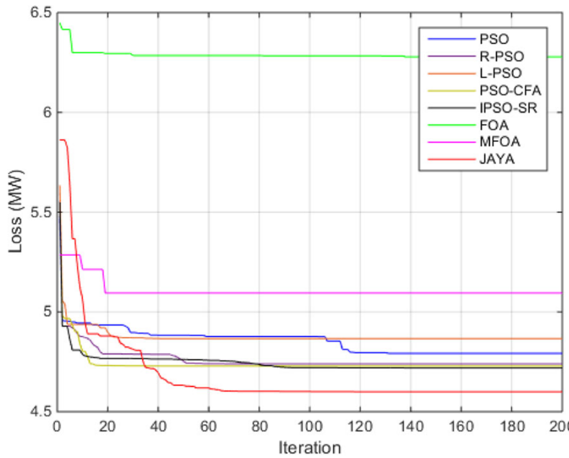

Fig. 3 Convergence characteristics of the algorithms for the IEEE 30 bus system without DG injection

that need to be satisfied are discussed in the following sub-sections.

2.1 Constraints

The constraints are mainly categorized into equality constraints and inequality constraints as follows:

2.1.1 Equality constraints

These constraints depict the load flow equations as:

$$P_{gi} - P_{di} - V_i \sum_{j=1}^{Nb} V_j \left(G_{ij} \cos\delta_{ij} + B_{ij} \sin\delta_{ij} \right) = 0 \tag{2}$$

$$Q_{gi} - Q_{di} - V_i \sum_{j=1}^{Nb} V_j \left(G_{ij} \cos\delta_{ij} + B_{ij} \sin\delta_{ij} \right) = 0 \tag{3}$$

where the total number of buses is Nb, P_{gi} and Q_{gi} represent the active and reactive power generation, and P_{di} and Q_{di} are the active and reactive power load demands for the i^{th} bus, respectively. G_{ij} and B_{ij} represent the conductance and susceptance between the i^{th} and j^{th} buses, respectively.

2.1.2 Inequality constraints

- *Generator constraints:*

The active and reactive power generation of the generator and its voltage magnitude are all set within their limits when solving the problem, as:

$$V_{gi}^{min} \le V_{gi} \le V_{gi}^{max}, \qquad i = 1, \ldots, N_g \tag{4}$$

$$P_{gi}^{min} \le P_{gi} \le P_{gi}^{max}, \qquad i = 1, \ldots\ldots\ldots\ldots, N_g \tag{5}$$

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max}, \qquad i = 1, \ldots\ldots\ldots\ldots, N_g \tag{6}$$

Table 5 Statistical analysis for case 2 of the IEEE 30 bus system

Algorithm	Best (MW)	Worst (MW)	Mean (p.u.)	Standard deviation (std.)	% of Power save	Average computation time (s)
C-PSO [34]	4.68017	5.69149	5.14339	2.8854×10^{-3}	17.3114	45.67
CI-PSO [34]	4.61244	4.87635	4.64732	5.834×10^{-4}	18.5081	56.76
LDI-PSO [34]	4.61243	4.93822	4.62908	4.851×10^{-4}	18.5083	49.57
B-DE [34]	4.61243	4.61333	4.61281	2.6×10^{-6}	18.5083	46.78
R-DE [34]	4.66755	4.98274	4.75088	6.54×10^{-4}	17.5344	54.07
SFLA [34]	4.61483	4.97653	4.72213	9.973×10^{-4}	18.4659	41.97
NMSFLA [34]	4.61181	4.61749	4.61264	9.8×10^{-6}	18.5192	23.06
ICA [34]	4.6155	4.6624	4.6397	2.7613×10^{-3}	18.4541	68.14
IWO [34]	4.6287	4.9206	4.7813	3.1584×10^{-2}	18.2208	70.45
MICA-IWO [34]	4.5984	4.6009	4.5991	8.006×10^{-6}	18.7562	69.04
PSO	4.7915	4.9387	4.9053	9.08×10^{-3}	15.3445	50.73
R-PSO	4.7392	5.0006	4.8695	8.707×10^{-3}	16.2686	50.75
L-PSO	4.8655	5.0222	4.9496	5.1176×10^{-3}	14.0371	48.53
PSO-CFA	4.7282	4.9185	4.8334	6.668×10^{-3}	16.4629	50.63
IPSO-SR	4.719	4.9316	4.84455	6.668×10^{-3}	16.6254	51.13
FOA	6.2775	6.3832	6.3605	5.3887×10^{-3}	−10.9099	49.28
MFOA	5.0957	5.1424	5.13425	1.724×10^{-3}	9.97	52.79
JAYA	4.5983	4.5986	4.5984	9.4281×10^{-5}	18.7579	50.44

Table 6 Frequency of convergence for the IEEE 30 bus system case 2 in 50 trial runs

Algorithms	4.59–4.60	4.61–4.70	4.71–4.80	4.81–4.90	4.91–5.0	5.01–5.10	5.11–5.20	> 6.01
PSO	0	0	1	30	19	0	0	0
R-PSO	0	0	11	33	6	0	0	0
L-PSO	0	0	3	25	22	0	0	0
PSO-CFA	0	0	18	27	5	0	0	0
IPSO-SR	0	0	4	29	17	0	0	0
FOA	0	0	0	0	0	0	0	50
MFOA	0	0	0	0	0	1	49	0
JAYA	50	0	0	0	0	0	0	0

where, N_g represents the total number of generator buses, V_{gi}^{min}, P_{gi}^{min} and Q_{gi}^{min} are the minimum limits and V_{gi}^{max}, P_{gi}^{max} and Q_{gi}^{max} are the maximum limits of the generator bus voltages, active and reactive power, respectively. V_{gi}, P_{gi} and Q_{gi} are the voltage, active and reactive power generation at the i^{th} bus, respectively.

- *Transformer constraints:*

$$T_i^{min} \leq T_i \leq T_i^{max}, \qquad i = 1, ..., N_T \tag{7}$$

- *VAR compensator constraints:*

$$Q_{ci}^{min} \leq Q_{ci} \leq Q_{ci}^{max}, \qquad i = 1, ..., N_C \tag{8}$$

- *Operating constraints:*

$$V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max}, \qquad i = 1, ..., N_{PQ} \tag{9}$$

$$S_{Li} \leq S_{Li}^{max}, \qquad i = 1, ..., NL \tag{10}$$

Equation 7 shows the maximum and minimum limits of the tap changing transformers, where N_T represents the number of tap-changing transformers in the system, T_i is the transformer tap-setting position at the i^{th} bus and T_i^{min} and T_i^{max} are its minimum and maximum limits. Equation 8 represents the limits of the reactive power to be injected by the VAR compensators, where N_C is the total number of shunt compensators at the buses, Q_{ci}^{min} and Q_{ci}^{max} are the minimum and maximum limits of the reactive power injection Q_{ci}, respectively. Equations 9 and 10 represent the operating constraints of load buses and the apparent power at the branches, where N_{PQ} depicts the total number of load buses, S_{Li}^{max} is the maximum apparent power flow at the i^{th} bus and S_{Li} is the apparent power at that branch. V_{Li} is the magnitude of the voltage at the i^{th} load bus and V_{Li}^{min} and V_{Li}^{max} are its minimum and maximum limits. The objective function in (1) is modified by considering the dependent variables as constraints using penalty coefficients as:

$$f = P_{\text{loss}} + \lambda_V \sum_{i=1}^{N_V^{lim}} \left(V_i - V_i^{lim}\right)^2 + \lambda_Q \sum_{i=1}^{N_Q^{lim}} \left(Q_{gi} - Q_{gi}^{lim}\right)^2 \tag{11}$$

The limits of V_i^{lim} and Q_{gi}^{lim} are:

$$V_i^{lim} = \begin{cases} V_i^{min}, & if\ V_i < V_i^{min} \\ V_i^{max}, & if\ V_i > V_i^{max} \end{cases} \tag{12}$$

$$Q_i^{lim} = \begin{cases} Q_i^{min}, & if\ Q_{gi} < Q_i^{min} \\ Q_i^{max}, & if\ Q_{gi} > Q_i^{max} \end{cases} \tag{13}$$

where, λ_V and λ_Q are the penalty coefficients, N_V^{lim} is the number of buses for which the voltages are outside limits and N_Q^{lim} is the number of buses for which the reactive power generations are outside limits.

