Journal of Ambient Intelligence and Humanized Computing
https://doi.org/10.1007/s12652-020-02673-w

ORIGINAL RESEARCH

Optimal reactive power dispatch for minimization of real power loss using SBDE and DE-strategy algorithm

V. Suresh[1] · S. Senthil Kumar[1]

Received: 6 August 2020 / Accepted: 3 November 2020

Abstract
The power system related optimal reactive power dispatch (ORPD) generates crucial optimization issues. Equality and Inequality constraints possess the multi-variable and abridge characteristics. The differential evolution (DE) calculation enabled productive stochastic search technique helped for fathoming ORPD problems. The achievement of DE depends on transformation methodologies and their related control parameter values. In the research work, the proposed power system based self-balanced differential evolution (SBDE) algorithm used for the reduction of power loss. In transmission techniques, positions of tap, total shunts compensator, and generator terminal voltages are the control variable settings get to be switched, which is evaluated for reduction of losses in real power. SBDE algorithm concerned to the bus systems namely as IEEE 14 and IEEE 30 for enhanced results. The performance analyses get to compared with the Genetic Algorithm. The proposed analysis exhibit the capability that illustrates the ORPD issues with the effective and robust performance.

Keywords Optimal reactive power dispatch (ORPD) · Real power loss · Differential evolution (DE) algorithm · Self balanced differential evolution (SBDE) algorithm

1 Introduction

One of the issues of optimal power flow (OPF) is the Optimal Reactive Power Dispatch (ORPD), which are the most essential tasks in the power system network operation. Within the limitations, the reduced loss of power and the stability of voltage gets sustained. Dommel and Tinney (1968) proposed a concept on optimized power system enable the optimal voltage generator combination, changing the tap in the transformers enabled taps positions, and the overall capacitors banks to be switched. In recent years, the conventional and non-conventional algorithms are the many optimization techniques are established. A conventional method which is based on mathematical programming was used to perform the OPF. Sun and Ashley (1984) and Bjelogrlic and Ristanovic (1990) proposes with the conventional Newton method such as, linear programming (LP) method that was proposed by the Alsac et al. (1990). Also Granville (1994) put forth the interior point (IP) method. Also Lu and Hsu (1995) comes along with the concept of dynamic programming and quadratic programming method that proposed by Quintana and Santos-Nieto (1989) and Varadarajan and Swarup (2008a; b, c), are used to meet the several objective function necessities the nature restrictions based type of applications. The disadvantages in the above methods consist of poor convergence, stuck at local optimum, and handling qualitative restrictions.

To control the above limitations, Zimmerman et al. (2005), Bakirtzis and Petridis (2002) and Yan et al. (2006) proposes the concept of Genetic Algorithms, followed by Mezura-Montes and Coello (2011) optimization of biogeography (Lee and Yang 1998; Liang and Chung 2006), programming evolutionary, also followed by evolution methods that was proposed by Das and Patvardhan (2003) and Gomes and Saavedra (2002), and optimization name as Particle Swarm Optimization (PSO) proposed by Abido (2002), Yoshida and Nakanishi (2000), Zhao et al. (2005) and Vlachogiannis and Lee (2006) and differential equation evolution proposed by Varadarajan and Swarup (2008a; b, c) are the evolutionary optimization methods helped to attain the ORPD issues. An unconstrained search done by concerning evolutionary algorithms (EAs) that require the handling restrictions based additional mechanisms. The multiple

✉ V. Suresh
vsuresh2020@yahoo.com

[1] Department of Electrical and Electronics Engineering, Government College of Engineering, Salem, India

Published online: 27 November 2020

optimal solutions, which is flexible and through the single run. So the multi objective optimization issues are entirely suitable. The different handling restrictions techniques have been proposed and concerned with Evolutionary Algorithms by Mezura and Coello (2003), Qu and Suganthan (2011) and Zhou and Zhang (2011) represents in literature part. The global optimum solution found in many cases (Ghorbani et al. 2020).

Differential evolution (DE) is the main important handling constrained based optimization issues, which is maximum efficient. DE has some advantages like finding nearest-optimal results not necessary of initial parameters, fast convergence and less control parameters only needed. In this paper, new variant of differential evolutionary, named SBDE is presented which was proposed by Sharma et al. (2014). Global search and local search are the important terms in optimization. To take care of the right balance between the above two search techniques, a replacement mutation operation is introduced. SBDE algorithm helps for discrete optimal dispatch of reactive power issue evaluation. The important thing of discretization process is to realize a solution quality, which is better in ORPD issues. The algorithm gets evaluated on IEEE 14-bus power systems and IEEE 30-bus power systems. The performance of the proposed SBDE algorithm gets compared to the existing methods. The organization of the paper given below: Sect. 2 depicts an ORPD issue formulation. Section 3 explains the overview of DE briefly; Sect. 4 presented the proposed SBDE algorithm for ORPD issue evaluation. Section 5 depicts the proposed SBDE algorithm performance gets examined by testing on IEEE 14-bus power systems and power system of IEEE 30-bus and the results. Section 6 illustrates the concludes the work.

2 Problem statement

The restrictions and the objective functions in the form of mathematical representation that can be represents as follow below:

$$\min/\mathrm{Max}\ f(x,u) \tag{1}$$

$$g(x,u) = 0 \tag{2}$$

$$h(x,u) \le 0 \tag{3}$$

$$U^{min} \le U \le U^{max} \tag{4}$$

$$X^{min} \le X \le X^{max} \tag{5}$$

where $f(x, u)$ describes the objective function, $g(x, u)$ referred as the restrictions on equal, $h(x, u)$ refers the restrictions on unequal vector arguments x and u. x refers the magnitude based load bus voltage, the output of generator based reactive power and the transmission flow line. u describes the control variable consisting of generator bus voltage, settings on taps of the transformer and shunt based VAR compensation.

The transmission network enabled the loss of real power, which is the abridge function. The phase angles, and the magnitude of bus voltage are the control variable functions. The representation function of power loss given below:

$$f = \min P_{loss} = F_{obj}(x,u) = \sum_{\substack{k \in N_l \\ k \in (i,j)}} g_k\left(V_i^2 + V_j^2 - 2V_iV_j\cos\theta_{ij}\right). \tag{6}$$

In the above equation, P_{loss} is the overall loss of real power, N_l is the overall transmission lines, g_k is the branch k conductance, V_i is the ith bus voltage, V_j is the jth bus voltage, θ_{ij} is the difference of i and j based voltage phase.

2.1 Equality constraints

The equations of power balance for both real and reactive power described as

$$P_i - V_i\sum_{j=1}^{N_B} V_j\left(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right) = 0 \quad i = 1,2,\ldots N_B - 1 \tag{7}$$

$$Q_i - V_i\sum_{j=1}^{N_B} V_j\left(G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}\right) = 0 \quad i = 1,2,\ldots N_{PQ} \tag{8}$$

where P_i is the generation of real power,Q_i is the generation of reactive power, G_{ij} is mutual conductance, B_{ij} is the mutual susceptance, N_B is the total buses, $N_B - 1$ is the excluding slack bus over the total buses, N_{PQ} is the total PQ buses, respectively.

The Inequality constraints given below.

2.2 Restrictions on voltage

The restricted generator bus voltage through the low and high limits given below:

$$V_i^{min} \le V_i \le V_i^{max}; \quad i \in N_g \tag{9}$$

where V_i^{min} and V_i^{max} define minimum and maximum generator voltage.

2.3 Real power capability limit based generator

The restricted real power generator through the low and high limits given below:

$$P_{gi}^{min} \le P_{gi} \le P_{gi}^{max} \tag{10}$$

where P_{gi}^{min} and P_{gi}^{max} define min and max of real power generator.

2.4 Reactive power capability limit based generator

The restricted reactive power generator through the low and high limits given below:

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max}; \quad i \in N_g \tag{11}$$

where Q_{gi}^{min} and Q_{gi}^{max} define min and max of reactive power generator, Ng is the total generator buses.

