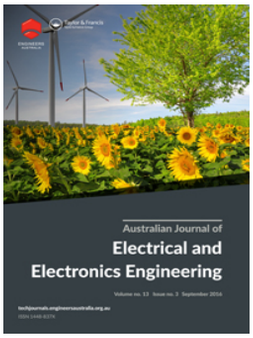

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Optimal reactive power dispatch using backtracking search algorithm

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ABSTRACT

Optimal reactive power dispatch (ORPD) problem has a mounting effectuation on secure and economical operation of electrical power systems. It is well-known as a non-linear, multimodal and mixed-variable problem which has been solved using various computation intelligence-based techniques in the last decades. In this paper, as a new approach, backtracking search algorithm (BSA) is applied to solve the ORPD problem to minimise the power losses and/or improve the voltage profile under control and dependent variable constraints. The BSA is a new evolutionary algorithm for solving real-valued numerical optimisation problems. It has a simple structure and single control parameter. It memorises a population from a randomly chosen previous generation for use in generating the search-direction matrix. This grants BSA the advantage of experiences gained from previous generations to generate the offsprings. The proposed BSA is applied to the IEEE standard 30-bus system, and a real power system at West Delta Network as a part of the Unified Egyptian Network. Simulation results show the capability of the proposed BSA for solving the ORPD problem.

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KEYWORDS
Reactive power dispatch; optimisation; backtracking search algorithm; losses; voltage profile

1. Introduction

In a typical power system, the network losses account for 5 to 10% of the total generation in the power system, which would cost millions of dollars every year (Conejo et al. 2001). Added to that, maintaining the bus load voltages within their limits is one of the major operating tasks in power systems for high-quality consumer services since electric power loads vary from time to time and any change in the power demand causes lower or higher voltages (Mamundur and Chenoweth 1981). The loss minimisation and voltage profile improvement have a great influence on operating the power systems (Roy, Ghoshal, and Thakur 2012; Abdelmoumene, Mohamed, and Boubakeur 2013; Suresh et al. 2013a). Both can be achieved by adjusting the control variables like generator bus voltage magnitude, transformer tap settings and reactive power injected from switchable capacitor banks, while satisfying the units and system constraints (Ghasemi et al. 2015; Shaheen et al. 2016).

The ORPD problem is solved effectively by conventional optimisation techniques such as linear programming (LP) (Lobato et al. 2001), non-linear programming (Pudjianto, Ahmed, and Strbac 2002) and quadratic programming (Lin, David, and Yu 2003). It has been handled also by computational intelligence-based techniques such as genetic algorithm (GA) (Baran, Biswas, and Mukhopadhyay 2013), particle swarm optimization (PSO) (Zhao, Guo, and Cao 2005; Cai, Ren, and Yu 2007) and differential evolution (DE), (Abou El Ela, Abido, and Spea 2011; Shaheen, El Sehiemy, and Farrag 2015). In Abou El Ela, El Sehiemy, and Shaheen (2013), a hybrid between the fuzzy modelling technique and the linear programming (LP) method, which is addressed multi-objective fuzzy linear programming (MFLP) procedure, has been introduced for solving the problem of reactive power management. In El Sehiemy, Abou El Ela, and Shaheen (2015), this MFLP procedure has been applied for preparing different preventive control actions to overcome any emergency condition when they occurred and to restore the system to the normal state. In Shahbazi and Kalantar (2013), seeker optimization algorithm (SOA) has been executed to the ORPD problem to minimise the real losses as a single objective function. In Dai et al. (2009), SOA has been implemented to minimise the power losses, voltage deviation and increasing voltage stability using L-index. The ORPD has been handled to minimise different single objective functions. But, SOA is heavily dependent on its structures and parameters.

In Dai et al. (2009), a multi-objective reactive power control has been addressed using SOA. In that paper, the multi-objective functions were to minimise the transmission loss and voltage deviations, while the voltage stability

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margin would be maximised by minimising the eigenvalue of the non-singular power flow Jacobian matrix.

In Abou El-Ela et al. (2011), the ORPD problem has been solved using ant colony optimization (ACO) method to minimise the power losses as a single objective function. Sensitivity parameters has been used to express objectives and dependent variables in terms of control variables and based on a modified model of fast decoupled load flow.

BSA is a new nature-inspired algorithm proposed by Civicoglu (2013). It is effective, fast and capable of solving different numerical optimisation problems with a simple structure. In Civicioglu (2013), it has been proved that BSA can solve 75 boundary-constrained and three real-world benchmark problems more successfully compared with PSO, artificial bee colony algorithm (ABC), covariance matrix adaptation evolution strategy (CMAES), adaptive differential evolution algorithm (JDE), comprehensive learning particle swarm optimizer (CLPSO) and self-adaptive differential evolution algorithm (SADE). The simulations and comparisons showed that BSA can solve the benchmark problems more successfully than the compared algorithms. In Liu et al. (2004), the idea behind backtracking has been implemented for solving the problem of power system restoration where, the latest operating state of the system has been saved and recalled if the new state didn't provide any success. In Shafiullah, Abido, and Coelho (2015), BSA has been executed for optimal tuning the parameters of power system stabilizers in multi-machine power networks.

In the current paper, BSA is investigated to solve the ORPD problem that minimises the transmission power losses and/or to improve the voltage profile under control and dependent variable constraints. The main benefit of the BSA is feeding the search space with experiences gathered from previous generations to create the new individuals. The proposed BSA is applied to the IEEE standard 30-bus system and a real power system at West Delta Network as a part of the Unified Egyptian Network. The obtained results are compared with different methods in the literature. Simulation results show the capability of the proposed BSA for solving the ORPD problem.

This paper is organised as follows: Section 2 presents the formulation of the ORPD problem. Section 3 introduces the proposed BSA for solving the ORPD problem. The application results of case studies are presented in Section 4. The outcome of the current work is concluded in the last section.

2. Formulation of the ORPD problem

The OPF problem includes the optimisation of a non-linear objective function, while maintaining different equality and inequality constraints. Mathematically, it can be expressed as follows:

$$\text{Min } F(x, u) \tag{1}$$

Subject to:

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

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

where F is the considered objective function; u is the control variables; x is the dependent variables.