Table 7 Control variable limits (p.u.) for the test cases

Limits of voltages and tap settings (p.u.)					
V_g^{min}	V_g^{max}	V_{PQ}^{min}	V_{PQ}^{max}	T^{min}	T^{max}
0.9	1.1	0.94	1.06	0.9	1.1
Limits of the reactive power sources (p.u.)					
Bus No.	**18**	**25**	**53**		
Q_c^{min}	0	0	0		
Q_c^{max}	0.1	0.059	0.063		

Table 8 Simulation results on the IEEE 57 bus system using different algorithms without DG

Control Variables (p.u.)	PSO	R-PSO	L-PSO	PSO-CFA	IPSO-SR	FOA	MFOA	JAYA
V_{G1}	1.1	1.1	1.1	1.1	1.1	0.9127	0.9	1.1
V_{G2}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0991
V_{G3}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0888
V_{G6}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0834
V_{G8}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.1
V_{G9}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0848
V_{G12}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0806
T_{4-18}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	0.9
T_{4-18}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	0.9
T_{21-20}	1.1	1.1	1.1	0.9918	1.1	0.9	0.9243	0.9824
T_{24-26}	1.0036	1.1	1.015	0.9971	1.0642	0.9	0.9	0.9865
T_{7-29}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	0.9
T_{34-32}	0.9671	1.1	0.9688	0.9662	1.1	1.1	0.9	0.9751
T_{11-41}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	0.9
T_{15-45}	1.1	1.0046	1.1	1.1	1.0133	0.9	0.9	0.9
T_{14-46}	1.1	1.0095	1.1	1.1	1.0176	0.9	0.9	0.9
T_{10-51}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	0.9101
T_{13-49}	1.1	0.9823	1.0333	1.1	0.9895	0.9	0.9	0.9
T_{11-43}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	0.9
T_{40-56}	1.1	1.1	1.1	1.027	1.1	0.9	0.9	1.0111
T_{39-57}	1.1	1.1	1.1	0.9829	1.1	0.9	0.9	0.9841
T_{9-55}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	0.9002
Q_{sc18}	0.0	0.0	0.0	0.10	0.0616	0.0012	0.008	0.0976
Q_{sc25}	0.059	0.059	0.059	0.059	0.059	0.0026	0.0059	0.059
Q_{sc53}	0.063	0.063	0.063	0.063	0.063	0.0014	0.0059	0.063
P_{loss} (MW)	24.8254	24.2539	24.5676	24.5873	24.2012	33.5557	23.0158	**21.5481**
ALC-PSO [18]	BBO [18]	GSA [18]	CPVEI HBMO [18]	HBMO [18]	OGSA [18]	BSO 1 [18]	BSO 2 [18]	BSO 3 [18]
23.39	24.544	24.439	22.78	23.24	23.43	24.5025	24.4856	24.4492
BSO 4 [18]	BSO 5 [18]	SGA (F_{f1}) [36]	SGA (F_{f2}) [36]	PSO [37]	ICA [37]	PSO-ICA [37]	MOALO [38]	DSA [39]
24.3744	24.6431	23.836	24.325	24.7742	24.1607	24.1386	26.593	23.35
BSO [40]	WCA [41]	GBWCA [41]	GSA [42]	CSA [42]	MCBOA [42]	BA [43]	FPA [43]	
24.3744	24.82	23.27	24.4922	24.2619	23.6943	24.9254	24.8419	

3 JAYA algorithm

Many stochastic and meta-heuristic techniques have been developed recently to solve this type of complex and non-linear problem such as is the ORPD, including the JAYA algorithm proposed by R.V. Rao [23]. This algorithm has the ability to solve the optimization problem quickly to determine the optimal solution. It has a very high success and convergence rate compared with other algorithms as it has a tendency to move towards the best solution and move away from the worst in every iteration. This helps the algorithm to update new solutions by comparing it with the best without being stuck in local optima.

Let an objective function be $f(x)$, where 'm' is the number of design variables (i.e. $a = 1, 2, \ldots, m$) and 'n' the number of populations ($b = 1, 2, \ldots, n$) for the i^{th} iteration. The population having the best solution of $f(x)$ (i.e. $f(x)_{\text{best}}$) is called the best candidate and the population having the worst solution to the objective function (i.e. $f(x)_{\text{worst}}$) is called the worst. Assuming the value for the a^{th} variable of the b^{th}

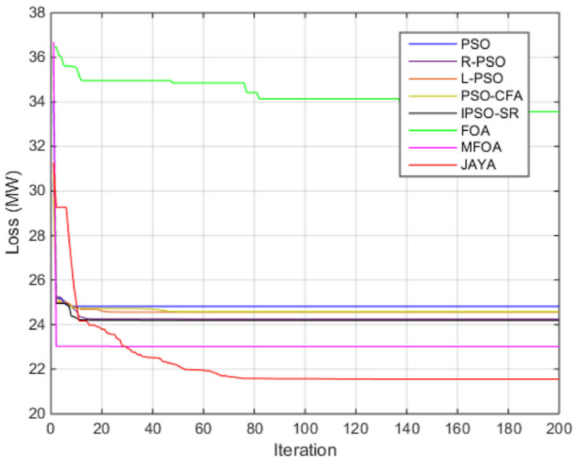

Fig. 4 Convergence characteristics of the algorithms for the IEEE 57 bus system without DG injection

population in the i^{th} iteration is represented as $J_{a,\ b,\ i}$, the value of the variable is updated as:

$$J'_{a,b,i} = J_{a,b,i} + r_1 \left(J_{a,best,i} - \left| J_{a,b,i} \right| \right) - r_2 \left(J_{a,worst,i} - \left| J_{a,b,i} \right| \right) \tag{14}$$

where $J_{a,\ best,\ i}$ and $J_{a,\ worst,\ i}$ are the best and worst solutions of the objective function of the a^{th} variable, respectively. r_1 and r_2 are two random numbers in the range of [0, 1]. Thus, this equation helps the variable to move closer to the best solution and away from the worst solution.

3.1 Implementation of JAYA algorithm in ORPD

The procedure for the implementation of the JAYA algorithm in solving the ORPD problem is shown in the flow chart in Fig. 1, and the detailed step by step descriptions are given below.

Table 9 Control variable limits (p.u.) for the test cases

Limits of voltages and tap-settings (p.u.)							
V_g^{min}	V_g^{max}	V_{PQ}^{min}	V_{PQ}^{max}	$\mathbf{T^{min}}$	$\mathbf{T^{max}}$		
0.9	1.1	0.94	1.06	0.9	1.1		
Limits of the reactive power sources (p.u)							
Bus No.	5	34	37	44	45	46	48
Q_c^{min}	−0.4	0	−0.25	0	0	0	0
Q_c^{max}	0	0.14	0	0.1	0.1	0.1	0.15
Bus No.	74	79	82	83	105	107	110
Q_c^{min}	0	0	0	0	0	0	0
Q_c^{max}	0.12	0.2	0.2	0.1	0.2	0.06	0.06

Step 1: The size of the population of the control variables and the total number of iterations for the problem are initialized.
Step 2: The values of the control variables are randomly selected within their corresponding constraint limits.
Step 3: A standard IEEE bus system is chosen and the bus data and line data of the system are updated using the new values from the respective control variables. Then, the load flow operation using the Newton-Raphson method is executed.
Step 4: The constraints are checked and if any constraint is violated, the control variables are re-initialized and steps 2 and 3 are repeated. If no constraint is violated, the power loss is then calculated using the results from the load flow.
Step 5: The best and worst solutions are identified from the set of populations, i.e. the set resulting in the least power loss is declared as the 'best solution' and the set with the highest power loss is declared as the 'worst solution'.
Step 6: The iteration cycle commences.
Step 7: The JAYA algorithm is initiated where the control variables forming the different populations are updated depending on the best and worst solutions using (14).
Step 8: AC load flow is re-executed and the power loss is calculated for all different sets of population.
Step 9: The results are compared to accept and reject the different sets of the control variables in each population depending on the best solution. The set of control variables having the best solution is accepted and ones with the worse solutions are updated with the previous best. Thus, a new best solution is determined after each iteration.
Step 10: The process continues until the iteration reaches the maximum iteration.
Step 11: The optimal solution is obtained and the corresponding control variables are saved.

This whole process helps obtain the optimal values of the control variables for the best solution among all the sets of population.

4 Simulation results and discussions

To evaluate the performance of the JAYA algorithm, it is initially tested on 24 standard constrained benchmark functions (G01 – G24) and the results are compared in Table 1. It shows that the proposed algorithm

Table 10 Simulation results on the IEEE 118 bus system using different algorithms without DG injection

Control Variables (p.u.)	PSO	R-PSO	L-PSO	PSO-CFA	IPSO-SR	FOA	MFOA	JAYA
V_{G1}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0801
V_{G4}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.1
V_{G6}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0932
V_{G8}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.1
V_{G10}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.1
V_{G12}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0896
V_{G15}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0882
V_{G18}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0886
V_{G19}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0869
V_{G24}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0912
V_{G25}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.1
V_{G26}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.1
V_{G27}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0812
V_{G31}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0755
V_{G32}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0813
V_{G34}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0989
V_{G36}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.096
V_{G40}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0784
V_{G42}	1.1	1.1	1.1	1.1	1.1	0.9437	0.9	1.078
V_{G46}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0855
V_{G49}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0977
V_{G54}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0771
V_{G55}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0756
V_{G56}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0765
V_{G59}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0994
V_{G61}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0994
V_{G62}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0956
V_{G65}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.1
V_{G66}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.1
V_{G69}	1.1	1.1	1.1	1.1	1.1	0.956	0.9	1.0999
V_{G70}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0776
V_{G72}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.081
V_{G73}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0769
V_{G74}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0669
V_{G76}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0673
V_{G77}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0867
V_{G80}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0994
V_{G85}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0995
V_{G87}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.1
V_{G89}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.1
V_{G90}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0854
V_{G91}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0895
V_{G92}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.1
V_{G99}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0969

Table 10 Simulation results on the IEEE 118 bus system using different algorithms without DG injection *(Continued)*