2.5 Reactive power compensation limits

The restricted compensation of shunt VAR through the low and high limits given below:

$$Q_{ci}^{min} \le Q_{ci} \le Q_{ci}^{max}; \quad i \in N_c \tag{12}$$

where Q_{ci}^{min} and Q_{ci}^{max} define minimum and maximum of i^{th} represents the bank of the capacitor, N_c is the total bank of the capacitor.

2.6 Transformer tap ratio

The transformer tap ratio lower and upper limits can be expressed as:

$$t_k^{min} \le t_k \le t_k^{max}; \quad k \in N_T \tag{13}$$

where t_k^{min} and t_k^{max} define minimum and maximum of transformer tap setting at branch k, N_T is the total transformer in the system.

2.7 Line flow limits

The apparent line flow limits are expressed as:

$$S_l \le S_l^{max} \quad l \in N_l. \tag{14}$$

3 Differential evolution algorithms

The Stochastic Population-based Optimization Algorithm based DE algorithm, which is the most powerful. It was created by Storn and Price (1995). The primary thought behind DE is a scheme is for creating a new offspring. The crossover and the mutation are utilized for new offspring generation, selection decides if the objective vector or the survival of preliminary vector to the next generation. The DE exhibition is sensitive to the mutation function, crossover function, and population size.

Algorithm:

The procedure of Differential Evolution algorithm given below:

Step 1: Generation G enabled individual i, which is a multidimensional vector

$$X_{i,k}^G = \left(X_{i,1}, \ldots, X_{i,D}\right).$$

To initialized the initial population as given below:

$$X_{i,k}^G = X_{k,min} + \text{rand}(0,1) \times \left(X_{k,max} - X_{k,min}\right) \quad i \in \left[i, N_p\right], k \in [1.D], \tag{15}$$

where N_p is the total population and D is the total control variables. $X_{k,min}$, $X_{k,max}$ define minimum and maximum of each variable k.

Step 2: For each $i \in \left[1, \ldots, N_p\right]$ the arbitrary selected individuals X_{r2} and X_{r3} i.e. weighted differences, which additioned of other arbitrary selection of an individuals X_{r1} to construct a V_i i.e. mutated vector.

Strategy 1: "DE/1/rand/1" (Classical strategy)

$$V_i = X_{r1}^G + F \cdot \left(X_{r2}^G - X_{r3}^G\right). \tag{16}$$

Strategy 2: "DE/local-to-best/1"

$$V_i = old_i^G + F.\left(best^G - old_i^G\right)F.\left(X_{r2}^G - X_{r3}^G\right). \tag{17}$$

Strategy 3: "DE/best/1 with jitter"

$$V_i = best^G + jitter + F \cdot \left(X_{r2}^G - X_{r3}^G\right). \tag{18}$$

The expression (18) is used, where jitter described as 0.0001 rand + F.

Strategy 4: "DE/rand/1 with per-vector-dither"

$$V_i = X_{r1}^G + dither \cdot \left(X_{r2}^G - X_{r3}^G\right). \tag{19}$$

By concerning of this expression, where the evaluation of dither as given, dither = F + rand.(1 − F).

By this concern, the DE has a much stronger.

Strategy 5: "DE/rand/1 with per-generation-dither".

By concerning of strategy 4 described, but dither is only evaluated per-generation once.

Strategy 6: "DE/rand/1 with either-or algorithm"

$$V_i = X_{r1}^G + K \cdot \left(X_{r2}^G - X_{r3}^G - 2 \cdot X_{r1}^G\right). \tag{20}$$

With K = 0.5.(F + 1).

In Eqs. (16)–(20), i, r_1, r_2 and r_3 are reciprocally several indices. F is the step size and it gets to selected from the range between [0, 2].

Step 3: The prey vector X_i is combined with V_i, the trial vector u_i gets to relented represented as follows:

$$u_i = u_{i,k}^{G+1} = \begin{cases} V_{i,k} & \textit{if}\ \mathrm{rand}_{k,i} \le CR\ \ (\mathrm{or})\ \ k = I_{rand} \\ X_{i,k}^{G} & \textit{if}\ \mathrm{rand}_{k,i} > CR\ \ \textit{and}\ \ k \ne I_{rand}. \end{cases} \tag{21}$$

where $\mathrm{rand}_{k,i} \in [0, 1]$ and I_{rand} is the random selection within the interval range of $[1, \ldots, D]$. To initiates each vector from V_i. The Eq. (21) represents the each vector component $i \in [1, \ldots, N_p]$, $k \in [1, \ldots, D]$. CR is the crossover operator and the wide range between as [0, 1].

Step 4: The next generation based individuals selection as follows:

$$X_i^{G+1} = \begin{cases} u_i^{G+1} & \textit{iff}\left(u_i^{G+1)} \le f\left(X_i^G\right)\right) \\ X_i^G & \textit{otherwise}. \end{cases} \tag{22}$$

Step 5: Repeat the steps i.e., mutation steps, crossover steps, and selection operator steps till the system termination happen like as the total generations get to maximum and get to met.

Figure 1 shows the Differential Evolution Algorithm flow diagram. Figure 2 shows the SBDE algorithm implementation for Optimal Reactive Power Dispatch (ORPD) issue.

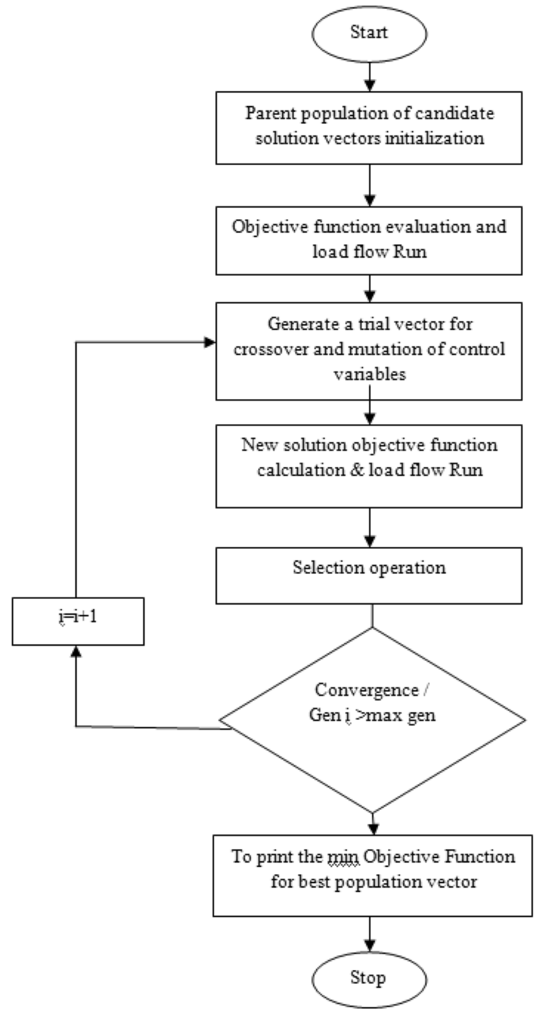

Fig. 1 Differential evolution algorithm flow diagram

4 Self-balanced differential evolution (SBDE) algorithm

SBDE is a new updation of DE technique, which is proposed by Harish et al. (2014). The proper balance get to sustain between the local and global search, a new mutation operation is introduced. It is given in Eq. (23).

$$V_i = C^* X_{r1}^G + F \cdot \left(X_{r2}^G - X_{r3}^G\right) \tag{23}$$

where G define generation and C define cognition learning factor.

The probability of fitness is calculated using Eq. (24).

$$F_i^{G+1} = (\mathrm{rand}(0, 1) - 0.5) \times \left(1.5 - \mathrm{prob}_i^G\right). \tag{24}$$

From above equation the probability is calculated as

$$\mathrm{prob}_i^G = \frac{0.9 \times \mathrm{fitness}^G}{\mathrm{maxfit}^G} + 0.1 \tag{25}$$

C varies between [0.1–1]. It controls the balance between search strategies. Hence the scale factor range as F gets varied energitically. By varying C and F, DE can be balanced easily.