Control variables are typically the generator voltages, transformer tap settings and reactive power injection of switched capacitors and reactors. The dependent variables are slack bus power, load bus voltages, generator reactive powers and line flows. The objective function of this study is to find the optimal settings of the control variables of ORPD problem which minimises the real power loss and voltage deviation. Thus, they can be formulated simply using the weighted sum approach as follows:

$$F = \omega_f.P_{loss} + (1 - \omega_f).\text{VD} \tag{4}$$

where F is the objective function to be considered; ω_f is the weighing factor for real power loss and voltage deviation; P_{loss} is the real power losses; VD is the sum of the voltage deviation of load buses. The transmission losses can be computed as:

$$P_{loss} = \sum_{i,j \in N_b} g_{ij}\left(V_i^2 + V_j^2 - 2V_iV_j\cos\theta_{ij}\right) \tag{5}$$

where g_{ij} is the conductance of branch between buses i and j; θ_{ij} is the voltage angle difference between bus i and bus j; V_i is the voltage magnitude at bus i; and V_j is the voltage magnitude at bus j. Also, the improvement of voltage profile is considered by minimising the voltage deviation (VD) of the load buses from 1 p.u. The objective function is chosen as follows:

$$\text{VD} = \sum_{i=1}^{N_{\text{Load}}} \left|V_i - V_{\text{ref}}\right| \tag{6}$$

where V_{ref} is the reference voltage of buses which is taken as 1 p.u, and N_{Load} is the number of load buses. The equality constraints are usually represented by the load flow balance equations which could be formulated as:

$$Q_{g_i} - Q_{L_i} + Q_{C_i} - V_i\sum_{j=1}^{N_b} V_j(G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}) = 0, \quad i = 1, 2, \ldots N_{PQ} \tag{7}$$

$$P_{g_i} - P_{L_i} - V_i\sum_{j=1}^{N_b} V_j(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}) = 0, \quad i = 1, 2, \ldots N_b - slack \tag{8}$$

where, G_{ij} and B_{ij} are mutual conductance and susceptance between bus i and j, respectively; N_{PQ} refers to load buses; P_{g_i} is the active power generated at bus i; P_{L_i} is the active power demand at bus i; Q_{g_i} is the reactive power generated at bus i; Q_{L_i} is the reactive power demand at bus i; Q_{C_i} is the capacitive or inductive power of VAR source installed at bus i; N_b is the number of buses. Furthermore, the power system has to satisfy inequality constraints corresponding to the operational variables as:

$$Q_{g_i}^{\min} \le Q_{gi} \le Q_{g_i}^{\max}, \quad i = 1, 2, \dots N_{pv} \tag{9}$$

$$V_i^{\min} \le V_i \le V_i^{\max}, \quad i = 1, 2, \dots N_b \tag{10}$$

$$T_k^{\min} \le T_k \le T_k^{\max}, \quad k = 1, 2, \dots N_t \tag{11}$$

$$\left|S_L^{\text{flow}}\right| \le S_L^{\max}, L = 1, 2, \dots N_L \tag{12}$$

$$0 \le Q_{Ce} \le Q_{Ce}^{\max}, e = 1, 2, \dots N_C \tag{13}$$

$$0 \le Q_{Cj}^{n} \le Q_{Cj}^{\max(n)}, j \in \quad \text{candidate buses} \tag{14}$$

where Q_{g_i} is the reactive power generated at bus i; N_{pv} refers to the total number of voltage-controlled buses; V_i is the voltage magnitude of bus i; T_k is the tapping change of a transformer k; and N_t refers to the total number of on-load tap changing transformers. S^{flow} refers to the apparent power flow, $S^{\max}$ is the maximum MVA rating of the transmission lines and transformers, and N_L refers to all transmission lines in the system. Q_{c_e} is the reactive power output of existing VAR source at bus e, $Q_c^{\max}$ is its maximum capacity, N_C refers to the total number of existing VAR sources, $Q_{C_i}^{n}$ refers to the capacitive or inductive power of new VAR source installed at bus i; Moreover, the active power output at slack bus generator isn't specified to supply the balance of the mismatch between the real power required and the summation of active power generation.

$$P_s^{\min} \le P_s \le P_s^{\max} \tag{15}$$

where P_s is the active power at slack bus. $P_s^{\min}$ and $P_s^{\max}$ are the minimum and maximum limits at slack bus.

3. Backtracking search algorithm

BSA is a population-based evolutionary algorithm designed for solving real-valued numerical optimisation problems. For this purpose, BSA maintains a population of N individual and D-dimensional individuals. The trial populations of BSA are generated with aid of three basic genetic operators (selection, mutation and crossover). It has a random mutation strategy that uses only one direction individual for each target individual and it possesses a memory in which it stores a population from a randomly chosen previous generation for use to identify the search-direction matrix (Civicioglu 2013). BSA uses a non-uniform crossover strategy that is much more complex than traditional crossover strategies. The major stages of BSA employ five evolutionary mechanisms: initialization, selection-I, mutation, crossover and selection-II. The general flowchart of BSA is described in Figure 1.

3.1. Initialization

BSA initially constructs a population, by randomising individuals within their feasible numerical range by a uniform random distribution function:

$$P_{ij} \sim U(\text{low}_j, \text{up}_j), \quad i = 1, 2, \dots, N, j = 1, 2, \dots, D \tag{16}$$

where N is the population size; D is the problem dimension; U is the uniform distribution function; P_i is the position of the ith population individual in the solution space; low_j and up_j are lower and upper limits of the solution space, respectively.

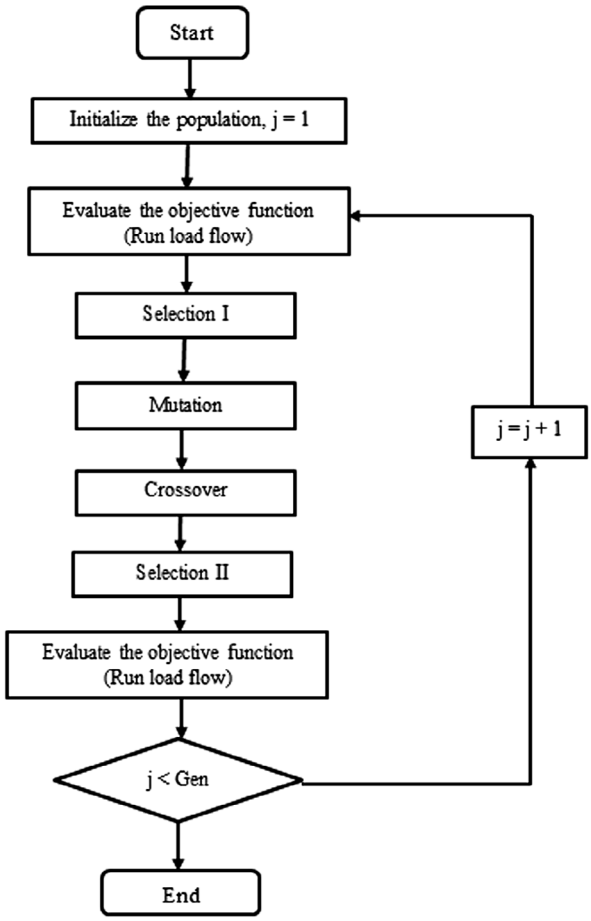

Figure 1. Major stages of the backtracking optimisation algorithm.