Control Variables (p.u.)	PSO	R-PSO	L-PSO	PSO-CFA	IPSO-SR	FOA	MFOA	JAYA
V_{G100}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.1
V_{G103}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0918
V_{G104}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.083
V_{G105}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.077
V_{G107}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0669
V_{G110}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0704
V_{G111}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0774
V_{G112}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0549
V_{G113}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0968
V_{G116}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0999
T_{5-8}	0.9905	1.1	1.1	1.1	1.1	0.9	0.9	0.9847
T_{25-26}	1.1	1.1	1.1	1.1	1.1	0.922	0.9	1.0967
T_{17-30}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	0.9964
T_{37-38}	1.1	1.1	1.1	1.1	0.9942	0.9	0.9	0.983
T_{59-63}	1.1	0.982	0.9820	0.9821	0.9667	0.9	0.9	0.9806
T_{61-64}	0.9859	0.9999	0.9999	1.0	1.1	0.9	0.9	1.005
T_{65-66}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.0043
T_{68-69}	1.1	1.1	1.1	1.1	0.9257	0.9	0.9	0.9569
T_{80-81}	0.9789	1.1	1.1	0.9766	1.1	0.9	0.9	0.9915
Q_{sc5}	0.0	0.0	0.0	0.0	0.0	0.0000	0.0	−0.2340
Q_{sc34}	0.0	0.0	0.0	0.0	0.0	0.0017	0.14	0.0007
Q_{sc37}	0.0	0.0	0.0	0.0	0.0	0.0000	0.0	0.0
Q_{s44}	0.0	0.0	0.0	0.0	0.0	0.0007	0.1	0.0566
Q_{sc45}	0.0	0.0	0.0	0.0	0.0	0.0009	0.1	0.0979
Q_{sc46}	0.0	0.0	0.0	0.0	0.0	0.0019	0.1	0.0467
Q_{sc48}	0.0	0.0	0.0	0.0	0.0	0.0007	0.15	0.0015
Q_{sc74}	0.0	0.0	0.0	0.0	0.0	0.0008	0.12	0.0080
Q_{sc79}	0.0	0.0	0.0	0.0	0.0	0.0009	0.1604	0.1992
Q_{sc82}	0.0	0.0	0.0	0.0	0.0	0.0005	0.1604	0.2000
Q_{sc83}	0.0	0.0	0.0	0.0	0.0	0.0013	0.1	0.0741
Q_{sc105}	0.0	0.0	0.0	0.0	0.0	0.0008	0.1604	0.1991
Q_{sc107}	0.0	0.0	0.0	0.0	0.0	0.0013	0.06	0.0
Q_{sc110}	0.0	0.06	0.06	0.0	0.06	0.0028	0.06	0.0294
P_{loss} (MW)	111.7172	113.7233	113.7233	112.8162	112.6259	167.0409	107.9321	**105.4821**
CKHA [44]	PSO-TVIW [45]	PSO-TVAC [45]	SPSO-TVAC [45]	PSO-CF [45]	PG-PSO [45]	SWT-PSO [45]	PGSWT-PSO [45]	IPGS-PSO [45]
110.79	116.8976	124.3335	116.2026	115.6469	116.6075	124.1476	119.4271	115.0605
GSA [46]	OGSA [47]	CLPSO [48]	EMA [49]	NGBWCA [41]	WCA [41]	SARCGA [20]	HEP [20]	QOTLBO [20]
127.76	126.99	130.96	126.22	121.47	131.83	113.12	115.58	112.2789
TLBO [20]	FPA [20]	CSA [20]	SSA [20]	MSSA [20]	HSSSA [20]	SSO [20]	ISSO [20]	MSFS [50]
116.4003	129.6524	121.2732	125.8324	124.0818	126.6992	179.1816	114.5297	114.6251
SARCGA [51]	HEP [51]	ALO [21]	IALO [21]					
113.12	115.58	116.86	114.795					

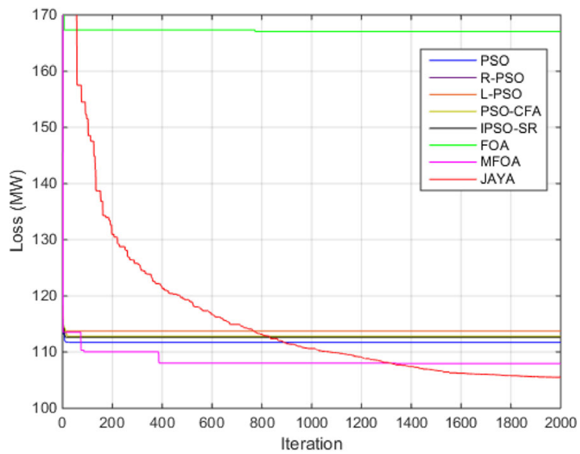

Fig. 5 Convergence characteristics of the algorithms for the IEEE 118 bus system without DG injection

is far superior and consistent in obtaining better results than the other well-established techniques. The results also depict the ability of the proposed technique in obtaining better results for all the functions under any constraints. The best and the mean values for each function using the JAYA algorithm are very close to each other, which implies that the algorithm is robust and produces results with minimum deviation compared to other techniques.

After obtaining this excellent performance of the proposed algorithm on the standard benchmark function with constraints, it is then implemented to solve the ORPD problem. In this paper, it is tested on the standard IEEE 14, 30, 57 and 118 bus systems along with other algorithms from the literature. It has also been tested to solve the minimum power loss of the ORPD problem with and without DG penetration, and the solutions are compared to those using different algorithms. The software used is MATLAB 2014b and the population size is 100 for all the cases in the paper.

The details of the number of individual parameters of the test systems are listed in Table 2 and the system data of these test systems are obtained from [31].

4.1 Minimization of active power loss without DG injection

4.1.1 IEEE 14 bus system

The IEEE-14 bus system has five generators at buses 1 (which is the slack bus), 2, 3, 6 and 8, respectively. There are 20 branches, and three tap-changing transformers between the lines 4–7, 4–9 and 5–6. Reactive power is injected at buses 9 and 14. The limits of the control variables (p.u. value) for the case study under the IEEE 14 bus system are as follows:

$0.95 \le V_g \le 1.1$; $0.95 \le V_{PQ} \le 1.05$; $0.9 \le T_i \le 1.1$ and $0 \le Q_c \le 0.3$.

The above control variables are used to solve the ORPD problem using the different algorithms and the simulation results are compared in Table 3 to determine the best among them. Comparing the results in the table and the convergence characteristics shown in Fig. 2, it can be concluded that the JAYA algorithm has produced the best solution to the ORPD problem with a minimum loss of 12.227 MW, and is superior to the other 37 algorithms.

4.1.2 IEEE 30 bus system

In the IEEE 30 bus system, there exist six generators situated at buses 1, 2, 5, 8, 11 and 13, respectively. Bus no. 1 is the slack bus, and there are 41 transmission lines with four branches having tap-changing transformers. Reactive power is injected by capacitor banks at bus no. 3, 10 and 24, respectively. The limits of the control variables (p.u. value) are as follows:

$0.95 \le V_g \le 1.1$; $0.95 \le V_{PQ} \le 1.1$; $0.9 \le T_i \le 1.1$ and $0 \le Q_c \le 0.36$.

Table 11 Optimum solution for the IEEE 14 bus system with DG individually injected at each bus using JAYA algorithm

Bus No.	Optimal DG value and Loss	Bus No.	Optimal DG value and Loss	Bus No.	Optimal DG value and Loss
2	DG = 178.8543 MW Loss =7.7859 MW	7	DG = 171.2628 MW Loss =3.903 MW	12	DG = 45.3501 MW Loss =9.9391 MW
3	DG = 145.6164 MW Loss =3.4680 MW	8	DG = 167.2458 MW Loss =3.9819 MW	13	DG = 77.5109 MW Loss =8.2191 MW
4	DG = 190.176833 MW Loss =2.9641 MW	9	DG = 151.8885 MW Loss =3.9819 MW	14	DG = 66.8016 MW Loss =8.3292 MW
5	DG = 186.7737 MW Loss =4.6521 MW	10	DG = 100.6044 MW Loss =7.1674 MW		
6	DG = 121.6318 MW Loss =7.1825 MW	11	DG = 72.7414 MW Loss =8.8081 MW		

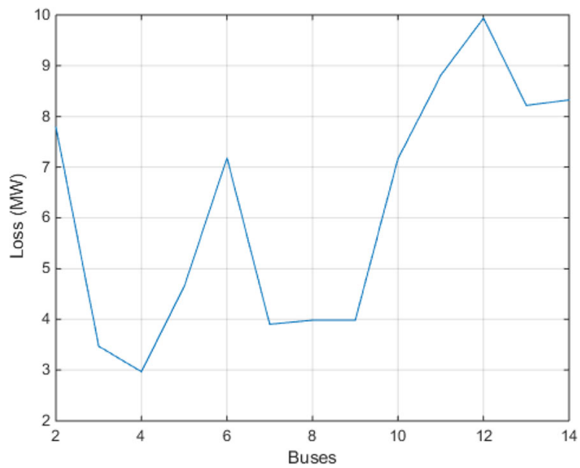

Fig. 6 Comparison of the results for the IEEE 14 bus system using the JAYA algorithm

The simulation results of the solution to the ORPD problem using the different algorithms for this test case are shown in Table 4 along with the convergence characteristics in Fig. 3. It can be seen that the JAYA algorithm has produced the best results under the conditions of the control variables, resulting in the lowest line loss of 4.5983 MW.

A statistical analysis of the algorithms is shown in Table 5 for this particular test system. The best and worst values of the solutions of the ORPD problem along with the mean, standard deviation (std.), percentage of power saved, and the average computation time of the results for the different algorithms are compared. The results prove that the JAYA algorithm has obtained the best solution to the problem and is also the most consistent and robust with small std. and the maximum reduction of power loss of almost 18.7579% (4.5983 MW). The time of convergence is modest and although the simulation speed is slower than a few others, the JAYA algorithm obtains the best solution and is much more favorable in terms of efficiency and economy than other methods.

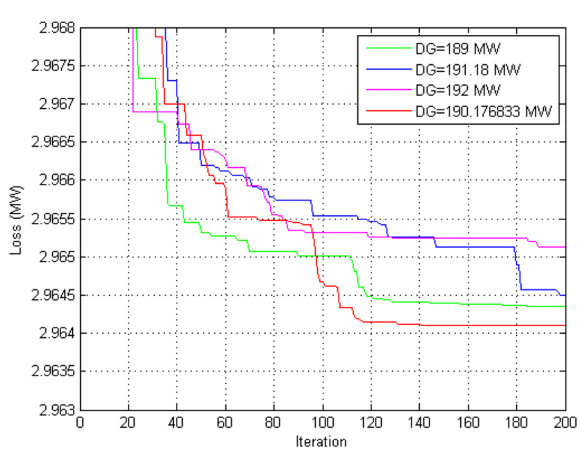

Fig. 7 Convergence characteristics with different DG power placed at bus no. 4 of IEEE 14 bus system using JAYA algorithm

In order to investigate how frequently the results from the different algorithms converge within a different range of solutions, the frequency of convergence for the IEEE 30 bus system under the inequality constraints of the control variables as mentioned earlier is compared in Table 6. It shows the number of times each algorithm has produced the solution within a specified range when the ORPD problem is run for 50 times for every single algorithm. The results show that the JAYA algorithm is undoubtedly the only one to produce all the results within the minimum range of 4.59–4.60 MW. Although the MFOA technique is also consistent and has frequently obtained the solutions within the range of 5.11–5.20 MW (49 times), the algorithm has failed to optimize the function to lower limits. Thus, the results prove that the JAYA algorithm has the capability of converging most frequently to the minimum solution.