4.1 Implementation of SBDE for ORPD

The implementation of SBDE is based on the retribution function method. The sum of objective functions and its retribution terms represented as given below:

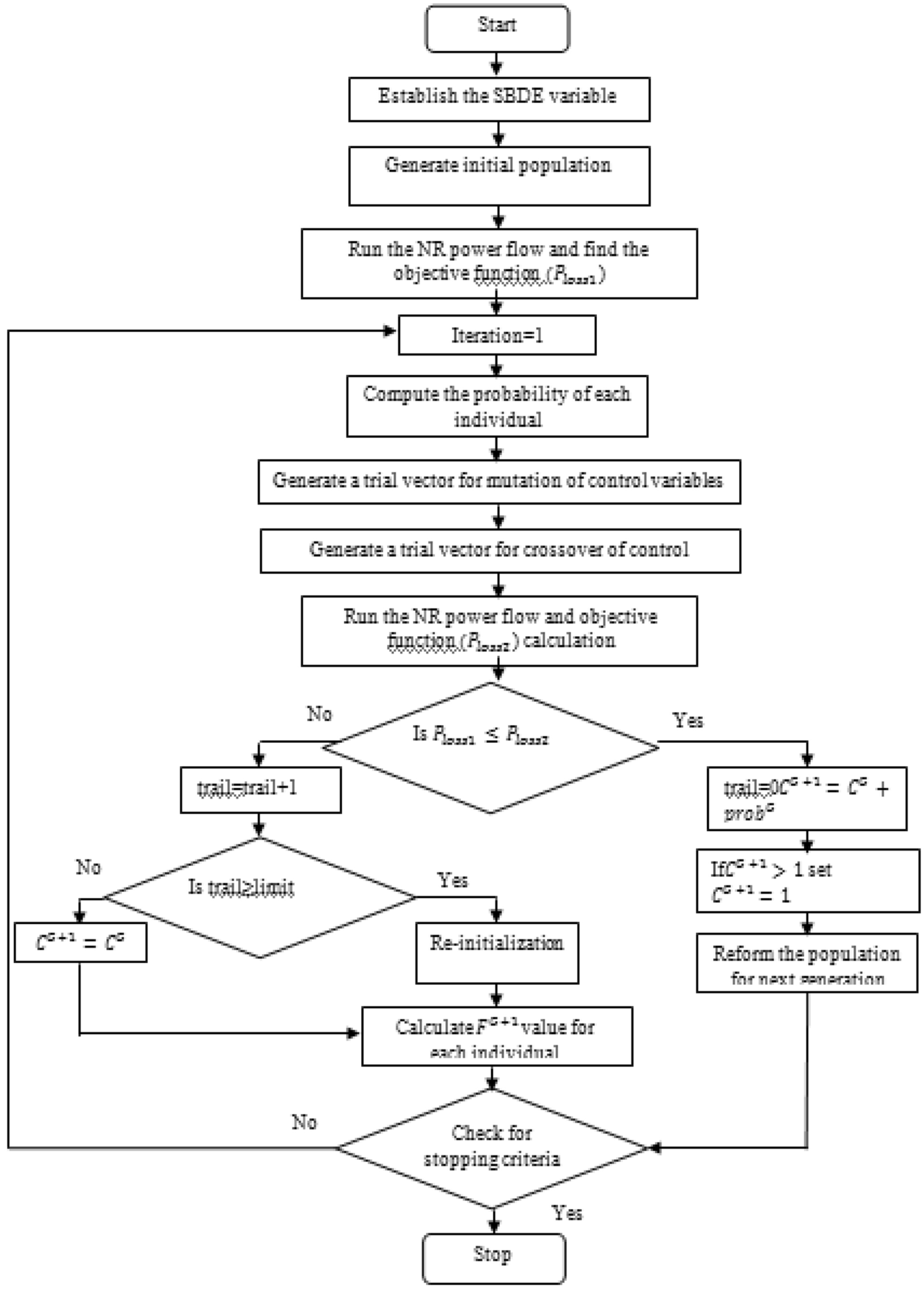

Fig. 2 Flow chart of the implemented SBDE

$$F = f + R_1\left(P_{g1} - P_{g1}^{lim}\right)^2 + \sum_{i=1}^{N_{PQ}} R_2\left(V_i - V_i^{lim}\right)^2 + \sum_{i=1}^{N_g} R_3\left(Q_{gi} - Q_{gi}^{lim}\right)^2 + \sum_{i=1}^{N_l} R_4\left(\left|S_l - S_l^{max}\right|\right)^2. \quad (26)$$

The associated retribution coefficient such as R_1,R_2,R_3, R_4 with the generation of real power, magnitude of bus voltage, generation of reactive power and the limit violation of apparent line flow independently.

5 Numerical results and discussions

Under several cases, to examine the proposed algorithm ability, the bus system namely as IEEE 14 and IEEE 30 gets review. Each test systems with the optimum solution

Table 1 Minimization parameter settings

System	Parameters	Algorithms		
		SBDE	DE	GA
14-bus system	Population size	50	50	50
	Mutation (F)	0.7	0.7	0.7
	Crossover ratio (CR)	0.8	0.8	0.8
	Number of population	100	100	100
30-bus system	Population size	50	50	50
	Mutation (F)	0.7	0.7	0.7
	Crossover ratio (CR)	0.8	0.8	0.8
	Number of population	100	100	100

to examine the proposed algorithms, 50 individual trials. The proposed algorithms implementation in MATLAB Platform and the simulation conducted on a personal computer "2.30 GHz of Turbo Boost up system, Core i5-2410M Processor with the range of 2.90 GHz—4 GB RAM". The flow power considered concerning the MATPOWER 6.0 software (Zimmerman et al. 2005). Table 1 shows the minimization parameter settings for the proposed algorithms for different system.

5.1 Bus power system: IEEE 14

There are 20 branches in the IEEE 14-bus, which consist of five generators at 1, 2, 3, 6 and 8 buses system, three transformer tap settings at 4–7, 4–9 and 5–6 and two capacitors are placed at bus 9 and bus 14. The system data was taken from Palappan and Thangavelu (2018), Amrane et al. (2015) and Ghasemi and Ghavidel (2014) followed by Anuradha et al. (2020). The boundary condition for control variables like the generator voltage magnitude is 0.95–1.1, transformer taps is 0.95–1.1 and shunt VARs are 0–0.3.

The system total generation, load and power loss are as follows:

$$\sum P_G = 272.55\text{ MW},\ \sum Q_G = 104.54\text{ MVAr}, \tag{27}$$

Table 2 The test system of IEEE 14-bus to the losses of real power and best control variables

(a)

Control variables	SBDE	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	GA
V_1	1.0751	1.0745	1.0740	1.0753	1.0741	1.7900	1.0750	1.0711
V_2	1.0763	1.0761	1.0742	1.0759	1.0748	1.0758	1.0742	1.0746
V_3	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	1.0850
V_6	1.0733	1.0622	1.0600	1.0600	1.0647	1.0641	1.0083	0.9894
V_8	0.9500	0.9580	0.9500	0.9500	0.9500	1.0000	0.9500	0.9527
T_{4-7}	1.0900	1.0900	1.0900	1.0900	1.1000	1.0953	1.1000	1.0582
T_{4-9}	0.9550	0.9500	0.9559	0.9579	0.9512	0.9600	0.9500	0.9400
T_{5-6}	0.9599	0.9500	0.9554	0.9580	0.9579	0.9553	0.9500	0.9419
Q_{c4}	–	–	–	–	–	–	–	–
Q_{c9}	0.2700	0.2680	0.2690	0.2700	0.2610	0.2500	0.2000	0.1982
Q_{c14}	0.0690	0.0690	0.0685	0.0690	0.0640	0.0560	0.0545	0.0564
P_{loss}(MW)	9.7671	9.7685	9.7705	9.7688	9.7707	10.2002	9.7732	10.3166