3.2. Fitness function evaluation

The constraints of the dependent variables are included into the considered objective function using quadratic penalty terms. So, the infeasible solutions, which violate the constraints, have a little chance to be transferred to the next generation. Thus, the objective function is generalised and expressed as follows:

$$f = F + \lambda_V \sum_{N\lim_V} \Delta V_{\text{Load}}^2 + \lambda_Q \sum_{N\lim_Q} \Delta Q_g^2 + \lambda_{Ps} \Delta P_s^2 + \lambda_{Sf} \sum_{N\lim_{Sf}} \Delta S_f^2 \quad (17)$$

where, λ_V, λ_Q, λ_{Ps}, λ_{Sf}, are the penalty factors, $N\lim_V$ is the set of load buses which are violated the limits, $N\lim_Q$ is the set of generator buses in which its reactive power outputs are outside the limits, $N\lim_{Sf}$ is the set of overflow lines, ΔV_{Load}, ΔQ_g, ΔP_s, and ΔS_f are defined as follows:

$$\Delta V_{\text{Load}} = \begin{cases} V_{\text{Load}}^{\min} - V_{\text{Load}} & \text{if } V_{\text{Load}} < V_{\text{Load}}^{\min} \\ V_{\text{Load}}^{\max} - V_{\text{Load}} & \text{if } V_{\text{Load}} > V_{\text{Load}}^{\max} \end{cases} \quad (18)$$

$$\Delta Q_g = \begin{cases} Q_g^{\min} - Q_g & \text{if } Q_g < Q_g^{\min} \\ Q_g^{\max} - Q_g & \text{if } Q_g > Q_g^{\max} \end{cases} \quad (19)$$

$$\Delta P_s = \begin{cases} P_s^{\min} - P_s & \text{if } P_s < P_s^{\min} \\ P_s^{\max} - P_s & \text{if } P_s > P_s^{\max} \end{cases} \quad (20)$$

$$\Delta S_f = S_f^{\max} - S_f \quad \text{if } S_f > S_f^{\max} \quad (21)$$

where superscripts 'min' and 'max' refer to the minimum and maximum of any variable.

3.3. Selection-I

In this stage, BSA generates the historical population utilized to determine the search direction as in the following equation:

$$P_{ij}^{\text{old}} \sim U(\text{low}_j, up_j), \quad i = 1, 2, \ldots, N, j = 1, 2, \ldots, D \quad (22)$$

where P_{ij}^{old} is the historical population. BSA gives a chance to redesign the historical population at the beginning of each iteration using the following rule:

$$P^{\text{old}} = \begin{cases} P, & \text{if } a < b \\ P^{\text{old}}, & \text{if } a \geq b \end{cases} \quad (23)$$

where a and $b \sim U(0,1)$ in order to decide if the historical population is selected from previous generation. Then the shuffling function is applied in order to rearrange the population individuals as follows:

$$P^{\text{old}} := \text{Permutting}\,(P^{\text{old}}) \quad (24)$$

where the permuting () function is a random shuffling function.

3.4. Mutation

After that, the mutation process generates mutant vectors of BSA (V) at every generation using the following function:

$$V = P + F.(P^{\text{old}} - P) \quad (25)$$

where F is a real number which controls the amplitude of the search direction. BSA employed historical experiences to determine the search direction of the population individuals by taking into account the values of the historical population.

In this paper, the value of F = 3.rndn, where rndn ~ $N(0,1)$ and N is the standard normal distribution (Figure 2). This strategy gives capability automatic variation of the value of F and avoids the specification problem of it.

3.5. Crossover

The crossover operation of the BSA creates trial population (T) by exchanging the components of the mutant vectors (V) and the target vectors in P. Figure 3 illustrates the crossover process of the BSA given in a pseudocode form. This process includes two stages. The first one uses *mixrate* to calculate a binary integer-valued matrix called map guiding crossover directions (Algorithm 1, lines 0–7).

The second one allows the application of the BSA's crossover strategy to generate the final form of the trial population (Algorithm 1, line 11) using the following equation:

$$T_{i,j} = \begin{cases} P_{i,j}, & \text{if map}_{i,j} = 1 \\ V_{i,j}, & \text{if map}_{i,j} = 0 \end{cases} \quad (26)$$

where $T_{i,j}$ is the trial individuals. In BSA's crossover process, the mix rate parameter (*mixrate*) controls the

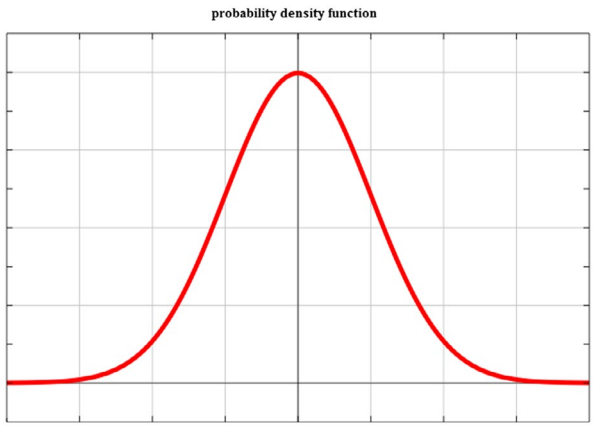

Figure 2. Probability density function of the normal distribution.

```
Input: V, mixrate, N and D.
Output: T: Trial-Population.
    0. map(1:N,1:D)= 0
    1.   if a < b | a, b ~ U(0, 1) then
    2.    for i from 1 to N do
    3.   map(i,u(1:⌈mixrate·rnd·D⌉))= 1 | u = permuting ((1, 2, 3, . . . ,D))
    4.   end
    5.   else
    6.   for i from 1 to N do, map(i,randi(D))= 1, end
    7.   end
    8.   T :=Mutant
    9.   for i from 1 to N do
    10.  for j from 1 to D do
    11.  if map(i,j)= 1 then T(i,j):= P(i,j)
    12.  end
    13.  end
```

Figure 3. Algorithm 1: BSA crossover strategy.

number of variables of individuals that will mutate in a trial population.