4.1.3 IEEE 57 bus system

The standard IEEE 57 bus system has seven generators situated at buses 1, 2, 3, 6, 8, 9 and 12, respectively, where bus 1 is the slack bus. There are 15 branches out of a total of 80 having tap-changing transformers connected. The reactive power compensating devices are placed at buses 18, 25 and 53. The maximum and minimum limits of the control variables are given in Table 7.

The simulation results for the ORPD problem using the different algorithms for the test case and the comparative convergence characteristics are shown in Table 8 and Fig. 4, respectively. It shows that the JAYA algorithm has reduced the power loss to 22.67%, a much lower level than the other algorithms. This is the best recorded solution for this particular test case under the mentioned inequality constraints.

4.1.4 IEEE 118 bus system

As the algorithm has successfully outperformed the other algorithms reported in the literature in optimizing the ORPD problem for the IEEE 57 bus system, it

Table 12 Comparison of real power loss at the IEEE 14 bus system with different DG power placed at bus no. 4 using the JAYA algorithm

DG values (MW)	189	190.176833 (Optimal)	191.18	192
Loss (MW)	2.9643	2.9641	2.9645	2.9651

is now tested on the larger IEEE 118 bus system to observe its performance and ability. The IEEE 118 bus system has 54 generators, 14 shunt compensators, 9 tap-changing transformers, and a total of 186 transmission lines. The control variable limits are given in Table 9. Table 10 and Fig. 5 shows the simulation results and the convergence characteristics for the ORPD problem using the different algorithms, respectively.

The results show the superiority of the JAYA algorithm in determining the optimal solution, thus reducing the power loss to the lowest value of 105.4821 MW (20.36%) for the test case compared to all the other algorithms without violating the limits of the constraints. This proves the JAYA algorithm to be the most efficient algorithms even for large scale power systems.

4.2 Minimization of power loss with DG injection

For the second part of the paper, DG power is injected individually at all the buses (except the slack bus) and the power losses are calculated using the same algorithms while keeping the constraints unchanged. The total number of control variables for each case without DG injection was listed in Table 2. When DG is penetrated into the system the number of control variables is increased by 1, and the DG power to be injected is taken as an additional control variable. The value of DG power is initially set at 100% of the maximum load demand for all the test cases considered in this paper. The algorithm then determines the optimal value of DG to be injected at each bus in order to produce the minimum power loss.

Moreover, the magnitude of the voltage of the bus at which the DG is injected is also considered as a control variable. Thus, when the DG is injected at any PV bus, the number of voltage control variables remains the same but for a PQ bus, it increases by 1.

The JAYA algorithm has been proved to be the best among all the reported algorithms in determining the minimum power loss without incorporating DG power. Thus, the proposed JAYA algorithm is used to determine the optimal value of DG to be injected at each bus to obtain the minimum power loss for all the test systems. The results are then compared and the optimal bus is located with the optimal value of DG to be injected for that particular bus. The study is repeated for all four test cases using different algorithms to determine which algorithm is able to determine the optimal value of DG at that optimal bus leading to minimum power loss. Such work on optimization of the ORPD problem with the concept of DG integration has not been discussed anywhere. This helps significantly reduce the power loss of the system that cannot be achieved using other methods of solving the ORPD problem. Moreover, it also encourages the use of non-conventional resources as the results obtained in this paper describes the details of the optimal amount of DG power to be integrated for a particular test case at the optimal bus location.

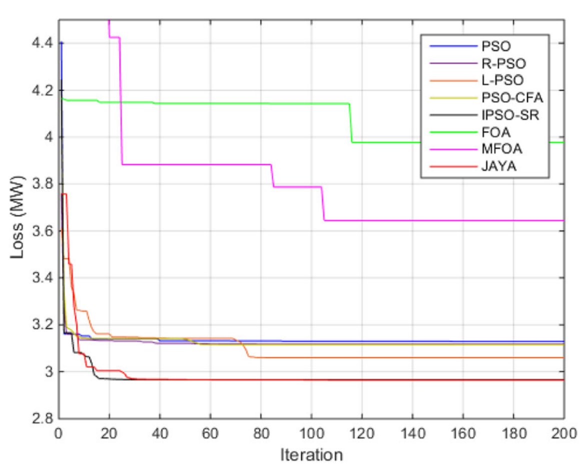

Fig. 8 Convergence characteristics of the algorithms for the IEEE 14 bus system with DG injection

4.2.1 IEEE 14 bus system

The total generation of the test system is 272.6 MW and the load demand is 259.11 MW. The control variable limits are the same as in Section 4.1.1 for the case with no DG. Table 11 shows the optimum solution of the ORPD problem for minimization of power loss when the optimal value of DG is injected at each bus, one at a time using the JAYA algorithm. The comparison of the results is also represented graphically in Fig. 6. From Table 11 and Fig. 6, it is observed that injecting the optimum DG power of 190.176833 MW, which is 73.3962% of the demand, at bus no. 4 can achieve the minimum power loss of 2.9641 MW.

Table 12 and Fig. 7 illustrate the significance of the DG power on power loss. The results show that

Table 13 Simulation results on IEEE 14 bus system with DG using different algorithms

Control Variables (p.u.)	PSO	R-PSO	L-PSO	PSO-CFA	IPSO-SR	FOA	MFOA	JAYA
V_{G1}	1.1	1.1	1.1	1.1	1.1	0.95	1.1	1.1
V_{G2}	1.1	1.1	1.1	1.1	1.1	0.95	1.1	1.0991
V_{G3}	1.1	1.1	1.1	1.1	1.0812	0.95	1.1	1.0803
V_{G6}	1.1	1.0534	1.1	1.0522	1.1	1.1	1.1	1.1
V_{G8}	1.1	1.0396	1.1	1.1	1.1	1.1	1.1	1.1
V_4(DG)	1.1	1.1	1.1	1.1	1.1	0.95	1.1	0.9564
T_{4-7}	0.9511	1.0286	0.9824	1.1	0.9704	0.9	1.1	1.0847
T_{4-9}	1.1	1.1	1.1	0.9434	1.1	0.9	1.1	0.9
T_{5-6}	1.1	1.1	1.0112	1.1	1.006	0.9	1.1	1.0026
Q_{sc9}	0.2309	0.3	0.3	0.0025	0.3	0.0027	0.0	0.1882
Q_{sc14}	0.0517	0.064	0.0604	0.0648	0.0606	0.0004	0.0	0.0588
Optimum DG value at bus no. 4 (MW)	**155.11478**	**192.441259**	**192.226747**	**192.468381**	**192.414496**	**194.465270**	**210.184649**	**190.176833**
Total P_{loss} (MW)	**3.1288**	**3.1179**	**3.0600**	**3.1156**	**2.9660**	**3.9772**	**3.6449**	**2.9641**

the power loss would increase from 2.9641 MW to 2.9645 MW and 2.9651 MW for the DG power increased from the optimal value of 190.176833 MW to 191.18 MW and 192 MW respectively, and to 2.9643 MW for the DG power decreased to 189 MW. The other reported algorithms are now used to obtain the optimal value of DG at bus no. 4 and the ORPD problem is solved by optimizing the objective function f from (11). Here, the total number of control variables is 12 as the optimal power loss is obtained when the DG is inserted at bus no. 4, which is not a PV bus. The results and the convergence characteristics are shown in Table 13 and Fig. 8, respectively. These prove that the JAYA algorithm produces the best-optimized value compared to all the other algorithms. The results from the two cases

Table 14 Optimum solution for the IEEE 30 bus system with DG individually injected at each bus using the JAYA algorithm

Bus No.	Optimal DG value and Ploss	Bus No.	Optimal DG value and Ploss	Bus No.	Optimal DG value and Ploss
2	DG = 65.135046 MW Ploss = 4.004 MW	12	DG = 61.407578 MW Ploss = 3.3274 MW	22	DG = 60.513691 MW Ploss = 2.7155 MW
3	DG = 79.182062 MW Ploss = 3.2109 MW	13	DG = 60.745933 MW Ploss = 3.3402 MW	23	DG = 36.462869 MW Ploss = 3.3324 MW
4	DG = 98.939426 MW Ploss = 2.3931 MW	14	DG = 26.770762 MW Ploss = 3.8475 MW	24	DG = 44.563769 MW Ploss = 2.9653 MW
5	DG = 73.540649 MW Ploss = 2.4196 MW	15	DG = 51.03197 MW Ploss = 3.0366 MW	25	DG = 33.070159 MW Ploss = 3.4552 MW
6	DG = 104.34914 MW Ploss = 1.8574 MW	16	DG = 44.027037 MW Ploss = 3.4411 MW	26	DG = 13.511932 MW Ploss = 4.0246 MW
7	DG = 81.668016 MW Ploss = 2.0835 MW	17	DG = 62.521769 MW Ploss = 3.1253 MW	27	DG = 46.93759 MW Ploss = 3.1827 MW
8	DG = 80.484846 MW Ploss = 2.3611 MW	18	DG = 37.518044 MW Ploss = 3.2661 MW	28	DG = 79.02644 MW Ploss = 2.3197 MW
9	DG = 93.083964 MW Ploss = 2.1163 MW	19	DG = 40.023052 MW Ploss = 3.1379 MW	29	DG = 21.634628 MW Ploss = 3.6982 MW
10	DG = 79.787423 MW Ploss = 2.4651 MW	20	DG = 41.612227 MW Ploss = 3.1633 MW	30	DG = 22.095693 MW Ploss = 3.5042 MW
11	DG = 92.481326 MW Ploss = 2.1247 MW	21	DG = 62.480468 MW Ploss = 2.6492 MW		

Table 15 Comparison of power loss at the IEEE 30 bus system with different DG power placed at bus no. 6 using JAYA algorithm

DG values (MW)	103.34914	104.34914 (Optimal)	105.34914
Loss (MW)	1.8576	1.8574	1.8587

with and without DG penetration clearly show that the DG penetration has successfully reduced the power loss by 78.03% compared to a reduction of 9.36% under the similar condition without DG injection.