(b)

Control variables	DFA	PSO	MTLA	BRCFF	ABC	CSS	LCA	PBIL
V_1	1.1000	1.1000	1.0746	1.0746	1.0751	1.0720	1.0742	1.0711
V_2	1.0946	1.0847	1.0566	1.0567	1.0566	1.0547	1.0580	1.0539
V_3	1.0570	1.0558	1.0272	1.0268	1.0279	1.0254	1.0257	1.0243
V_6	1.0946	1.0999	1.0506	1.0418	1.0361	1.0513	1.0089	1.0500
V_8	1.1000	1.0828	1.0111	1.0269	0.9802	1.0271	0.9640	1.0413
T_{4-7}	1.0094	1.0013	1.0400	1.0800	1.1000	0.9900	1.0800	0.9500
T_{4-9}	0.9000	0.9271	1.9300	0.9200	0.9000	1.0100	0.9900	1.1000
T_{5-6}	1.0115	1.0036	1.0400	1.0200	1.0800	1.0200	1.0700	1.0400
Q_{c4}	–	0.1800	–	–	–	–	–	–
Q_{c9}	0.1800	0.0600	0.3000	0.3000	0.2900	0.3000	0.2600	0.3000
Q_{c14}	0.0600	–	0.0700	0.0900	0.0900	0.0800	0.1000	0.0800
P_{loss}(MW)	12.0470	12.2324	12.9106	12.9264	12.9333	12.9748	12.9891	13.0008

Table 3 The test power system of IEEE 14 bus based statistical details

Methods	Best solution (MW)	Worst solution (MW)	Median (MW)	Standard deviation	Average CPU time (s)
SBDE	9.7671	9.8154	9.9667	0.0039	3.5436
Strategy 1	9.7685	11.4946	10.9626	0.0045	3.5589
Strategy 2	9.7705	9.8168	9.7950	0.0035	3.5590
Strategy 3	9.7688	9.7969	9.7813	0.0037	3.5589
Strategy 4	9.7707	9.7477	9.7785	0.0052	3.5590
Strategy 5	10.2002	10.2179	10.2076	0.0032	3.9478
Strategy 6	9.7732	9.7844	9.7774	0.0032	3.5592
GA	10.3166	11.9154	11.2315	0.0093	3.9557
DFA	12.0470	12.1569	12.1452	0.0026	4.0914
PSO	12.2324	13.8310	13.1470	0.0093	5.9500
MTLA	12.9106	12.92	12.9165	7.6832×10^{-5}	9.6400
BRCFF	12.9264	12.9778	12.9341	8.8191×10^{-5}	8.1300
ABC	12.9333	13.1172	12.9625	9.422×10^{-4}	9.1500
CSS	12.9748	13.2995	13.116	4.206×10^{-2}	10.0400
LCA	12.9891	13.1638	13.0474	5.5283×10^{-3}	10.8600
PBIL	13.0008	13.1947	13.0854	9.7075×10^{-4}	9.7500

$$P_{load} = 259.00\ \text{MW},\ Q_{load} = 73.50\ \text{MVAr}, \tag{28}$$

$$P_{loss} = 13.393\ \text{MW}. \tag{29}$$

The proposed SBDE algorithm, DE strategy, Genetic Algorithm (GA) and some existing algorithm gets to compared and provides the ORPD issue enabled control variables of optimal solution gets attained were described in Table 2a, b. From the Table 2a, b shows all the control factors attained within the well founded protected limitations. By consider the proposed algorithms, Table 3 illustrates overall comparison through the following separation of real power loss such as Minimum, Average, Maximum, Standard Deviation and Average Consumption Time. Above table shows the reduction of real power loss for the SBDE algorithm, DE-strategy techniques and GA of the proposed algorithms and existing methods such as 27.0731%, 27.0626%, 27.0477%, 27.0604%, 27.0462%, 23.8393%, and 27.0276% and 22.9702% respectively. Besides, the computational time is illustrated as 3.5436 s, 3.5589 s, 3.5590 s, 3.5589 s, 3.5590 s, 3.9478 s, 3.5592 s, where the computational times

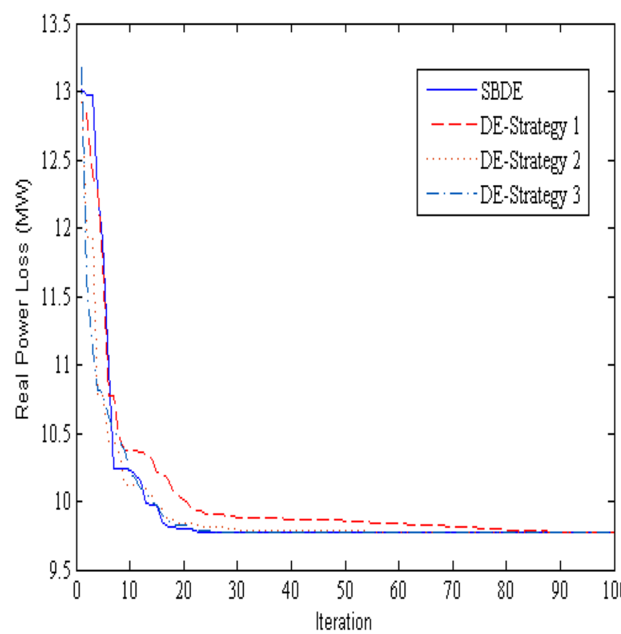

Fig. 3 Performance characteristics of real power loss for IEEE-14 bus system using SBDE-DE 3

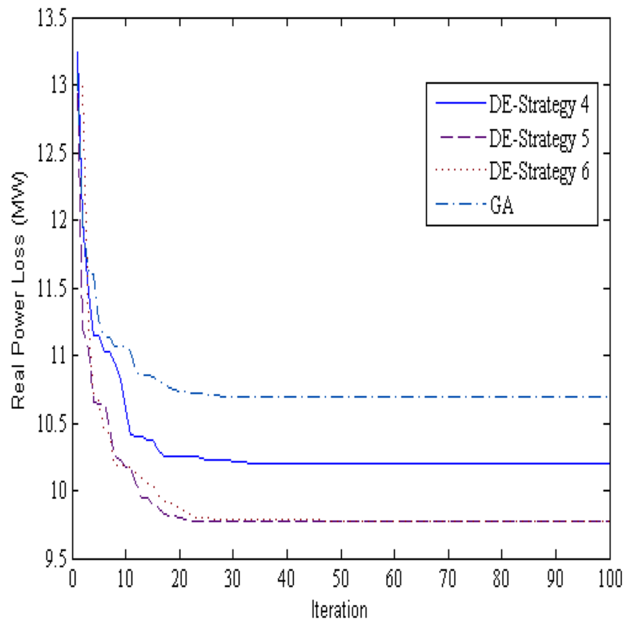

Fig. 4 Performance characteristics of real power loss for IEEE-14 bus system using DE

of GA and DFA proposed by Palappan and Thangavelu (2018) is 3.9557 s and 4.0914 s, independently. The performance of the loss reduction as minimum, which is greater with SBDE, DE-strategy 3, 5 and 6. Similarly, SBDE provides the computational time as lesser. The performance characteristics of real power loss by several methods like existing and proposed method illustrates in Figs. 3 and 4. From the simulation results the SBDE gives the better optimal solution compared to all other algorithms.

