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ORIGINAL ARTICLE

A reactive power planning procedure considering iterative identification of VAR candidate buses

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Abstract This article proposes two-step procedure for solving the reactive power planning (RPP) problem. An iterative method is introduced in the first step to place the additional sources of reactive power and their associated maximum sizes. In the second step, several integrated strategies of differential evolution (DE) are suggested to optimize the RPP variables. Three types of objective function are investigated which aims at minimizing system power losses, minimizing the costs of operation and VAR investment and improving the voltage profile distribution at load buses. The strategies performance is examined on IEEE 30-bus test system and on the West Delta network as a real Egyptian section. The evolution of the system considering the annual growth rate of peak load in the Egyptian system has been taken into consideration at different loading levels. Application of the proposed method is carried out on large-scale power system of 354-bus test system. The strategies robustness and consistency are compared to DE, genetic algorithm and particle swarm optimizer. The proposed two-step procedure using the proposed DE strategy is assessed compared to single-step RPP procedure. Furthermore, its mutation and crossover scales are optimally specified. Simulation outcomes denote that the proposed DE strategy is excessively superior, more powerful and consistent than the other compared optimizers which indicate that the proposed strategy of DE algorithm can be very efficient to solve the RPP. The proposed strategies are proven as alternative solution strategies, especially for large-scale power systems.

Keywords Reactive power planning problem · Annual growth rate · DE strategies · Control parameter · Two-step optimization procedure

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Abbreviations

CMAES	Covariance matrix adaptation evolution strategy
COMs	Classical optimization methods
DE	Differential evolution
DOE	Design of experiment
EP	Evolutionary programming
GA	Genetic algorithm
IM	Iterative method
IP	Interior point
LP	Linear programming
MFLP	Multi-objective fuzzy linear programming
MIP	Mixed integer programming
MNSGA-II	Modified nondominated sorted genetic algorithm-II
MOs	Meta-heuristic optimizers
NLP	Nonlinear programming
PSO	Particle swarm optimizer
QP	Quadratic programming
RGA	Real-coding genetic algorithm
RPP	Reactive power planning

SO	Seeker optimizer
SQP	Sequential quadratic programming
WDN	West Delta network

1 Introduction

Due to the constant growing of electrical loads, the existed VAR sources became insufficient which resulted in gradual drop of the system nodes voltage. Thus, VAR resources shall be planned and disseminated throughout the power systems to meet the future demands and ensure system performance which is indicated as RPP.

The control variables of RPP problem are the generator bus voltages, the injected reactive power from existing, additional reactive power sources and tap ratio of transformers. It has been exceedingly solved by various classical optimization methods (COMs) such as linear, quadratic, mixed integer, nonlinear programming techniques and interior point algorithm. COMs have still been implemented and developed for solving the RPP. A NLP solver has been applied in [1], while LP-based IP method has been used in the second stage to minimize both the power losses and the generator's reactive cost function for each zone by approximating it to a piecewise-linear function [2]. Both NLP and MINLP solver using GAMS software have also been implemented in [3]. Also, multiple stages of a stochastic nonlinear RPP model have been handled using MINLP [4]. A dual projected pseudoquasi-newton method has been utilized as a solution procedure in [5] for the capacitor placement patterns to reduce the transmission losses, while the investment cost for VAR sources has been handled as budget constraint. For the same purpose, IP method has been employed where the weak buses have been selected as candidates to install VAR sources based on L-index as a voltage stability index [6].

In the last two decades, the RPP has been widely solved using various meta-heuristic optimizers (MOs) such as GA [7, 8], real-coding GA (RGA) [9], modified nondominated sorted GA-II (MNSGA-II) [10], multi-objective fuzzy LP (MFLP) [11–13], covariance matrix adaptation evolution strategy (CMAES) [14], PSO [15–17], evolutionary programming [18, 19], seeker optimizer (SO) [20], differential search algorithm [21] and DE [22–29]. In [26], an improved model of it has been presented where the mutation factor changed dynamically instead of being constant. In [27, 28], the original DE strategy has been modified using a self-tuned mutation parameter. In [29], two DE versions have been applied to the RPP for minimizing the costs of operation and VAR investment. In spite of these multi-executed references of the DE algorithm to the RPP problem, the only applied DE strategy uses a randomly chosen base vector mutated by appending a scaled random difference vector [30]. In [31], a hybrid between DE algorithm and the ant system has been proposed to minimize the power losses, voltage deviation and operating costs. In [32], gravitational search algorithm has been utilized to enhance the voltage profile, the voltage stability or minimize the power losses. Furthermore, optimal planning of reactive power sources is proposed for enhancing the power systems under contingencies [33].

The RPP problem could be formulated with single or multiple objectives. However, modeling of each objective function has different formulations [34]. The searching for optimal solution is enhanced with unexpected locations for new VAR sources when all load buses are considered as candidate buses. However, the searching space, time-consuming, complexity and computational burden will be high, especially in large power systems [35]. Thus, the optimal placement of new reactive power sources may be considered a first step in RPP which have maximum effect on the technical and economical objects in power systems where different methods have been implemented to choose the candidate locations [36]. The reactive power dispatch problem is solved by several integrated strategies of backtracking search and ant colony algorithms in [37, 38], respectively.