After this process, the individuals may exceed the search space limits. Thus, the movement of the individuals must be restricted by randomly regeneration for the exceeded variables in the feasible search space.

3.6. Selection-II

The selection-II process is carried out in the last stage to compare the fitness of the trial vector and the corresponding target vector and select the parent which will survive in the next generation as follows:

$$P_{i,j}^{\text{next}} = \begin{cases} T_{i,j}, & \text{if } f(T_{i,j}) < f(P_{i,j}) \\ P_{i,j}, & \text{otherwise} \end{cases} \tag{27}$$

where $f()$ is the fitness function. Therefore, the population either gets better objective values or remains constant. Then, these stages are repeated across generations and stopped whenever maximum number of generations is reached or other stopping criterion is satisfied.

4. Simulation results

To evaluate the performance and effectiveness of the proposed BSA to solve the ORPD problem, the IEEE 30-bus system and the West Delta region (WDN) system as a real part of the Egyptian Unified Network is used. The simulation runs were performed using the proposed algorithm with $N_p = 50$, *mixrate* = 1, and a maximum of 300 iterations. The simulation runs were performed using the proposed algorithm with $N_p = 50$, *mixrate* = 1 and a maximum of 300 iterations.

4.1. IEEE 30-bus power system

To evaluate the performance and effectiveness of the proposed BSA to solve the ORPD problem, the IEEE 30-bus system is used. It consists of 30 buses, 41 branches, 6 generators, 4 under-load tap changing transformers and 2 shunt capacitive sources at buses 10 and 24. Bus 1 is the slack bus, 2, 5, 8, 11 and 13 are taken as generator buses and the rest are load buses. The initial active and reactive losses are 5.596 MW and 28.38 MVAR, respectively. The complete data for parameters, rating and operational constraints of the system components to implement the ORPD problem are given in Ghasemi et al. (2015). Table 1 described the considered security constraints of the voltage magnitudes of generator buses (V_g) and load buses (V_L), the reactive power limits of the shunt VAR injections (Q_c) and the transformers tap settings limits (*Tap*). Table 2 shows the generator data and limits.

4.1.1. Case 1: minimisation of power losses

The proposed BSA has been run for Case 1 and the optimal control variables and its corresponding results are shown in Table 3. It is clear from this table that the proposed BSA reduced the active power losses from 5.596 to 4.733 MW compared to the initial case. This reduction is equivalent to 15.42%. Also, the convergence characteristics of minimising the losses over iterations are shown in Figure 4.

Table 1. Considered security constraints for the IEEE 30-bus system.

Control variables	Min	Max
V_g	0.9	1.1
V_L	0.9	1.1
Tap	0.9	1.1
Q_c (MVAR)	0	10

Table 2. Generators power limits in MW and MVAR.

Bus	P_g (initial)	V_g (initial)	$Q_g^{\max}$	$Q_g^{\min}$
1	99.24	1.05	200	−20
2	80	1.04	100	−20
5	50	1.01	80	−15
8	20	1.01	60	−15
11	20	1.05	50	−10
13	20	1.05	60	−15

Table 3. Simulation results of the proposed BSA for different objective functions.

	Initial	Case 1	Case 2	Case 3
V_{g1}	1.05	1.0994	1.0233	1.0983
V_{g2}	1.04	1.0913	1.0196	1.0905
V_{g5}	1.01	1.0719	1.0214	1.0728
V_{g8}	1.01	1.0676	0.9952	1.069
V_{g11}	1.05	1.0818	1.0555	1.0822
V_{g13}	1.05	1.0925	1.0402	1.0411
Tap_{6-9}	1.078	1.0042	1.0619	1.0827
Tap_{6-10}	1.069	1.0188	0.9177	1.0243
Tap_{4-12}	1.032	1.0606	0.9778	1.068
Tap_{28-27}	1.068	0.9821	0.9431	1.0133
Qc_{10}	19	7.872	9.5222	7.5679
Qc_{24}	4.3	8.6558	9.6286	9.0011
P_{losses} (MW)	5.596	4.733	5.6088	4.8031
VD (p.u.)	0.8691	1.0648	0.1469	0.5075
F	4.1779	–	–	3.5144

4.1.2. Case 2: improving the voltage profile distribution

The proposed BSA has been run for Case 2 and the optimal control variables and its corresponding results are shown in Table 3. As shown, the proposed BSA reduced the sum of the voltage deviation of load buses from 0.8691 to 0.1469 p.u. compared to the initial case. Figure 5 is plotted the convergence characteristics of minimising the sum of the voltage deviation of load buses.

4.1.3. Case 3: minimisation of power losses and voltage profile improvement

In this case, the real power losses and voltage deviation are considered using the weighted sum objective where the weighing factor (ω_f) in Equation (4) is set to 0.7 (Suresh et al. 2013a). The proposed BSA has been run for this case and the optimal control variables and its corresponding results are shown in Table 3. It is clear from this table that the proposed BSA reduced the weighted sum objective (F) from 4.1779 to 3.5144 as the active power losses are reduced from 5.596 MW to 4.8031 MW with equivalent reduction of 14.17%. Added to that, the sum of the voltage deviation of load buses from 0.8691 to 0.5075 p.u. The convergence characteristics for this case are shown in Figure 6.

Table 4 summarises the results of the optimal solution obtained by harmony search algorithm (HSA) (Khazali and Kalantar 2011), big bang–big crunch algorithm (BBBCA) (Suresh et al. 2013b), adaptive genetic algorithm (AGA) (Wu, Cao, and Wen 1998), PSO (Zhao, Guo, and Cao 2005), biogeography-based optimization (BBO) (Roy, Ghoshal, and Thakur 2012), GA (Khazali and Kalantar 2011) and PSO (Roy, Ghoshal, and Thakur 2012) methods. It reveals that the reduction of real power loss after optimisation via the proposed BSA algorithm is better than these techniques. Reduction in power losses indicated by the BSA algorithm is highly encouraging and it is only 4.733 MW. Moreover, the proposed BSA algorithm better optimises both real power loss and voltage deviation as shown in Table 5 compared to gravitational search algorithm (GSA) (Suresh et al. 2013a).