5.2 Bus power system: IEEE 30

IEEE 30-bus system is the second test system there are 41 branches which six generators 1, 2, 5, 8, 11 and 13 at buses. 6–9, 6- 10, 4–12, and 27–28 are the four transformer tap settings. For case 1, to placed the bus 10 and 24 are the two capacitors banks as given in Amrane et al. (2015). In case 2, three capacitor banks were placed at bus 3, 10 and 24 as given in Ghasemi and Ghavidel (2014). The new emplacement of capacitor banks done in case 3, which generated at buses 10, 12, 15, 17, 20, 21, 23, 24 and 29 represented in Sahli and Hamouda (2018). The boundary condition for control variables like the generator voltage magnitude is 0.95–1.1, transformer taps is 0.95–1.1. For case 1 and case 2 the shunt VARs limits is 0–0.3, and for case 3 0–0.05.

The system total generation, load and power loss are as follows:

$$\sum P_G = 290.71 \text{ MW}, \quad \sum Q_G = 122.49 \text{ MVAr}, \tag{30}$$

$$P_{load} = 283.40 \text{ MW}, \quad Q_{load} = 126.20 \text{ MVAr}, \tag{31}$$

$$P_{loss} = 7.307 \text{ MW}. \tag{32}$$

Case 1: The bus test system of IEEE-30 with restrictions used in Sahli and Hamouda (2018), Ghasemi and Ghavidel (2014) and Jeyadevi and Baskar (2011), (12 control variables).

Case 2: The bus test system of IEEE-30 with restrictions used in Ghasemi and Ghavidel (2014) and Sulaiman and Mustaffa (2015) (13 control variables).

Case 3: The bus test system of IEEE-30 with restrictions used in Abaci and Yamacli (2016), Davoodi and Babaei (2019), Villa-Acevedo and Lopez-Lezama (2018) and Medani and Sayah (2017) (19 control variables).

ORPD issue based control variables attained by SBDE, DE-strategy (1–6) and GA algorithm and the several existing algorithms shown in Tables 4a, b, 5a, b, 6a, b. By consider the table, the proposed system seemed as better and all the control factors achieved within the corresponding protected limits. Table 6a, b shows the best optimal solutions calculation through the different systems of 50 runs for the test systems of IEEE 30-bus for three different cases. From the table, the loss of real power for the proposed SBDE performance for three different cases is 0.04905, 0.04571 and 0.042946 p.u, independently. The SBDE algorithm, DE-strategy (1–6) and GA performance for different cases for IEEE 30-bus system in Figs. 5, 6, 7, 8, 9 and 10. From the simulation results the SBDE gives the optimal solution compared to all other algorithms. Table 7 illustrates the overall comparison i.e. the loss of real power, standard deviation and average computation time represented as follows: minimum, average, maximum for proposed algorithms, SBDE, DE strategy (1–6) and the current performance shown in the

Table 4 For case 1, the bus test system of IEEE 30 enabled best control variables

(a)

Control variables	SBDE	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	GA	TS-PSO
V_1	1.0990	1.1000	1.1000	1.1000	1.0980	1.1000	1.1000	1.0950	1.0992
V_2	1.0951	1.0940	1.0910	1.0900	1.0600	1.0700	1.0890	1.0600	1.0948
V_5	1.0800	1.0798	1.0700	1.0700	1.0680	1.0690	1.0700	1.0620	1.0766
V_8	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	1.0977
V_{11}	1.0900	1.0900	1.0800	1.0800	1.0710	1.0740	1.0790	1.0690	1.0837
V_{13}	1.0800	1.0800	1.0800	1.0800	1.0700	1.0800	1.0800	1.0790	1.0754
T_{6-9}	0.9500	0.9540	0.9690	0.9500	0.9560	0.9500	0.9590	0.9500	0.9257
T_{6-10}	1.0300	1.0300	1.0200	1.0200	1.0000	1.0100	1.0100	0.9989	1.0291
T_{4-12}	0.9500	0.9500	0.9600	0.9500	0.9530	0.9540	0.9598	0.9500	0.9265
T_{27-28}	0.9512	0.9506	0.9600	0.9589	0.9540	0.9510	0.9590	0.9510	0.9422
Q_{c10}	0.2980	0.2940	0.2950	0.2971	0.2960	0.2910	0.2976	0.2000	0.2864
Q_{c24}	0.1396	0.1380	0.1370	0.1360	0.1290	0.1210	0.1370	0.1200	0.1363
P_{loss}(MW)	4.5905	4.5982	4.6749	4.6623	4.7601	4.7174	4.6630	4.8029	4.6304

(b)

Control variables	MICA-IWO	ICA	MNSGA-II	CMAES	RGA	MOPSO	NSGA-II	BBO	PSO
V_1	1.0700	1.0695	1.0731	1.0716	1.0695	1.0500	1.0705	1.1000	1.1000
V_2	1.0613	1.0597	1.0641	1.0625	1.0613	1.0439	1.0613	1.0943	1.0943
V_5	1.0440	1.0405	1.0416	1.0402	1.0403	1.0231	1.0402	1.0804	1.1000
V_8	1.0459	1.0453	1.0425	1.0404	1.0405	1.0216	1.0404	1.0939	1.1000
V_{11}	1.1000	1.0984	1.0202	1.0365	1.0369	1.0120	1.0323	1.1000	0.9505
V_{13}	1.1000	1.0983	1.0531	1.0602	1.0602	1.0422	1.0599	1.1000	1.1000
T_{6-9}	1.0000	1.0000	1.0300	1.0000	0.9900	1.0200	1.0200	1.1000	1.0547
T_{6-10}	0.9100	0.9200	0.9200	0.9200	0.9800	1.0300	0.9200	0.9058	1.1000
T_{4-12}	1.0000	0.9800	0.9700	0.9800	0.9800	0.9500	0.9800	0.9521	0.9000
T_{27-28}	0.9500	0.9600	0.9900	0.9900	0.9900	0.9900	0.9900	0.9638	0.9468
Q_{c10}	0.0600	0.0500	0.1800	0.1900	0.1800	0.2000	0.1700	0.2891	0.3000
Q_{c24}	0.0500	0.0500	0.1000	0.1000	0.0600	0.0900	0.0900	0.1007	0.0000
P_{loss}(MW)	4.9178	4.9444	4.9454	4.9450	4.9510	4.9510	4.9520	4.9650	4.9819

literature section. From the performance analysis, we can represent that the SBDE gives the better optimal solution matched to the existing DE-strategies technique and GA. At the initial search phase, the control variables have an initial fluctuation, and next settled down at the final search phase to a steady state. The nearest optimal solution achieved by the SBDE algorithm, which gives the best characteristic performance, which is effectiveness and robustness to the other existing algorithms.

Table 5 For case 2, the bus test system of IEEE 30 enabled best control variables

(a)

Control variables	SBDE	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	GA
V_1	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000
V_2	1.0986	1.0982	1.0990	1.0985	1.0980	1.0974	1.0985	1.0962
V_5	1.0790	1.0720	1.0740	1.0800	1.0750	1.0713	1.0740	1.0730
V_8	1.0814	1.0801	1.0820	1.0890	1.0824	1.0831	1.0820	1.0817
V_{11}	1.0990	1.1000	1.0980	1.1000	1.0980	1.0970	1.1000	1.1000
V_{13}	1.1000	1.1000	1.1000	1.0998	1.1000	1.1000	1.0999	1.0940
T_{6-9}	1.0500	1.0490	1.0500	1.0480	1.0500	1.0480	1.0410	1.0400
T_{6-10}	0.9800	0.9709	0.9830	0.9830	0.9840	0.9813	0.9811	0.9850
T_{4-12}	0.9900	0.9892	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900
T_{27-28}	0.9700	0.9700	0.9700	0.9600	0.9700	0.9700	0.9700	0.9700
Q_{c3}	0.1900	0.1970	0.1950	0.1960	0.1900	0.1910	0.1940	0.1900
Q_{c10}	0.3000	0.2980	0.2800	0.2880	0.2700	0.2730	0.2790	0.2680
Q_{c24}	0.0800	0.0790	0.0700	0.0790	0.0698	0.0700	0.0710	0.0670
P_{loss}(MW)	4.5471	4.5482	4.5563	4.5509	4.5602	4.5573	4.5560	4.5838