In the optimization field, several novel optimizers of bioinspired meta-heuristic algorithms have been still proposed for solving global numerical optimization problems such as earthworm optimization algorithm [39], monarch butterfly optimization [40] and krill herd algorithm incorporated a mutation scheme [41]. In [42], a novel chaotic cuckoo search optimizer has been presented by emerging chaotic effect into cuckoo search technique. Another novel improved version of firefly algorithm has been applied for global numerical optimization [43]. In [44], a hybridized technique between krill herd and quantum PSO is presented for handling engineering optimization problems. In [45], the fruit fly optimization algorithm was developed for solving global optimization problem and applied for the optimal design of shape design of tubular linear synchronous motor.

COMs have been widely applied to solve the RPP for years [1–6] because they are fast and so they provide the capability to solve a high number of single optimizations in case of different loading conditions and contingencies. However, their main drawbacks are that they are usually based on some simplifications such as linear approximations of nonlinear functions and constraints or using their first and second differentiations. Another shortage of COMs is the weakness treatment of multi-objective nonlinear optimization problems [35]. They may trap in a local optimum result in divergences in solving RPP problems [19, 35]. Furthermore, they cannot handle the nondifferentiable factor in VAR sources installation function [8, 14].

This paper proposes two-step procedure on account of solving the reactive power planning (RPP). In the first step, the candidate VAR locations are selected based on the weakness voltage levels of the load buses with iterative VAR injection. In the second step, various DE strategies are proposed for handling the RPP. The proposed strategies are distinguished with diverse exploration and exploitation search capability which give diversified solutions. They are analyzed in a comparison with the computation intelligence techniques which have often been used to solve this problem. Else, the optimal tuning of the mutation and crossover parameters of the proposed algorithm is discussed. Its robustness indices are checked in comparison with the other optimization algorithms. Added to that, the proposed two-step procedure was assessed compared to single-step RPP procedure.

In [46], a two-step approach has been implemented analytically for voltage support by use of the design of experiment (DOE) method where the optimal locations of the VAR devices have been firstly identified and then a sizing process of those devices has been carried out. Compared to the proposed procedure, the DOE approach [44] has been tested on a small distribution networks (28-bus radial medium voltage network) based on some simplifications by reducing the number of control variables (only 2) in the second stage which may not be suitable for medium- and large-scale power systems. The DOE approach employed the screening approach over a small set of buses to identify the optimal VAR locations, and it did not discuss the effects of the others. However, the reduction of the losses and including the voltage profile has been utilized as objectives in the DOE approach, minimizing the costs of operation, and VAR investment is a considerable objective function in the planning problem [35] since it has great effects on the optimal decision.

However, the presented paper deals with one of the important optimization problems in power systems which has been taken into consideration in many previous published articles; it provides various contributions as follows:

- Three types of objective function are investigated: (1) minimizing system power losses, (2) minimizing the costs of operation and VAR investment and (3) improving the voltage profile distribution.
- Several strategies of differential algorithm are proposed, compared and examined on IEEE 30 bus and West Delta network (WDN) as a section in the Egyptian power system. The strategies robustness and consistency are compared to genetic algorithm (GA), particle swarm optimizer (PSO) and DE.
- Also, application of the proposed method is carried out on large-scale power system of 354-bus test system.
- The proposed two-step procedure using the proposed DE strategy is assessed compared to single-step RPP procedure.
- Furthermore, its mutation and crossover scales are optimally specified. Simulation outcomes denote that the proposed DE strategy is excessively superior, more powerful and consistent than the other compared optimizers which indicate that the proposed strategy of DE algorithm can be very efficient to solve the RPP. The proposed strategies are proven as alternative solution strategies, especially for large-scale power systems.
- Nevertheless, the evolution of the system considering the annual growth rate of peak load in the Egyptian system has been taken into consideration with different loading levels.

The rest sections of this paper are ordered as follows: Sect. 2 presents the RPP formulation. Section 3 introduces the suggested procedure for solving the RPP. The simulation results of the case studies are presented in Sect. 4, while the last section represents the conclusion of the work.

2 Formulation of the reactive power planning

Conventionally, the RPP objective is to minimize the investment cost of new VAR sources and the system operational cost [27–29].

2.1 Objectives

2.1.1 Minimizing the costs of energy loss and investment

The operational cost (O_C) is related to the annual cost of energy losses, while the investment cost (I_C) has two components, fixed installation part and variable purchase cost as follows:

$$\text{Min}\, F = \text{Min}\ (O_C + I_C)$$

$$\text{where}, O_C = H\sum_{L=1}^{N_{\text{Load}}} d_L P_{\text{loss}}^L \text{and}\, I_C = \sum_{i=1}^{N_c} e_i + C_{c_i}|Q_{c_i}^n| \tag{1}$$

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

where N_{Load} indicates the number of load levels; H indicates the energy cost in per unit; d_L refers to each load duration (hours); P_{Loss}^L is the losses during each load period L; N_c is the reactive compensator buses; e refers to fixed installation cost of VAR sources; C_{c_i} is its corresponding purchase cost; Q_C^n refers to the reactive power output of the additional VAR source; N_b indicates the buses number; g_{ij} and θ_{ij} indicate the branch conductance and voltage angle difference between buses i and j, respectively; V refers to the voltage magnitude.