4.2.2 IEEE 30 bus system

The study on the IEEE 30 bus system has been performed on two different cases. In the first case, the optimal DG power is determined and the value is then fixed to obtain the power loss. However, in the second case, the DG power is considered variable, representing a probabilistic approach to observe the performance penetration of variable DG realistically in the ORPD problem. Here, the probabilistic approach of wind power is considered for the variable DG in the second case.

4.2.2.1 Without considering the variability of DG power

The total active power generation of the test system is 288.7 MW and the load demand is 283.4 MW. The control variable limits are the same as Section 4.1.2 with no DG. Table 14 shows the optimal results of the ORPD problem when DG is individually placed on each bus. As shown, the minimum power loss for the IEEE 30 bus system is obtained when 104.34914 MW DG, which is 36.8204% of the total demand, is placed at load bus no. 6. This reduces the power loss to 1.8574 MW (67.18% reduction), whereas for the case without DG the loss was reduced by only 18.75%.

The significance of the optimum value of DG obtained by the JAYA algorithm is illustrated in Table 15, which shows that when the DG value is increased or decreased by 1 MW from the optimal value, there is an increase in power loss. Thus, the result obtained from the proposed algorithm is the optimal value of DG to be injected into the system for minimum power loss. Other reported algorithms are then used to optimize the ORPD problem by determining the optimal value of DG at bus no. 6 for minimum power loss. The results from Table 16 and the convergence characteristics from Fig. 9 conclude that the minimum power loss is obtained by using the JAYA algorithm, indicating the superiority of the JAYA algorithm over other reported algorithms.

4.2.2.2 Considering the variability of DG power

In the work shown in Section 4.2.2.1, the uncertainty of DG power was not considered. In practical cases, the DG power is of a variable nature and thus needs to be considered to make the study more realistic. There are several reported cases in which the variability of renewable energy is integrated into the ORPD problem with a maximum capacity of DG of up to 110 MW considered at bus 6. The Weibull probability distribution function [52], which considers the stochastic nature of wind power, is used and the variability of wind power is considered in two ways as follows.

Case 1: Overestimated wind power

This study shows the impact of overestimated power from the wind farm into the ORPD problem considering the uncertainty condition. The maximum power output from the wind farm is set as 110 MW, as the optimal value of injected DG into the IEEE 30 bus system determined by the JAYA algorithm is 104.34914 MW. The overestimated probabilistic approach of the Weibull probability distribution function determines the more realistic nature of the optimal wind power to be injected to minimize the power loss in the ORPD problem using the following equation:

$$P_{owi} = w_f\left\{1 - \ exp\left(-\left(\frac{v_i}{c}\right)^k\right) + \ exp\left(-\left(\frac{v_o}{c}\right)^k\right)\right\} + \int_0^{W_1} (w_f - w) f_w(w) dw \tag{15}$$

Table 16 Simulation results on the IEEE 30 bus system with DG injection using different algorithms

Algorithms	PSO	R-PSO	L-PSO	PSO-CFA	IPSO-SR	FOA	MFOA	JAYA
Optimum DG value at bus no. 6 (MW)	118.087165	104.493446	104.604412	104.431680	101.445626	100.164506	104.929867	104.34914
P_{loss} (MW)	2.2330	2.0701	2.0853	2.1283	2.0084	2.5057	2.2652	1.8574

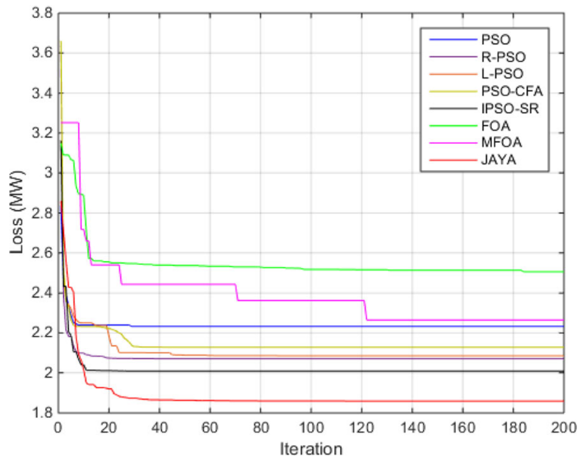

Fig. 9 Convergence characteristics of the algorithms for the IEEE 30 bus system with DG injection

where, P_{owi} represents the optimal value of injected wind power obtained using the overestimation of the Weibull probability distribution function, and k and c represent the shape and scale factors referred from [52]. w_f represents the forecasted wind power and W_1 represents the actual power produced. The term $f_w(w)$ is a probability density function of wind power output w, whereas v_i and v_o are the cut-in and cut-out wind velocities, respectively.

The analysis is carried out using the same number of techniques as discussed earlier and the details of the calculated results are shown in Table 17. The convergences of the different algorithms for this case are compared in Fig. 10. The results show that for the overestimation case, the optimal value of wind power is 59.2683 MW (a reduction of 56.82% compared to the base case) as obtained by the JAYA algorithm, for which the power loss is 2.4442 MW. This happens to be the lowest for this case among all the other algorithms. Thus, the analysis gives a realistic outcome of the penetration of wind power for the overestimated condition.

Case 2: Underestimated wind power

In this case, the underestimated approach of the Weibull probability distribution function is considered. The maximum wind power limit is set as 110 MW and the optimal value of wind power is obtained for minimizing the power loss for the IEEE 30 bus system. The optimal value of the wind power using the Weibull probability distribution function is given as

$$P_{uwi} = w_f\left\{1 - exp\left(-\left(\frac{v_r}{c}\right)^k\right) - exp\left(-\left(\frac{v_o}{c}\right)^k\right)\right\} + \int_{w_1}^{w_r}(w - w_f)f_w(w)dw \tag{16}$$

Table 17 Simulation results on the IEEE 30 bus system with overestimated Weibull probability distribution function of wind power on ORPD using different algorithms

Control Variables (p.u.)	PSO	R-PSO	L-PSO	PSO-CFA	IPSO-SR	FOA	MFOA	JAYA
V_{G1}	1.1	1.1	1.1	1.1	1.1	0.95	1.1	1.1
V_{G2}	1.1	1.1	1.1	1.1	1.1	0.95	1.1	1.1
V_{G5}	1.1	1.1	1.1	1.1	1.089	0.95	1.1	1.1
$V_{G6\ (DG)}$	1.1	1.1	1.1	1.1	1.1	0.95	1.1	1.1
V_{G8}	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
V_{G11}	1.1	1.1	1.0998	1.1	1.1	0.95	1.1	1.1
V_{G13}	1.1	1.0879	1.0692	1.0807	1.1	1.1	1.1	0.95
T_{6-9}	1.1	1.1	1.1	1.1	1.1	0.9	0.9	1.1
T_{6-10}	1.1	1.1	1.1	1.0852	1.1	0.9	0.9	0.9
T_{4-12}	1.1	1.0965	1.1	1.1	1.1	1.1	0.9	0.9305
T_{28-27}	1.0351	1.0243	1.0277	1.0427	1.0219	0.9	0.9	0.9532
Q_{sc3}	0	0	0.0008	0.0008	0	0.003	0.0819	0.0897
Q_{sc10}	0.3241	0.2143	0.1281	0.1945	0.2827	0.003	0.0818	0.3104
Q_{sc24}	0.0753	0.1109	0.0983	0.1173	0.1038	0.003	0.0819	0.1244
Optimum DG value at bus no. 6 (MW)	2.3931	43.4629	48.4923	58.5706	6.5336	53.6444	58.7457	59.2683
P_{loss} (MW)	2.6374	2.6006	2.605	2.6157	2.5767	3.236	2.7915	2.4442

Table 18 Simulation results on the IEEE 30 bus system with underestimated Weibull probability distribution function of wind power on ORPD using different algorithms

Control Variables (p.u.)	PSO	R-PSO	L-PSO	PSO-CFA	IPSO-SR	FOA	MFOA	JAYA
V_{G1}	1.1	1.1	1.1	1.1	1.1	0.95	1.1	1.1
V_{G2}	1.1	1.1	1.1	1.1	1.1	0.95	1.1	1.1
V_{G5}	1.1	1.0887	1.1	1.1	1.1	0.95	1.1	1.1
$V_{G6\ (DG)}$	1.1	1.1	1.1	1.1	1.1	0.95	1.1	1.1
V_{G8}	1.1	1.1	1.1	1.1	1.1	0.95	1.1	1.1
V_{G11}	1.1	1.1	1.1	1.1	1.0452	0.95	1.1	1.1
V_{G13}	1.1	1.0722	1.1	1.1	1.1	1.1	1.1	1.1
T_{6-9}	1.1	1.1	1.1	1.0311	1.1	0.9	0.9	1.058
T_{6-10}	1.1	1.1	0.999	1.1	1.1	0.9	0.9	0.9766
T_{4-12}	1.1	1.1	1.1	1.1	1.015	1.1	0.9	0.9521
T_{28-27}	1.1	1.0321	1.1	1.1	1.004	0.9	0.9	0.9745
Q_{sc3}	0	0.0007	0	0	0	0.0005	0.1313	0
Q_{sc10}	0.126	0.1335	0.0907	0.1021	0.36	0.0003	0.1313	0.36
Q_{sc24}	0.1376	0.1266	0.1429	0.1224	0.0753	0.001	0.1313	0.0945
Optimum DG value at bus no. 6 (MW)	9.6579	33.4181	16.7047	11.0877	35.7986	35.7864	50.4481	45.856
P_{loss} (MW)	3.1203	2.9217	3.082	3.0669	2.8972	4.0559	3.0159	2.805

where, P_{uwi} represents the optimal value of injected wind power obtained using the underestimation of the Weibull probability distribution function, The term v_i is the rated wind velocity and w_r the equivalent rated power of the wind farm.