(b)

Control variables	GWO	MICA-IWO	ICA	TLA	HSA	BRCFF	CSS	ABC
V_1	1.1000	1.0797	1.0785	1.0762	1.0726	1.0737	1.0725	1.0724
V_2	1.0961	1.0705	1.0694	1.0670	1.0625	1.0646	1.0637	1.0636
V_5	1.0800	1.0483	1.0469	1.0447	1.0399	1.0424	1.0413	1.0414
V_8	1.0804	1.0486	1.0471	1.0448	1.0422	1.0427	1.0417	1.0417
V_{11}	1.0934	1.0751	1.0348	1.0403	1.0318	1.0483	1.0429	1.0422
V_{13}	1.1000	1.0707	1.0710	1.0695	1.0681	1.0649	1.0698	1.0699
T_{6-9}	1.0400	1.0300	1.0800	1.0400	1.0100	1.0200	1.0200	1.0200
T_{6-10}	0.9500	0.9900	0.9500	0.9900	1.0000	1.0300	1.0200	1.0200
T_{4-12}	0.9500	1.0000	1.0000	1.0000	0.9900	0.9900	1.0000	1.0000
T_{27-28}	0.9500	0.9800	0.9700	0.9700	0.9700	0.9700	0.9700	0.9700
Q_{c3}	0.1200	−0.0700	−0.0600	−0.1100	0.3400	−0.0500	−0.0500	−0.0500
Q_{c10}	0.3000	0.2300	0.3600	0.3600	0.1200	0.3600	0.3600	0.3600
Q_{c24}	0.0800	0.1200	0.1100	0.1100	0.1000	0.1200	0.1300	0.1300
P_{loss}(MW)	4.5984	4.8599	4.8637	4.9047	4.9059	4.9059	4.9062	4.9064

6 Conclusion

The proposed self-balanced differential evolution (SBDE) algorithm, DE-approach (1–6) and GA approaches for ORPD issue evaluation. SBDE algorithm helps to manipulate the mutation and crossover are flexible on the existing suitable value. SBDE algorithm enabled the bus test system like as IEEE 14 and IEEE 30. The performance analysis compared to the DE-strategy, GA and other methods addressed in the reference. From the SBDE algorithm illustrates the losses of real power were minimized more than any other techniques. In addition the computation time is also very less. This demonstrates that the system is progressively powerful in worldwide looking through capacity and computational effectiveness. The investigations of the outcomes are extremely encouraging the proposed system gets accomplished. The minimum loss of real power attained in the state and control variables were carried to its corresponding boundary condition.

Table 6 For case 3, the bus test system of IEEE 30 enabled best control variables

(a)

Control variables	SBDE	Strategy 1	Strategy 3	Strategy 6	GA	SDP	NGBWC
V_1	1.1000	1.1000	1.1000	1.1000	1.1000	1.1	1.0502
V_2	1.0931	1.0934	1.0940	1.0956	1.0996	1.0946	1.0382
V_5	1.0830	1.0790	1.0930	1.0714	1.0834	1.0753	1.0107
V_8	1.0741	1.0732	1.0745	1.0713	1.0740	1.0773	1.0212
V_{11}	1.0947	1.1000	1.0970	1.0941	1.1000	1.0998	1.0503
V_{13}	1.0996	1.0998	1.0990	1.0912	1.0951	1.0996	1.0500
T_{6-9}	0.9511	0.9500	0.9504	0.9504	0.9512	1.0204	0.9520
T_{6-10}	0.9642	0.9650	0.9641	0.9700	0.9500	0.9201	1.0295
T_{4-12}	0.9554	0.9624	0.9671	0.9618	0.9611	0.9775	0.9720
T_{27-28}	1.0320	1.0214	0.9500	0.9500	0.9551	0.9653	0.9661
Q_{c10}	0.0500	0.0500	0.0490	0.0500	0.0500	0.0499	0.0097
Q_{c12}	0.0500	0.0500	0.0500	0.0500	0.0400	0.0499	0.0125
Q_{c15}	0.0491	0.0495	0.0492	0.0499	0.0498	0.0499	0.0212
Q_{c17}	0.0497	0.0495	0.0492	0.0500	0.0500	0.0499	0.0541
Q_{c20}	0.0500	0.0500	0.0500	0.0500	0.0500	0.0497	0.0043
Q_{c21}	0.0500	0.0433	0.0500	0.0440	0.0439	0.0499	0.0289
Q_{c23}	0.0500	0.0500	0.0500	0.0496	0.0497	0.0385	0.0229
Q_{c24}	0.0490	0.0500	0.0498	0.0500	0.0493	0.0499	0.0498
Q_{c29}	0.0373	0.00375	0.0378	0.0384	0.0400	0.0264	0.0106
P_{loss}(MW)	4.2946	4.4090	4.4093	4.4088	4.4578	4.3400	4.4800

(b)

Control variables	OGSA	DSA	HFA	SGA	MFO	BBO	CLPSO	WOA
V_1	1.0510	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000
V_2	1.0410	1.0897	1.0543	1.0940	1.0943	1.0944	1.1000	1.0963
V_5	1.0154	1.0660	1.0751	1.0745	1.0747	1.0749	1.0795	1.0789
V_8	1.0267	1.0636	1.0868	1.0767	1.0766	1.0768	1.1000	1.0774
V_{11}	1.0082	1.1000	1.1000	1.1000	1.1000	1.0999	1.1000	1.0955
V_{13}	1.0500	1.1000	1.1000	1.1000	1.1000	1.0999	1.1000	1.0929
T_{6-9}	1.0585	0.9890	0.9800	1.0510	1.0433	1.0435	0.9154	0.9936
T_{6-10}	0.9089	0.9349	0.9500	0.9000	0.9000	0.9011	0.9000	0.9867
T_{4-12}	1.0141	0.9841	0.9701	0.9830	0.9792	0.9824	0.9000	1.0214
T_{27-28}	1.0182	0.9579	0.9700	0.9670	0.9647	0.9691	0.9397	0.9867
Q_{c10}	0.0330	0.0500	0.0470	0.0500	0.0500	0.0499	0.0492	0.0316
Q_{c12}	0.0249	0.0500	0.0470	0.0500	0.0500	0.0498	0.0500	0.0204
Q_{c15}	0.0177	0.0500	0.0470	0.0500	0.4880	0.0499	0.0500	0.0429
Q_{c17}	0.0500	0.0500	0.0230	0.0500	0.0500	0.0499	0.0500	0.0267
Q_{c20}	0.0334	0.0500	0.0480	0.0435	0.0402	0.0499	0.0500	0.0481
Q_{c21}	0.0403	0.0500	0.0490	0.0500	0.0500	0.0499	0.0500	0.0481
Q_{c23}	0.0269	0.0475	0.0480	0.0270	0.0251	0.0387	0.0500	0.0357
Q_{c24}	0.0500	0.0500	0.0480	0.0500	0.0500	0.0498	0.0500	0.0419
Q_{c29}	0.0194	0.0500	0.0339	0.0240	0.0219	0.0290	0.0500	0.0200
P_{loss}(MW)	4.4900	4.5100	4.5200	4.5399	4.5410	4.5435	4.5600	4.5943

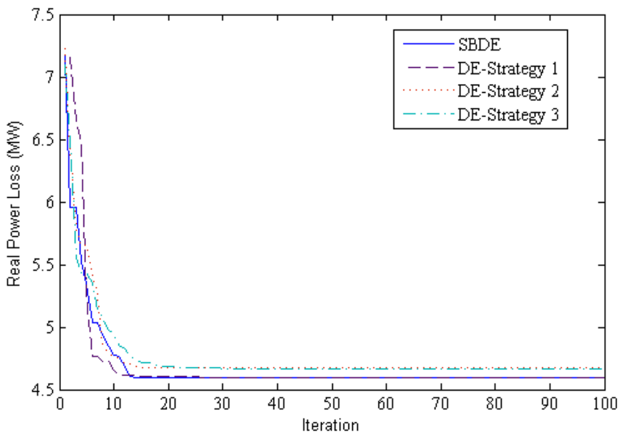

Fig. 5 Real power loss analysis for IEEE-30 bus system using SBDE-DE3 (Case 1)