The distribution of the system voltage profile obtained by the proposed BSA compared to the initial case is shown in Figure 7. As shown, the voltage

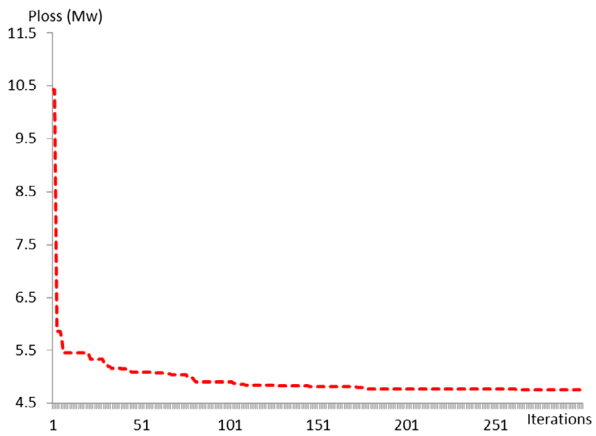

Figure 4. Convergence characteristics of power losses minimisation (Case 1).

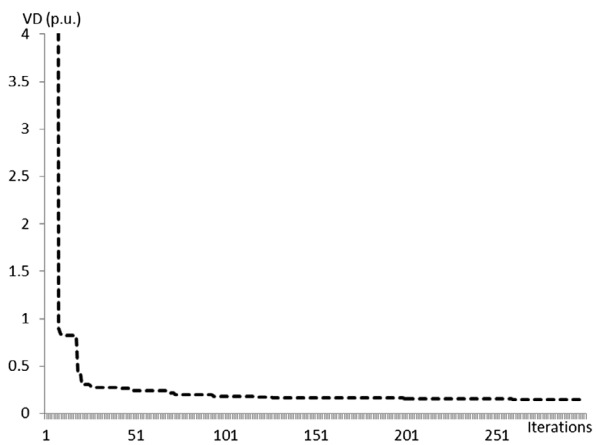

Figure 5. Convergence characteristics of minimising the sum of the voltage deviation of load buses (Case 2).

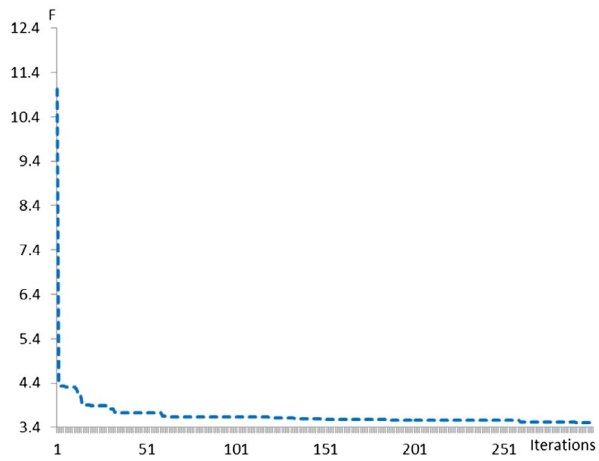

Figure 6. Convergence characteristics of minimising the weighted sum objective (F) (Case 3).

Table 4. Comparison results of different methods.

Sl. No	P_{losses} (MW)
Initial value	5.596
Proposed BSA	4.733
HSA (Khazali and Kalantar 2011)	4.7624
BBBCA (Suresh et al. 2013)	4.807
AGA (Wu, Cao, and Wen 1998)	4.926
PSO (Zhao, Guo, and Cao 2005)	4.9262
BBO (Roy, Ghoshal, and Thakur 2012)	4.9650
GA (Khazali and Kalantar 2011)	4.98
PSO (Roy, Ghoshal, and Thakur 2012)	5.09219

Table 5. Comparison results of different methods.

Sl. No	P_{losses} (MW)	VD (p.u.)	F
Initial value	5.596	0.8691	4.1779
Proposed BSA	4.8031	0.5075	3.5144
GSA (Suresh et al. 2013)	4.8210	0.5366	3.5350

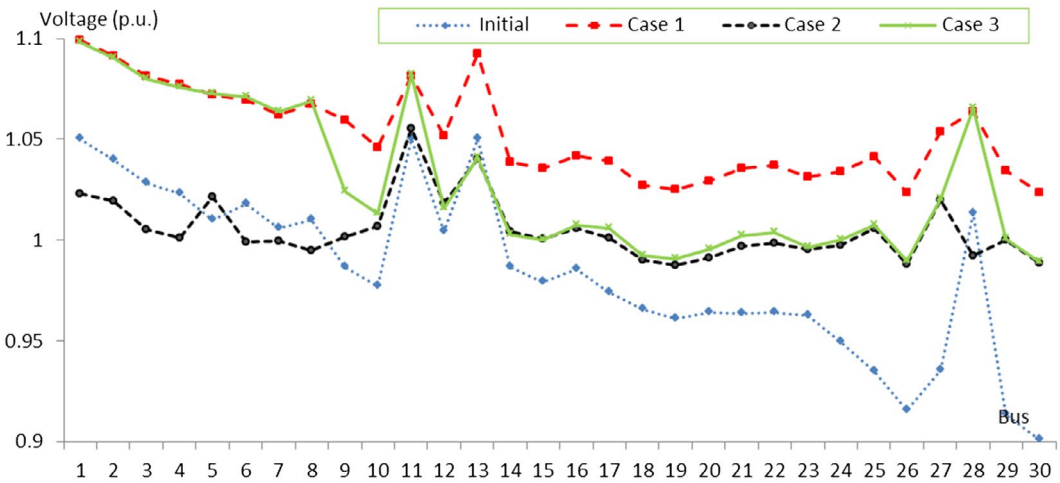

Figure 7. Voltage profile distribution for all studied cases.