The analysis is carried out using the different techniques and the results are displayed in Table 18, along with the convergence characteristics shown in Fig. 11. The results show that for the underestimated case of uncertain wind power, the optimal power output from the wind farm is 45.856 MW for a power loss of 2.805 MW (50.44% reduction compared to the base case). This optimal result is obtained using the JAYA algorithm and hence it is proved to be the best in optimizing this Weibull probability distribution function-based ORPD problem. The uncertainty of

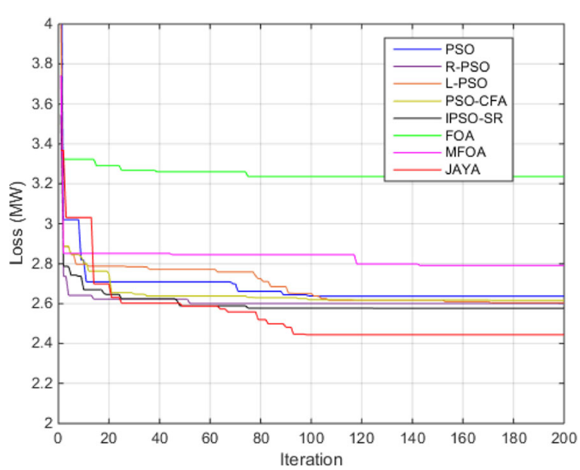

Fig. 10 Convergence characteristics of the algorithms for the IEEE 30 bus system with overestimated Weibull probability distribution function of wind power on ORPD

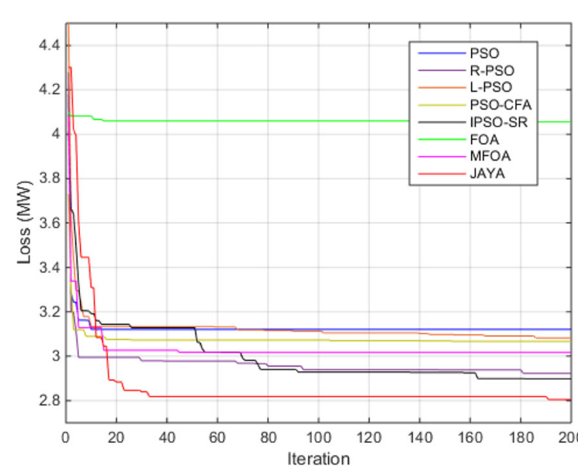

Fig. 11 Convergence characteristics of the algorithms for the IEEE 30 bus system with underestimated Weibull probability distribution function of wind power on ORPD

Table 19 Optimum solution for the IEEE 57 bus system with DG individually injected at each bus using the JAYA algorithm

Bus No.	Optimal DG value and Ploss	Bus No.	Optimal DG value and Ploss	Bus No.	Optimal DG value and Ploss
2	DG = 85.9022 MW Ploss = 22.9538 MW	21	DG = 62.3349 MW Ploss = 19.8914 MW	40	DG = 66.0233 MW Ploss = 18.7275 MW
3	DG = 180.4761 MW Ploss = 18.3962 MW	22	DG = 128.6296 MW Ploss = 16.1145 MW	41	DG = 106.9548 MW Ploss = 18.5122 MW
4	DG = 154.6043 MW Ploss = 18.2421 MW	23	DG = 114.9209 MW Ploss = 16.8096 MW	42	DG = 50.4274 MW Ploss = 20.214 MW
5	DG = 97.4521 MW Ploss = 19.6006 MW	24	DG = 61.6723 MW Ploss = 19.4454 MW	43	DG = 155.9366 MW Ploss = 16.2739 MW
6	DG = 128.7671 MW Ploss = 18.2827 MW	25	DG = 49.9298 MW Ploss = 20.019 MW	44	DG = 130.7442 MW Ploss = 17.0793 MW
7	DG = 108.5867 MW Ploss = 19.5623 MW	26	DG = 62.1794 MW Ploss = 19.3917 MW	45	DG = 164.6702 MW Ploss = 18.7277 MW
8	DG = 95.4473 MW Ploss = 20.9896 MW	27	DG = 59.1934 MW Ploss = 20.364 MW	46	DG = 187.5735 MW Ploss = 15.7753 MW
9	DG = 182.4026 MW Ploss = 15.8598 MW	28	DG = 69.4704 MW Ploss = 20.4721 MW	47	DG = 155.3579 MW Ploss = 15.9026 MW
10	DG = 156.9776 MW Ploss = 16.0904 MW	29	DG = 91.2441 MW Ploss = 20.7023 MW	48	DG = 162.0502 MW Ploss = 15.1216 MW
11	DG = 171.2313 MW Ploss = 15.7826 MW	30	DG = 37.9154 MW Ploss = 20.5292 MW	49	DG = 164.5209 MW Ploss = 15.22 MW
12	DG = 253.8512 MW Ploss = 12.6387 MW	31	DG = 30.4513 MW Ploss = 20.761 MW	50	DG = 92.749 MW Ploss = 18.1263 MW
13	DG = 271.898815 MW Ploss = 10.7774 MW	32	DG = 38.8860 MW Ploss = 20.3155 MW	51	DG = 131.6244 MW Ploss = 17.3217 MW
14	DG = 231.8587 MW Ploss = 13.9697 MW	33	DG = 34.5838 MW Ploss = 20.6314 MW	52	DG = 50.9403 MW Ploss = 20.5556 MW
15	DG = 274.1193 MW Ploss = 15.2984 MW	34	DG = 50.41 MW Ploss = 19.4297 MW	53	DG = 49.6756 MW Ploss = 20.2202 MW
16	DG = 176.7618 MW Ploss = 17.1757 MW	35	DG = 62.3285 MW Ploss = 18.7095 MW	54	DG = 48.7095 MW Ploss = 20.7028 MW
17	DG = 137.62678 MW Ploss = 20.5061 MW	36	DG = 78.0449 MW Ploss = 17.9115 MW	55	DG = 144.5947 MW Ploss = 17.3363 MW
18	DG = 119.7668 MW Ploss = 19.3995 MW	37	DG = 90.9933 MW Ploss = 17.3753 MW	56	DG = 65.5031 MW Ploss = 18.8386 MW
19	DG = 28.9124 MW Ploss = 21.9544 MW	38	DG = 168.8586 MW Ploss = 14.1612 MW	57	DG = 48.1161 MW Ploss = 19.9331 MW
20	DG = 41.2858 MW Ploss = 21.1097 MW	39	DG = 75.1376 MW Ploss = 18.3595 MW		

DG power shows that the actual power under the realistic condition obtained from the wind farm is less than that obtained from Table 14. The overestimated output of wind power is higher than the underestimation and thus gives lower power loss. The difference in power loss is about 0.3608 MW between the two estimations considering the best solutions from the JAYA algorithm.

4.2.3 EEE 57 bus system

The IEEE 57 bus system has a total active power generation of 1278.7 MW and a load demand of 1250.8 MW. The limits of the control variables are the same as Section 4.1.3 with no DG. Table 19 shows the complete results of ORPD for minimizing power loss for 56 different cases where the DG is individually injected at

Table 20 Comparison of power loss at the IEEE 57 bus system with different DG power placed at bus no. 13 using the JAYA algorithm

DG values (MW)	270.898815	271.898815 (Optimal)	272.898815
Loss (MW)	10.7857	10.7774	10.7797

Table 21 Simulation results on IEEE 57 bus system with DG using different algorithms

Algorithms	PSO	R-PSO	L-PSO	PSO-CFA	IPSO-SR	FOA	MFOA	JAYA
Optimum DG value at bus no. 13 (MW)	337.506395	275.969626	275.829595	276.086357	286.388354	276.823206	541.412358	271.898815
Total P_{loss} (MW)	13.5103	13.3015	13.5081	13.3868	13.0453	17.6167	12.4927	10.7774

each bus (except the slack bus no. 1). Table 19 shows that the power loss is minimum (i.e., 10.7774 MW) when 271.898815 MW DG is injected at the.

PQ bus 13, which is 21.738% of the total load demand of the system. These results are again obtained by the JAYA algorithm. The results from Table 20 show the significance of the optimal value of DG determined by the JAYA algorithm, as a small variation can lead to increased power loss. Other algorithms have also been used to optimize the ORPD problem by determining the optimum DG value at bus 13 and the results are illustrated in Table 21 and Fig. 12.

From the results, it is concluded that the JAYA algorithm results in significantly lower power loss than the other algorithms.

The study shows that DG penetration reduces the power loss by 61.32% compared to 22.67% without DG penetration using the same algorithm.