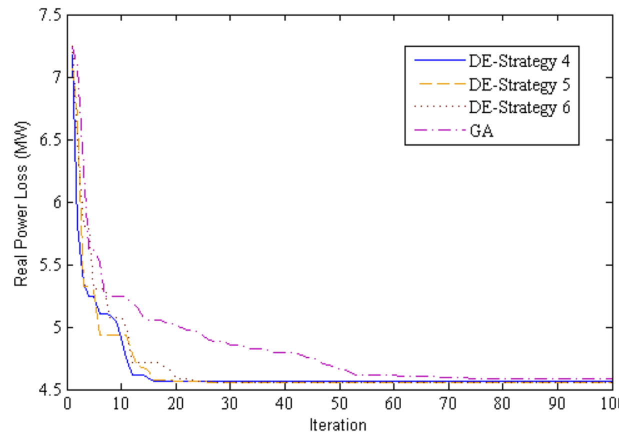

Fig. 8 Real power loss analysis for IEEE-30 bus system using DE 4-GA (Case 2)

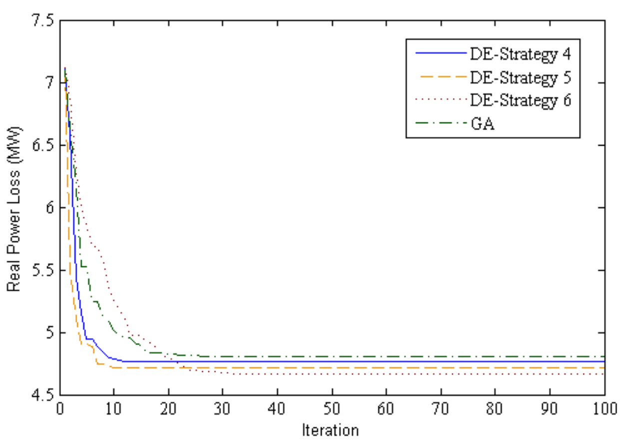

Fig. 6 Real power loss analysis for IEEE-30 bus system using DE 4-GA (Case 1)

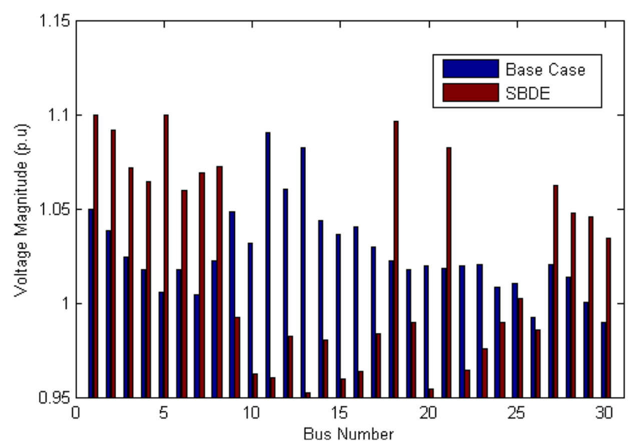

Fig. 9 IEEE-30 bus system voltage profile

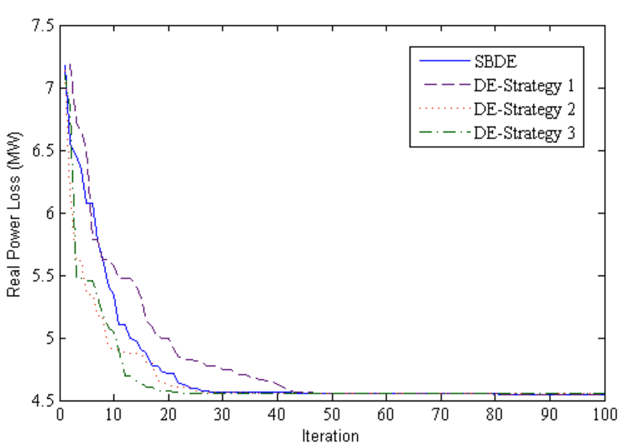

Fig. 7 Real power loss analysis for IEEE-30 bus system using SBDE-DE 3 (Case 2)

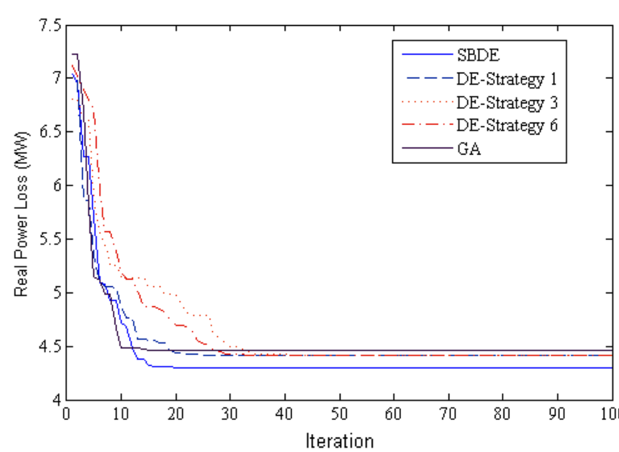

Fig. 10 Real power loss analysis for IEEE-30 bus system using DE 4-GA (Case 3)

Table 7 Statistical details for IEEE 30–bus test power system

Methods	Best solution	Worst solution	Median solution	Standard deviation	Average CPU time (s)
IEEE 30-bus system					
Case 1					
SBDE	0.04590	0.05708	0.07205	0.00025	NR
Strategy 1	0.04598	0.05716	0.07213	0.00026	NR
Strategy 2	0.04674	0.06650	0.07562	0.00035	NR
Strategy 3	0.04662	0.05778	0.07275	0.00026	NR
Strategy 4	0.04760	0.06496	0.07377	0.00045	NR
Strategy 5	0.04717	0.05894	0.07789	0.00019	NR
Strategy 6	0.04663	0.05741	0.07271	0.00027	NR
GA	0.04802	0.06176	0.06491	0.00034	NR
TS-PSO	0.04630	NR	NR	NR	NR
MICA-IWO	4.9178	4.9202	4.9197	8.7255×10^{-6}	66.92
ICA	4.9444	5.1186	4.9735	8.4282×10^{-4}	66.45
MNSGA-II	4.9454	NR	NR	NR	NR
CMAES	4.9545	4.950	4.946	0.00002	19.582
RGA	4.951	4.969	4.953	0.00005	18.42
MOPSO	4.951	NR	NR	NR	NR
NSGA-II	4.952	NR	NR	NR	NR
BBO	4.9650	NR	NR	NR	NR
PSO	4.9819	NR	NR	NR	NR
Case 2					
SBDE	0.04547	0.05665	0.07162	0.00024	NR
Strategy 1	0.04548	0.05666	0.07163	0.00025	NR
Strategy 2	0.04556	0.06532	0.07444	0.00035	NR
Strategy 3	0.04550	0.05666	0.07163	0.00025	NR
Strategy 4	0.04560	0.06296	0.07176	0.00045	NR
Strategy 5	0.04557	0.05734	0.07629	0.00019	NR
Strategy 6	0.04556	0.05634	0.07164	0.00027	NR
GA	0.04583	0.05957	0.06272	0.00034	NR
GWO	0.04598	NR	NR	NR	NR
MICA-IWO	4.8599	4.8669	4.861	6.4126×10^{-6}	63.22
ICA	4.8637	5.0396	4.9257	9.813×10^{-4}	67.15
TLA	4.9047	4.9875	4.944	5.2742×10^{-4}	19.63
HSA	4.9059	4.9653	4.924	NR	NR
BRCFF	4.9059	4.9391	4.9118	9.4472×10^{-5}	15.67
CSS	4.9062	5.0667	4.9555	7.1138×10^{-3}	21
ABC	4.9604	4.972	4.9338	6.6051×10^{-4}	20.87
Case 3					
SBDE	0.04294	0.05411	0.06909	0.00023	NR
Strategy 1	0.04409	0.06385	0.07024	0.00035	NR
Strategy 3	0.04409	0.05525	0.07022	0.00025	NR
Strategy 6	0.04408	0.05486	0.07016	0.00027	NR
GA	0.04457	0.05921	0.06146	0.00034	NR
SDP	0.0434	NR	NR	NR	NR
NGBWC	0.0448	NR	NR	NR	NR
OGSA	4.49	NR	NR	NR	NR
DSA	4.51	NR	NR	NR	NR
HFA	4.52	NR	NR	NR	NR
SGA	4.5399	NR	NR	NR	NR