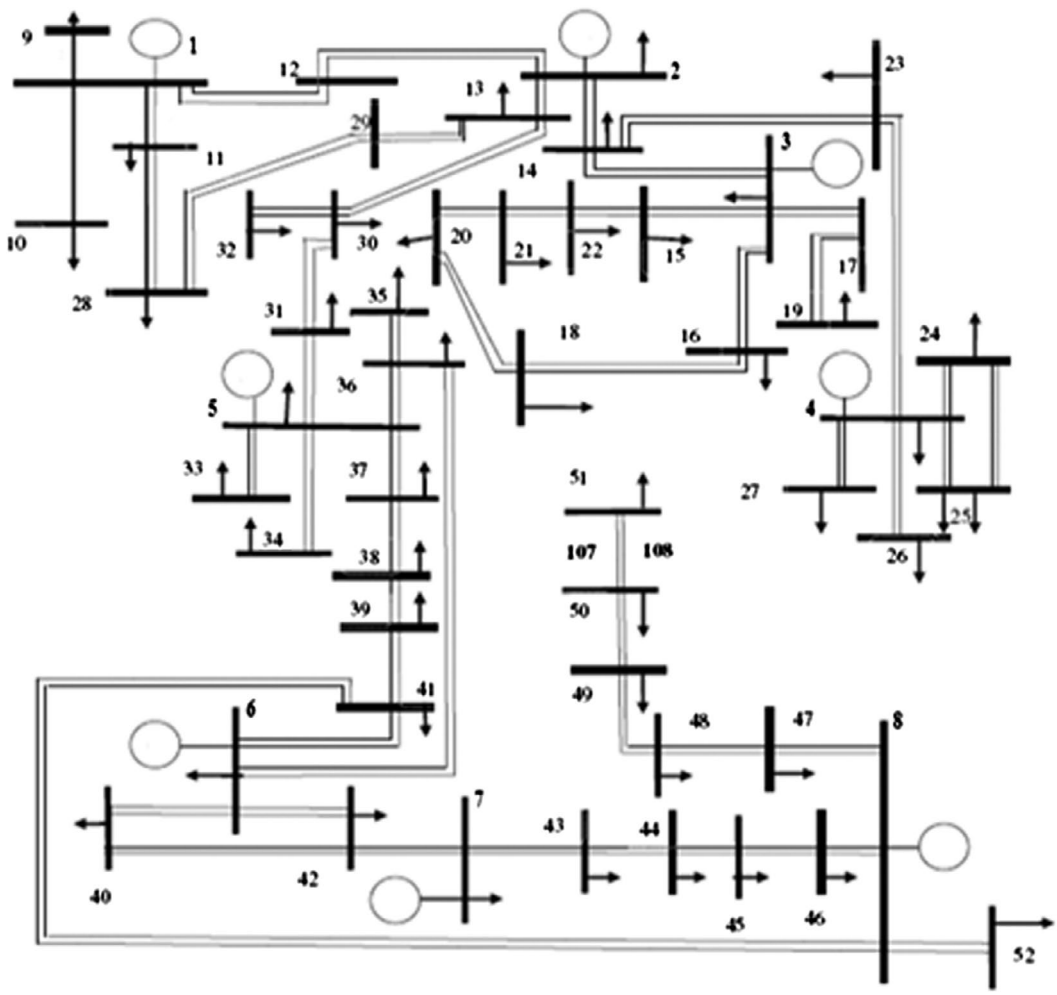

Figure 8. Single-line diagram for 52-bus actual system of WDN.

profile is greatly improved compared to that of the initial case. Also, the voltage magnitudes of the load buses are around the reference value of 1 p.u. when considering the voltage profile as objective function (Case 2).

4.2. West Delta region system

The West Delta region (WDN) system is a part of the Unified Egyptian network, which consists of 52 buses and 8 generators connected by 108 lines (Abou El Ela, Abido, and Spea 2011; Abou El Ela, El Sehiemy, and

Table 6. Generators power limits in MW and MVAR.

Control/dependent variable (p.u.)	Min	Max
V_{g1}	1	1.1
V_{g2}	0.95	1.05
V_{g3}	0.95	1.05
V_{g4}	0.95	1.05
V_{g5}	0.95	1.05
V_{g6}	0.95	1.05
V_{g7}	0.95	1.05
V_{g8}	0.95	1.05
Q_{g1}	−1.5	1.5
Q_{g2}	−1.5	1.5
Q_{g3}	−1.2	1.2
Q_{g4}	−2	1.5
Q_{g5}	−1	1.2
Q_{g6}	−1.5	1.5
Q_{g7}	−1.5	1.5
Q_{g8}	−2.5	1.2

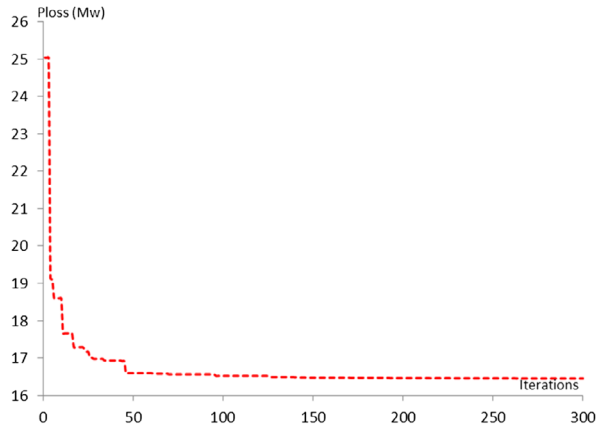

Figure 9. Convergence characteristics of power losses minimisation (Case 1).

Table 7. Simulation results of the proposed BSA for Case 1.

Control/dependent variable (p.u.)	Initial Case	LP (Abou El-Ela et al. 2011)	GA (Abou El-Ela et al. 2011)	PSO (Abou El-Ela et al. 2011)	ACO (Abou El-Ela et al. 2011)	DE (Abou El Ela, Abido, and Spea 2011)	Proposed BSA
V_{g1}	1.05	1.0744	1.0753	1.0313	1.0385	1.0560758	1.0554
V_{g2}	1	1.0159	1.0435	1.0478	0.9692	1.05	1.05
V_{g3}	1	0.9950	0.9872	0.9986	0.9695	1.05	1.0496
V_{g4}	1	1.0019	1.0374	1.0241	0.9835	1.0495903	1.0495
V_{g5}	1	1.0130	0.9638	1.0113	1.0465	1.049137	1.0491
V_{g6}	1	1.0084	1.0223	0.9794	0.9544	1.0178004	1.0226
V_{g7}	1	1.0076	1.0125	1.0387	1.0182	1.0103975	1.016
V_{g8}	1	1.0066	0.9872	0.9686	0.9673	1.0249314	1.029
Q_{g1}	0.6837	−0.9314	−0.4238	−0.106	−0.682	0.3921513	0.388
Q_{g2}	−0.216	0.7907	0.4649	0.530	0.131	0.0037864	0.0094
Q_{g3}	1.0816	−0.7342	0.6398	0.940	−0.898	1.0369948	1.0355
Q_{g4}	1.0315	−1.7452	−1.2347	−1.470	−1.237	1.0220706	1.0221
Q_{g5}	0.4663	1.1691	0.9674	0.630	0.862	0.8135661	0.761
Q_{g6}	0.8388	−1.4325	−1.3832	−1.001	−0.799	0.5366202	0.5805
Q_{g7}	0.9836	1.4185	1.4924	1.362	1.037	0.8150724	0.8314
Q_{g8}	0.3114	−2.0135	−0.1865	−0.500	−0.217	0.4057566	0.3957
P_{losses} (MW)	19.0443	27.68	21.16	18.73	16.98	16.461342	16.4515

Table 8. Simulation results of the proposed BSA for Cases 1 and 2.