4.2.4 IEEE 118 bus system

The active power generation and load demand of the IEEE 118 bus system are 4374.9 MW and 4242.45 MW, respectively. The limits of the control variables considered for this case are the same as Section 4.2.4 with no DG. Bus 69 is the slack bus, and the ORPD problems are solved using the JAYA algorithm with the individual injection of DG power at each of the other 117 buses. Table 22 shows the details of the 117 solutions and indicates that the minimum power loss of 91.4174 MW is obtained when a DG of power of 235.926829 MW (5.5611% of the total load demand) is injected at bus 40. The penetration of DG reduces the power loss by almost 30.98% with the use of the JAYA algorithm, whereas for the system without DG injection, the proposed algorithm was only able to reduce the power loss by 20.36%.

The significance of the optimal value of DG obtained by the JAYA algorithm is illustrated in Table 23. The data from Table 24 and the convergence characteristics in Fig. 13 compare the results of the ORPD problem using different algorithms. It shows that the results obtained using the JAYA algorithm are the best of all the algorithms. In this case, the JAYA algorithm is not stuck in local optima and is able to optimize the problem to a much larger extent than the others. Thus, the JAYA algorithm is superior to other algorithms reported in the literature for all the test cases shown in this paper with the injection of DG in optimizing the ORPD problem.

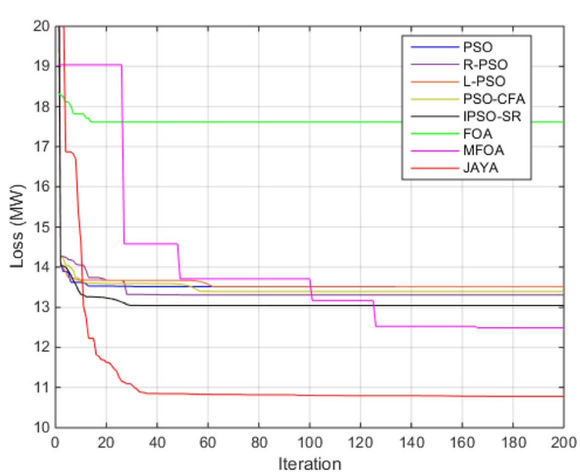

Fig. 12 Convergence characteristics of the algorithms for the IEEE 57 bus system with DG

5 Efficacy of JAYA algorithm

The efficacy of the JAYA algorithm can be explained as follows:

i. **Benchmark function** – The JAYA algorithm has been tested on 24 standard constrained benchmark functions (G01 – G24) and the results were shown in Table 1. It has been proved to be the most robust and efficient algorithm by obtaining the best solution to all the different functions. Thus, this benchmark test has proved JAYA to be the best of all the algorithms reported on the optimization problem and thus can be tested on the non-linear and highly constrained ORPD problem.

ii. **ORPD problem without DG** – The JAYA algorithm has proved to be the most efficient by consistently providing the optimal solutions to

Table 22 Optimum solution for the IEEE 118 bus system with DG individually injected at each bus using JAYA algorithm

Bus No.	Optimal DG value and Ploss	Bus No.	Optimal DG value and Ploss	Bus No.	Optimal DG value and Ploss
1	DG = 126.691685 MW Ploss = 102.1306 MW	40	DG = 235.926829 MW Ploss = 91.4174 MW	80	DG = 56.72296 MW Ploss = 111.63 MW
2	DG = 121.389574 MW Ploss = 104.5923 MW	41	DG = 206.527776 MW Ploss = 98.5241 MW	81	DG = 118.496073 MW Ploss = 109.2481 MW
3	DG = 132.474896 MW Ploss = 106.2292 MW	42	DG = 205.316671 MW Ploss = 99.1168 MW	82	DG = 79.090821 MW Ploss = 106.9809 MW
4	DG = 115.851608 MW Ploss = 104.297 MW	43	DG = 122.943056 MW Ploss = 104.8476 MW	83	DG = 28.963277 MW Ploss = 111.2587 MW
5	DG = 126.830533 MW Ploss = 102.2818 MW	44	DG = 127.95713 MW Ploss = 105.9838 MW	84	DG = 0.285584 MW Ploss = 109.675 MW
6	DG = 135.795184 MW Ploss = 102.7085 MW	45	DG = 152.793032 MW Ploss = 101.936 MW	85	DG = 0.262262 MW Ploss = 106.7078 MW
7	DG = 141.976923 MW Ploss = 105.5292 MW	46	DG = 129.549348 MW Ploss = 106.5249 MW	86	DG = 0.167232 MW Ploss = 112.0001 MW
8	DG = 137.322819 MW Ploss = 106.3051 MW	47	DG = 143.984783 MW Ploss = 106.5703 MW	87	DG = 0.693603 MW Ploss = 109.3171 MW
9	DG = 86.098538 MW Ploss = 108.9833 MW	48	DG = 119.983949 MW Ploss = 108.3803 MW	88	DG = 0.403614 MW Ploss = 109.7036 MW
10	DG = 31.763133 MW Ploss = 108.6617 MW	49	DG = 238.49512 MW Ploss = 100.5761 MW	89	DG = 0.000003 MW Ploss = 106.1475 MW
11	DG = 158.561438 MW Ploss = 103.3529 MW	50	DG = 128.806798 MW Ploss = 105.5056 MW	90	DG = 0.330903 MW Ploss = 110.2137 MW
12	DG = 152.120457 MW Ploss = 102.8647 MW	51	DG = 163.27574 MW Ploss = 102.8127 MW	91	DG = 0.316752 MW Ploss = 109.6929 MW
13	DG = 126.151012 MW Ploss = 105.477 MW	52	DG = 136.609037 MW Ploss = 99.9051 MW	92	DG = 2.233726 MW Ploss = 108.8771 MW
14	DG = 107.545112 MW Ploss = 107.204 MW	53	DG = 150.923477 MW Ploss = 105.3903 MW	93	DG = 0.366261 MW Ploss = 111.7052 MW
15	DG = 211.945829 MW Ploss = 98.2005 MW	54	DG = 298.042439 MW Ploss = 98.1309 MW	94	DG = 27.96989 MW Ploss = 109.041 MW
16	DG = 114.670716 MW Ploss = 104.1251 MW	55	DG = 253.003086 MW Ploss = 95.9371 MW	95	DG = 56.557722 MW Ploss = 112.6194 MW
17	DG = 215.842192 MW Ploss = 103.8536 MW	56	DG = 300.090378 MW Ploss = 97.6436 MW	96	DG = 75.554861 MW Ploss = 108.4198 MW
18	DG = 174.288927 MW Ploss = 104.1887 MW	57	DG = 134.914338 MW Ploss = 103.1027 MW	97	DG = 55.32614 MW Ploss = 110.343 MW
19	DG = 208.34031 MW Ploss = 101.3572 MW	58	DG = 151.54828 MW Ploss = 104.0325 MW	98	DG = 43.497228 MW Ploss = 105.1687 MW
20	DG = 134.353492 MW Ploss = 104.3742 MW	59	DG = 266.252851 MW Ploss = 99.2146 MW	99	DG = 28.720925 MW Ploss = 110.7502 MW
21	DG = 104.928143 MW Ploss = 107.9008 MW	60	DG = 180.029737 MW Ploss = 109.0783 MW	100	DG = 27.109957 MW Ploss = 112.093 MW
22	DG = 93.847526 MW Ploss = 107.3988 MW	61	DG = 217.188289 MW Ploss = 110.277 MW	101	DG = 3.152974 MW Ploss = 109.6081 MW
23	DG = 112.485273 MW Ploss = 107.6156 MW	62	DG = 148.991549 MW Ploss = 108.5313 MW	102	DG = 0.365233 MW Ploss = 108.2081 MW
24	DG = 122.226052 MW Ploss = 103.1782 MW	63	DG = 271.532796 MW Ploss = 100.6808 MW	103	DG = 74.70484 MW Ploss = 106.3845 MW
25	DG = 19.467003 MW Ploss = 105.3804 MW	64	DG = 279.219469 MW Ploss = 106.4706 MW	104	DG = 85.591999 MW Ploss = 107.7868 MW
26	DG = 45.752497 MW Ploss = 109.4005 MW	65	DG = 239.779886 MW Ploss = 106.263 MW	105	DG = 97.612459 MW Ploss = 102.0538 MW
27	DG = 131.689427 MW Ploss = 104.9029 MW	66	DG = 87.578865 MW Ploss = 109.5058 MW	106	DG = 93.781891 MW Ploss = 109.4429 MW

Table 22 Optimum solution for the IEEE 118 bus system with DG individually injected at each bus using JAYA algorithm *(Continued)*

Bus No.	Optimal DG value and Ploss	Bus No.	Optimal DG value and Ploss	Bus No.	Optimal DG value and Ploss
28	DG = 124.185209 MW Ploss = 101.9163 MW	67	DG = 74.527333 MW Ploss = 110.09 MW	107	DG = 77.445529 MW Ploss = 106.6032 MW
29	DG = 123.581598 MW Ploss = 104.5658 MW	68	DG = 346.448424 MW Ploss = 104.3674 MW	108	DG = 84.482368 MW Ploss = 110.0862 MW
30	DG = 202.292999 MW Ploss = 105.6273 MW	70	DG = 215.307567 MW Ploss = 101.3420 MW	109	DG = 73.879514 MW Ploss = 106.8489 MW
31	DG = 138.863925 MW Ploss = 106.1876 MW	71	DG = 158.006651 MW Ploss = 106.6297 MW	110	DG = 79.585522 MW Ploss = 105.6344 MW
32	DG = 162.13668 MW Ploss = 102.2741 MW	72	DG = 90.968385 MW Ploss = 105.4622 MW	111	DG = 50.012701 MW Ploss = 104.4401 MW
33	DG = 145.322161 MW Ploss = 99.898 MW	73	DG = 111.141505 MW Ploss = 103.8292 MW	112	DG = 72.84045 MW Ploss = 102.0659 MW
34	DG = 265.489241 MW Ploss = 97.0874 MW	74	DG = 199.515402 MW Ploss = 100.6688 MW	113	DG = 137.217961 MW Ploss = 106.7375 MW
35	DG = 212.607941 MW Ploss = 99.6775 MW	75	DG = 257.726006 MW Ploss = 102.4429 MW	114	DG = 128.504699 MW Ploss = 108.2676 MW
36	DG = 218.137821 MW Ploss = 97.5311 MW	76	DG = 167.499121 MW Ploss = 100.5155 MW	115	DG = 131.714016 MW Ploss = 100.0972 MW
37	DG = 283.577128 MW Ploss = 103.4836 MW	77	DG = 198.98593 MW Ploss = 106.7565 MW	116	DG = 313.132375 MW Ploss = 108.1146 MW
38	DG = 324.563925 MW Ploss = 100.3577 MW	78	DG = 166.514813 MW Ploss = 104.9669 MW	117	DG = 86.677252 MW Ploss = 105.3631 MW
39	DG = 219.426062 MW Ploss = 112.9535 MW	79	DG = 132.713358 MW Ploss = 108.0646 MW	118	DG = 180.156097 MW Ploss = 104.5194 MW

the problems for all the different bus systems. It has successfully obtained the best solution reported in the literature for the above four mentioned IEEE test bus systems for the ORPD problem.