Table 7 (continued)

Methods	Best solution	Worst solution	Median solution	Standard deviation	Average CPU time (s)
MFO	4.5410	NR	NR	NR	NR
BBO	4.5435	NR	NR	NR	NR
CLSPO	4.56	NR	NR	NR	NR
WOA	4.5943	NR	NR	NR	NR

NR not reported

References

Abaci K, Yamacli V (2016) Optimal reactive power dispatch using differential search algorithm. Electr Eng 99:213–225

Abido MA (2002) Optimal power flow using particle swarm optimization. Int J Electr Power Energy Syst 24:563–571

Alsac O, Bright J, Prais M, Stott B (1990) Further developments in LP-based optimal power flow. IEEE Trans. Power Syst 5:697–711

Amrane Y, Boudour M, Ladjici AA, Elmaouhab A (2015) Optimal VAR control for real power loss minimization using differentialevolution algorithm. Int J Electr Power Energy Syst 66:262–271

Anuradha M, Ganesan V, Oliver S, Jayasankar T, Gopi R (2020) Hybrid firefly with differential evolution algorithm for multi agent system using clustering based personalization. J Ambient Intell Human Comput:1–10

Bakirtzis AG, Petridis V (2002) Optimal power flow by enhanced genetic algorithm. IEEE Trans Power Syst 17:229–236

Bjelogrlic MR, Ristanovic P (1990) Application of Newton's optimal power flow in voltage/reactive power control. IEEE Trans Power Syst 5:1447–1454

Das DB, Patvardhan C (2003) A new hybrid evolution strategy for reactive power dispatch. Int J Electr Power Energy Syst 65:83–90

Davoodi E, Babaei E (2019) A novel fast semidefine programming-based approach for optimal reactive power dispatch, pp 288–298

Dommel HW, Tinney WF (1968) Optimal power flow solutions. IEEE Trans Power Appar Syst:1866–1876

Ghasemi M, Ghanbarian M (2014) Modified teaching learning algorithm and double differential evolution algorithm for optimal reactive power dispatch problem: a comparative study. Inf Sci 278:231–249

Ghasemi M, Ghavidel S (2014) A new hybrid algorithm for optimal reactive power dispatch problem with discrete and continuous control variables. Appl Soft Comput 22:126–140

Ghorbani N, Aghahosseini A, Breyer C (2020) Assessment of a cost-optimal power system fully based on renewable energy for Iran by 2050–achieving zero greenhouse gas emissions and overcoming the water crisis. Renew Energy 146:125–148

Gomes JR, Saavedra OR (2002) A Cauchy-based evolution strategy for solving the reactive power dispatch problem. Int J Electr Power Energy Syst 24:277–283

Granville S (1994) Optimal reactive dispatch through interior point methods. IEEE Trans Power Syst 9:136–146

Jeyadevi S, Baskar S (2011) Solving multiobjective reactive power dispatch using modified NSGA-II. Electr Power Syst Energy Syst 33:219–228

Lee KY, Yang FF (1998) Optimal reactive power planning using evolutionary algorithms: a comparative study for evolutionary programming, evolutionary strategies, genetic algorithms and linear programming. IEEE Trans Power Syst 13:101–108

Liang CH, Chung CY (2006) Comparison and improvement of evolutionary programming techniques for power system optimal reactive power flow. IEEE Proc Gener Trans Distrib 153:228–236

Lu FC, Hsu YY (1995) Reactive power/voltage control in a distribution substation using dynamic programming. IEEE Proc Gener Transm Distrib 142:639–645

Medani K, Sayah S (2017) Whale optimization algorithm based optimal reactive power dispatch: a case study of the Algerian power system. Electr Power Syst Res

Mezura-Montes E, Coello CA (2011) Constraint-handling in nature-inspired numerical optimization: past, present and future. Swarm Evol Comput 1:173–194

Palappan A, Thangavelu J (2018) A new meta heuristic dragonfly optimization algorithm for optimal reactive power dispatch problem. Gazi Univ J Sci 31(4):1107–1121

Power system test case archive. http://www.ee.washington.edu/research/pstca/pf30/pg_tca30bus.html (Online)

Qu BY, Suganthan PN (2011) Constrained multi-objective optimization algorithm with ensemble of constraint handling methods. Eng Optim 43:403–416

Quintana VH, Santos-Nieto M (1989) Reactive-power dispatch by successive quadratic programming. IEEE Trans Energy Convers 4:425–435

Sahli Z, Hamouda A (2018) Reactive power dispatch optimization with voltage profile improvement using an efficient hybrid algorithm. Energies

Sharma H, Bansal JC, Arya KV (2014) Self-balanced differential evolution. J Comput Sci:312–323

Storn R, Price K (1995) Differential evolution—a simple and efficient adaptive scheme for global optimization over continuous spaces, Technical report TR-95-012, ICSI

Sulaiman M, Mustaffa Z (2015) Using the grey wolf optimizer for solving optimal reactive power dispatch problem. Appl Soft Comp 32:286–292

Sun DI, Ashley B (1984) Optimal power flow by Newton approach. IEEE Trans Power Appar Syst:2864–2880

Varadarajan M, Swarup KS (2008a) Differential evolution approach for optimal reactive power dispatch. Appl Soft Comput 8:1549–1561

Varadarajan M, Swarup KS (2008b) Differential evolutionary algorithm for optimal reactive power dispatch. Electr Power Energy Syst 30:435–441

Varadarajan M, Swarup KS (2008c) Solving multi-objective optimal power flow using differential evolution. IEE Proc Gener Transm Distrib 2:720–730

Varadarajan M, Swarup KS (2008d) Volt-var optimization using differential evolution. Electr Power Compon Syst 36:387–408

Villa-Acevedo WM, Lopez-Lezama JM (2018) A novel constraint handling approach for the optimal reactive power dispatch problem. Energies

Vlachogiannis JG, Lee KY (2006) A comparative study on particle swarm optimization for optimal steady-state performance of power systems. IEEE Trans Power Syst 21:1718–1728

Yan W, Liu F, Wong KP (2006) A hybrid genetic algorithm–interior point method for optimal reactive power flow. IEEE Trans Power Syst 2:1163–1169
Yoshida H, Nakanishi Y (2000) A particle swarm optimization for reactive power and voltage control considering voltage security assessment. IEEE Trans Power Syst 15:1232–1239
Zhao B, Guo CX, Cao YJ (2005) A multi agent based particle swarm optimization approach for reactive power dispatch. IEEE Trans Power Syst 20:1070–1078
Zhou A, Zhang Q (2011) Multi objective evolutionary algorithms: a survey of the state-of-the-art. Swarm Evol Comput 1:32–49
Zimmerman R, Murillo-Sanchez CE, Gan D (2005) MATPOWER 6.0, power systems engineering research center (PSERC) [online]. http://www.pserc.cornell.edu/matpower