Case study		Case 2				Case 3			
Control/dependent variable (p.u.)	Initial case	GA (Abou El-Ela et al. 2011)	PSO (Abou El-Ela et al. 2011)	DE (Abou El Ela, Abido, and Spea 2011)	Proposed BSA	GA (Abou El-Ela et al. 2011)	PSO (Abou El-Ela et al. 2011)	DE (Abou El Ela, Abido, and Spea 2011)	Proposed BSA
V_{g1}	1.05	1.0070866	1.0061429	1.0063963	1.0069	1.0267717	1.0294586	1.0269061	1.0270917
V_{g2}	1	1.0248031	1.0245017	1.0257804	1.0275	1.0452756	1.0460768	1.0451059	1.0453953
V_{g3}	1	1.0492126	1.0482797	1.05	1.05	1.05	1.0499584	1.05	1.0499775
V_{g4}	1	1.0098425	1.0099596	1.0086506	1.0088	1.0208661	1.0208788	1.0212033	1.0212012
V_{g5}	1	1.0224409	1.0178781	1.018522	1.018	1.0374016	1.0391201	1.0383879	1.0386979
V_{g6}	1	1.0019685	1.0019121	1.0052128	1.0057	1.0129921	1.0129446	1.0126209	1.01283
V_{g7}	1	1.0169291	1.0167366	1.0161819	1.0162	1.0098425	1.0080736	1.0078625	1.0081705
V_{g8}	1	1.026378	1.0286738	1.026272	1.0263	1.0240157	1.0244481	1.0244172	1.0242526
Q_{g1}	0.6837	0.2470908	0.2468118	0.2409162	0.2346	0.2418153	0.252584	0.2427555	0.2420054
Q_{g2}	−0.216	0.1049728	0.119336	0.1334846	0.1589	0.2355017	0.2289571	0.2285471	0.2315203
Q_{g3}	1.0816	1.1723737	1.1695599	1.1719042	1.1635	1.0738494	1.0698906	1.074476	1.0730166
Q_{g4}	1.0315	0.954772	0.9568229	0.9459521	0.9398	0.921439	0.9184725	0.9234403	0.9223449
Q_{g5}	0.4663	0.7016736	0.6383067	0.6153042	0.5985	0.736851	0.7562369	0.7540898	0.7557613
Q_{g6}	0.8388	0.1337806	0.1544702	0.2995602	0.3217	0.5025043	0.5041977	0.5035197	0.5052465
Q_{g7}	0.9836	1.1683638	1.1565436	1.1059507	1.0988	0.8799391	0.846243	0.8472742	0.8504937
Q_{g8}	0.3114	0.6275756	0.6741719	0.5962041	0.5917	0.4652085	0.4772885	0.4823835	0.4755937
P_{losses} (MW)	19.0443	18.074109	18.21754	18.070247	18.0467	16.975549	16.910462	16.958759	16.949295
VD (p.u.)	1.1148	0.5125694	0.516893	0.5080154	0.5072	0.7105247	0.7366209	0.7150986	0.7187961
F	6.4937	–	–	–	–	5.5900321	5.5887733	5.5881968	5.5879456

Shaheen 2013). Figure 8 shows the single line diagram of the real power system for the WDN. The operational minimum and maximum limits of generation and load buses voltages are 0.94 and 1.06, respectively. On load tap changer (OLTC) limits between buses 4–25 and 11–28 are considered between 0.9 and 1.1 p.u. (the base voltage is 66 kV, while the base MVA is 100). The WDN system active and reactive loads equal 889.75 MW and 539.98 MVAR. There are four violated bus voltages at buses 18, 20, 21 and 22. Table 6 shows the initial values of active power and voltages at generators, and the limits of reactive power outputs.

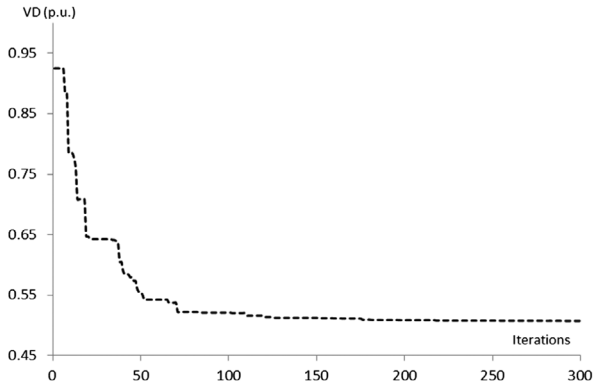

Figure 10. Convergence characteristics of minimising the sum of the voltage deviation of load buses (Case 2).

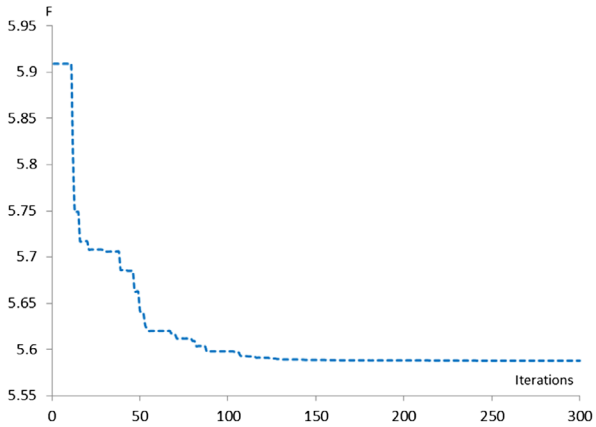

Figure 11. Convergence characteristics of minimising the weighted sum objective (*F*) (Case 3).