iii. **ORPD problem with DG** – The JAYA algorithm has provided the best solution to the ORPD problem with DG compared to other algorithms discussed above. It has obtained the best value of DG to be penetrated to the system to minimize the power loss for all the four test bus systems.
iv. **Statistical analysis** – The statistical analysis of the JAYA algorithm and others was tested on the IEEE 30 bus system, and the results shown in Table 5 demonstrate that the JAYA algorithm is the most robust and has a minimum standard deviation compared to the others.
v. **Frequency of convergence** – This test, which is another method to judge the robustness of the algorithms, was performed for the different algorithms and the results were shown in Table 6 and its significance discussed in Section 4.1.2. Each algorithm was run 50 times and the results show that the JAYA algorithm has obtained the best solution for all 50 times within the range of 4.59–4.60 MW, thus proving to be the most robust algorithm.
vi. **Convergence speed** – The convergence characteristics from the different test cases show that the JAYA algorithm may not be the fastest in terms of computation time, but it provides a good balance between convergence speed and obtaining the best solution.

Table 23 Comparison of power loss at the IEEE 118 bus system with different DG power placed at bus no. 40 using the JAYA algorithm

DG values (MW)	234.926829	235.926829 (Optimal)	236.926829
Loss (MW)	92.1347	91.4174	91.7172

Thus, these detailed comparisons show the ability of the JAYA algorithm to obtain the best solution to this critical optimization problem and to outperform many other well established techniques in respect of robustness, efficiency and, convergence speed.

Table 24 Simulation results on the IEEE 118 bus system with DG using different algorithms

Algorithms	PSO	R-PSO	L-PSO	PSO-CFA	IPSO-SR	FOA	MFOA	JAYA
Optimum DG value at bus no. 40 (MW)	217.915656	234.001257	233.530451	233.862928	233.041745	353.130050	466.923186	235.926829
Total P_{loss} (MW)	98.2287	99.8411	97.2316	100.6191	96.1849	147.2732	99.5879	91.4174

6 Conclusion

This paper has shown the effect of the penetration of distributed generation (DG) into the ORPD problem for reducing the transmission line losses for the very first time and has provided a unique contribution in the study of the ORPD problem. A comprehensive study was carried out to locate the optimal bus and determine the corresponding optimal value of DG to be injected to minimize transmission line loss. The results show that power loss is minimized to a large extent when DG is injected into the system, establishing the advantages of the DG penetration in the optimization problem of ORPD. Using four different IEEE standard bus systems, it shows that if the optimal bus and value of DG are known, the power loss can be significantly reduced and system stability improved. This work reveals a new way of analyzing the ORPD problem and offers encouragement towards the utilization of renewable resources. The simulation results confirm that the JAYA algorithm is the best and efficient among the others reported in the literature, in terms of reliability, robustness, consistency, and rate of convergence in solving the ORPD problem for all the case studies. The JAYA algorithm gives consistent results under any condition without violating any equality and inequality constraint.

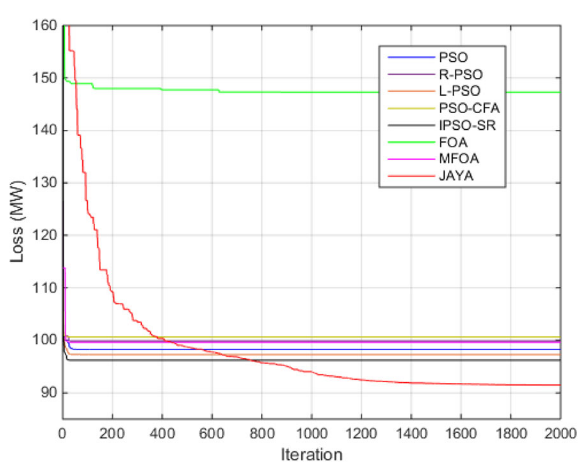

Fig. 13 Convergence characteristics of the algorithms for IEEE 118 bus system with DG

Abbreviations

ABC: Artificial Bee colony algorithm; ACO_R: Ant colony optimization algorithm extended to continuous domains; ALC-PSO: Particle Swarm Optimization with Aging Leader and Challengers; ALO: Ant lion optimizer; BA: Bat algorithm; BBDE: Bare-bones DE; BBO: Biogeography-based Optimization; BBPSO: Barebones particle swarm optimization; B-DE: Binary differential evolution; B-DE: Best/1/bin DE; BFO: Bacterial-foraging optimization; BSO: Backtracking search optimizer; CI-PSO: Constant inertia weight conventional PSO; CKHA: Chaotic krill herd algorithm; CLPSO: Comprehensive Learning PSO; C-PSO: Conventional PSO; CPVEI HBMO: Chaotic Parallel Vector Evaluated Interactive Honey Bee Mating Optimization; CSA: Common Scrambling Algorithm; DDE: Double differential evolution; DE: Differential evolution; DG: Distributed generation; DSA: Digital Signature Algorithm; EMA: Exchange market algorithm; EP: Evolutionary programming; FOA: Fruit Fly optimization algorithm; FPA: Flower Pollination Algorithm; GA: Genetic algorithm; GBTLBO: Gaussian barebones TLBO; GBWCA: Gravity-Base Objects' Weight Clustering Algorithm; GSA: Gravitational search algorithm; HBMO: Honey Bee Mating Optimization; HEP: Hybrid evolutionary programming; HSSSA: Hyper-Spherical Search Algorithm; HTS: HIV testing services Algorithm; IALO: Antlion optimization algorithm; ICA: Imperialist competitive algorithm; IPGS-PSO: Improved pseudo gradient search-particle swarm optimization; IPSO-SR: Improved PSO Based on Success Rate; ISSO: Improved social spider optimization algorithm; IWO: Invasive weed optimization; LDI-PSO: Linearly decreasing inertia weight PSO; LPSO: Lévy PSO; MCBOA: Modified colliding bodies optimization algorithm; MDE: Modified differential evolution; MFOA: Modified Fruit Fly optimization algorithm; MGBTLBO: Modified Gaussian barebones TLBO; MICA: Modified imperialist competitive algorithm; MICA-IWO: Hybrid MICA-IWO; MOALO: Multi-objective Ant Lion Optimizer; MSFS: Modified stochastic fractal search algorithm; MSSA: Multi-objective Salp Swarm Algorithm; MTLA: Modified teaching learning algorithm; MTLA-DDE: Hybrid MTLA-DDE; NGBWCA: Gaussian bare-bones WCA; OGSA: Opposition-based gravitational search algorithm; OPF: Optimal power flow; ORPD: Optimal Reactive Power Dispatch; PG-PSO: Pseudo-gradient PSO; PGSWT-PSO: Pseudo-gradient Search Particle Swarm Optimization; PSO: Particle Swarm Optimization; PSO-CF: Particle Swarm Optimization Collaborative filtering; PSO-CFA: PSO with constriction factor; PSO-ICA: Particle Swarm Optimization Imperialist competitive algorithm hybrid; PSO-TVAC: Particle swarm optimization with time varying acceleration coefficients; PSO-TVAC: Particle Swarm Optimization with Time Varying Acceleration Coefficients; PSO-TVIW: Time-varying inertia weighting strategy based on particle swarm optimization GSA; QOTLBO: Quasi-oppositional teaching learning based optimization; R-DE: Rand/1/bin DE; R-PSO: Rapid PSO; RTS: Real-Time Scheduling; SARCGA: Self-adaptive real coded genetic algorithm; SARGA: Using self-adaptive real coded genetic algorithm; SFLA: Shuffled frog leaping algorithm; SGA (F_{f1}): Specialized genetic algorithm using (Ff1); SGA (F_{f2}): Specialized genetic algorithm using (Ff2); SOA: Seeker optimization algorithm; SPSO-TVAC: Self-organizing hierarchical PSO with Time Varying Acceleration Coefficients; SSA: Salp Swarm Algorithm; SSO: Social spider optimization; SWT-PSO: Stochastic weight trade-off particle swarm optimization; TLA: Teaching learning algorithm; TLBO: Teaching Learning Based Optimization; WCA: Water Cycle Algorithm; WOA: Whale Optimization algorithm

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Authors' contributions

Mr. Tanmay Das carried out basic design, simulation work and prepared draft paper. Dr. Ranjit Roy and Dr. Kamal Krishna Mandal participated in checking simulation work, results & discussions, sequence of paper and helped to prepare the manuscript. All authors read and approved the final manuscript.

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The datasets used and analysed during the current study are available from the corresponding author on reasonable request.

Competing interests
The authors declare that they have no competing interests.

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