4.2.1. Case 1: minimisation of power losses

The proposed BSA has been run for Case 1 and the optimal control variables and its corresponding results are shown in Table 7 where, the convergence characteristics of minimising the power losses over iterations are shown in Figure 9. From both, the proposed BSA reduced the active power losses from 19.0443 MW to 16.4515 MW. This reduction is equivalent to 13.61%. In Table 7, the use of BSA for solving the ORPD problem leads to obtain the highest reduction of power losses (P_{losses} = 16.4515 MW) while, other optimisation techniques lead to the following losses 27.86, 21.16, 18.73 and 16.98 MW for LP, GA, PSO and ACO, respectively.

4.2.2. Case 2: improving the voltage profile distribution

In this case, the optimal control variables and its corresponding results obtained by the proposed BSA are shown in Table 8 and the convergence characteristics of minimising the sum of the voltage deviation of load

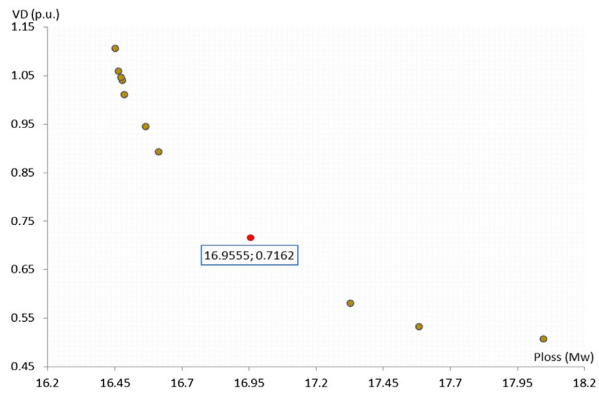

Figure 13. Voltage deviation vs. power losses with different weight factors.

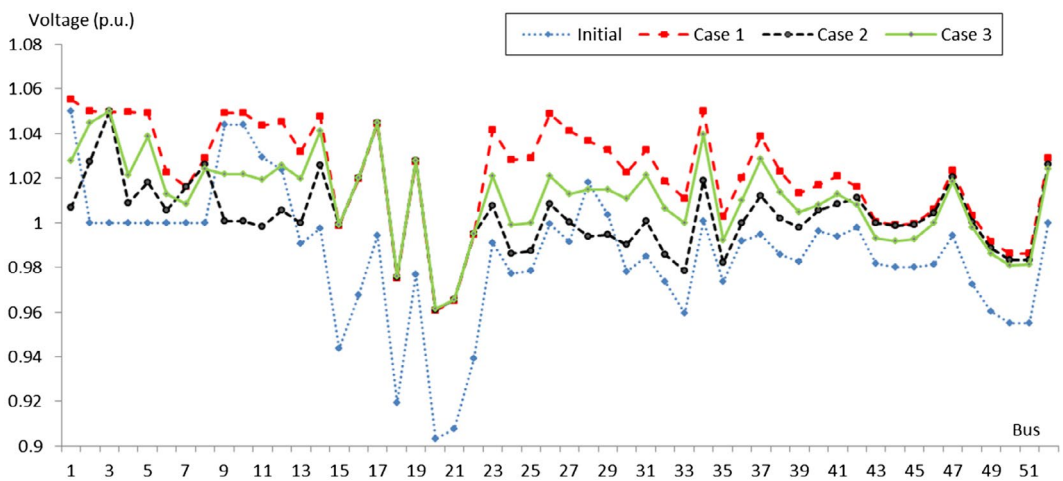

Figure 12. Voltage profile distribution for all studied cases.

buses are illustrated in Figure 10. As shown, the proposed BSA reduced the sum of the voltage deviation of load buses from 1.1148 to 0.5072 p.u. Added to that, the proposed BSA is better than GA, PSO and DE in handling Case 2 as demonstrated from the comparisons in Table 8.

4.2.3. Case 3: minimisation of power losses and voltage profile improvement

For considering the real power losses and voltage deviation, the weighing factor (ω_f) in Equation (4) is set to 0.3. The proposed BSA has been run for this case and the optimal control variables and its corresponding results are shown in Table 8. The convergence characteristics for this case are shown in Figure 11. From both, the proposed BSA reduced the weighted sum objective (F) from 6.4937 to 5.588. For this case, the obtained power losses (16.9433 MW) and the sum of the voltage deviation of load buses (0.7214 p.u.) are much closed to the best losses acquired in Case 1 (16.4515 MW) and the best sum of the voltage deviation of load buses recorded in Case 2 (0.5072 p.u.). From Table 8, the proposed BSA outperforms the other existing methods such as GA, PSO and DE in handling Case 3. Figure 12 plotted the voltage profile obtained by the proposed BSA for all cases which demonstrated that the violated bus voltages at buses 18, 20, 21 and 22 are corrected. Also, the voltage magnitudes of the load buses when considering the voltage profile as objective function (Case 2) are better than the corresponding values in other cases.

Despite the weight factor in Equation (4) is set to 0.7 as provided in Suresh et al. (2013a), it is usually chosen by the operator and his experience to differentiate between the competed objectives. Therefore, different weight factors are taken into consideration from 0 to 1 with step 0.1 to provide corresponding operating settings as plotted in Figure 13:-

5. Conclusions

BSA is a newly-proposed evolutionary optimisation search algorithm, which is simply designed to benefit from previous populations. In each generation, BSA mutation strategy produces very efficient trial populations since it produces both large amplitude values for global search and small amplitude values for local search. The current paper handled the ORPD problem using BSA. The ORPD problem has been modelled to minimise the power losses and/or improve the voltage profile under control and dependent variable constraints. The proposed algorithm has been tested on the IEEE standard 30-bus system, and a real power system at West Delta Network as a part of the Unified Egyptian Network. Simulation results show the capability of the proposed BSA for solving the ORPD problem. In addition, the BSA results were compared with the other heuristic methods reported in the literature and demonstrated its effectiveness and robustness. According to the raised results, there are no limitations for applying the BSA approach to solve the considered ORPD problem since it doesn't require determining any fixed value for its strategic parameter where, the value of the mutation factor is automatically varied using the standard normal distribution. It is worthy mentioned that diversified generation strategies of mutation factor, as an extension work, are proposed to be applied for solving the ORPD problem.

Disclosure statement

No potential conflict of interest was reported by the authors.

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