2.1.2 Improvement in voltage profile

The enchantment of voltage profile can be formulated by minimizing the deviation of the load voltages (VD) at N_{PQ} load buses as:

$$\text{Min VD} = \left(\sum_{i=1}^{N_{PQ}} \left| V_i - V_i^{\text{ref}} \right| \right) \tag{3}$$

This objective could be simply included to the classical objective of the RPP using the weighted sum approach [35]:

$$\text{Min } F = \text{Min} \left(O_C + I_C \right) + \omega * VD \tag{4}$$

where ω is a suitable weight factor selected by the planner to give an importance to each one of the objective functions.

2.2 Equality and inequality constraints

The electric power networks have to maintain the equality constraints, which are denoted by the load flow balance equations and the inequality operational constraints of the operational variables. These constraints could be formulated as:

$$Q_{gi} - Q_{Li} + Q_{Ci}^n + Q_{Ci} - V_i \sum_{j=1}^{N_b} V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) = 0, \quad i = 1, 2, \ldots N_{PQ} \tag{5}$$

$$P_{gi} - P_{Li} - V_i \sum_{j=1}^{N_b} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) = 0, \quad i = 1, 2, \ldots N_b - \text{slack} \tag{6}$$

$$Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max}, \quad i = 1, 2, \ldots N_{pv} \tag{7}$$

$$V_i^{\min} \le V_i \le V_i^{\max}, \quad i = 1, 2, \ldots N_b \tag{8}$$

$$T_q^{\min} \le T_q \le T_q^{\max}, \quad q = 1, 2, \ldots N_t \tag{9}$$

$$\left| S_L^{\text{flow}} \right| \le S_L^{\max}, \quad L = 1, 2, \ldots N_L \tag{10}$$

$$0 \le Q_{Cx} \le Q_{Cx}^{\max}, \ldots x = 1, 2, \ldots N_C \tag{11}$$

$$0 \le Q_{Cj}^n \le Q_{Cj}^{\max(\text{n})}, \quad j \in \text{candidate buses} \tag{12}$$

$$P_s^{\min} \le P_s \le P_s^{\max} \tag{13}$$

where Q_g, Q_L and Q_C are the reactive power of generator, power demand and for the existing VAR injections, respectively; G_{ij} and B_{ij} are mutual conductance and susceptance between bus i and j, respectively; P_g and P_L are the active power output of generator and the active demand, respectively; N_{pv} is the voltage-controlled buses number; T_q and N_t are the tapping change of a transformer q and their total number, respectively; S^{flow}, $S^{\max}$ and N_L refer to the MVA flow through the transmission lines, their maximum MVA rating and their total number, respectively. Q_{c_x} and $Q_c^{\max}$ are the existing VAR injection at bus x and its capacity; P_s, $P_s^{\min}$ and $P_s^{\max}$ are the slack active power, its minimum and maximum limits.

In the equality constraints, the tapping change of a transformer (T_k) is modeled inside the bus admittance matrix where the branches, phase shifters and transformers are formulated with the standard π model [47]. Each transmission line is modeled with branch admittance matrix (Y_{br}) as follows:

$$Y_{\text{br}} = \begin{bmatrix} \left(y_k + j \dfrac{b_k}{2} \right) \dfrac{1}{T_k^2} & -y_k \dfrac{1}{T_k e^{-j\theta_{\text{shift}}}} \\ -y_k \dfrac{1}{T_k e^{j\theta_{\text{shift}}}} & y_k + j \dfrac{b_k}{2} \end{bmatrix} \tag{14}$$

where y_k and b_c are the series admittance and the total charging capacitance of the line; θ_{shift} is the phase shift angle of the transformer.

3 Proposed procedure for reactive power planning

3.1 Salient stages of DE algorithm

The major stages of DE algorithm are shown in Fig. 1. As shown, it begins with initialization step after identifying its parameters, the population size (NP) of the individuals (X) with D-dimensional variables and the maximum iterations number ($I^{\max}$). The individuals in this initial population are randomly distributed over the D-dimensional search space. Then, the objective value of each individual is evaluated. After that, each individual is updated according to the mutation and crossover operations as follows:

$$X_{i,j}(I+1) = \begin{cases} V_{i,j}(I+1) = X_{r1,j}(I) + F * (X_{r2,j}(I) - X_{r3,j}(I)) & \text{if} \quad rand(0,1) < Cr \\ X_{i,j}(I) & \text{else} \end{cases} \tag{15}$$

where X_{r1}, X_{r2} and X_{r3} are three randomly chosen and similar vectors, V is the mutant vector, F is the mutation constant in the range of [0.4–1], and Cr is the crossover probability within the range [0, 1]. Then, the corresponding objectives of the individuals are evaluated. Afterward, each new individual is compared with the previous one on the basis of the objective value and new population is selected in the next iteration which provides better solutions. These

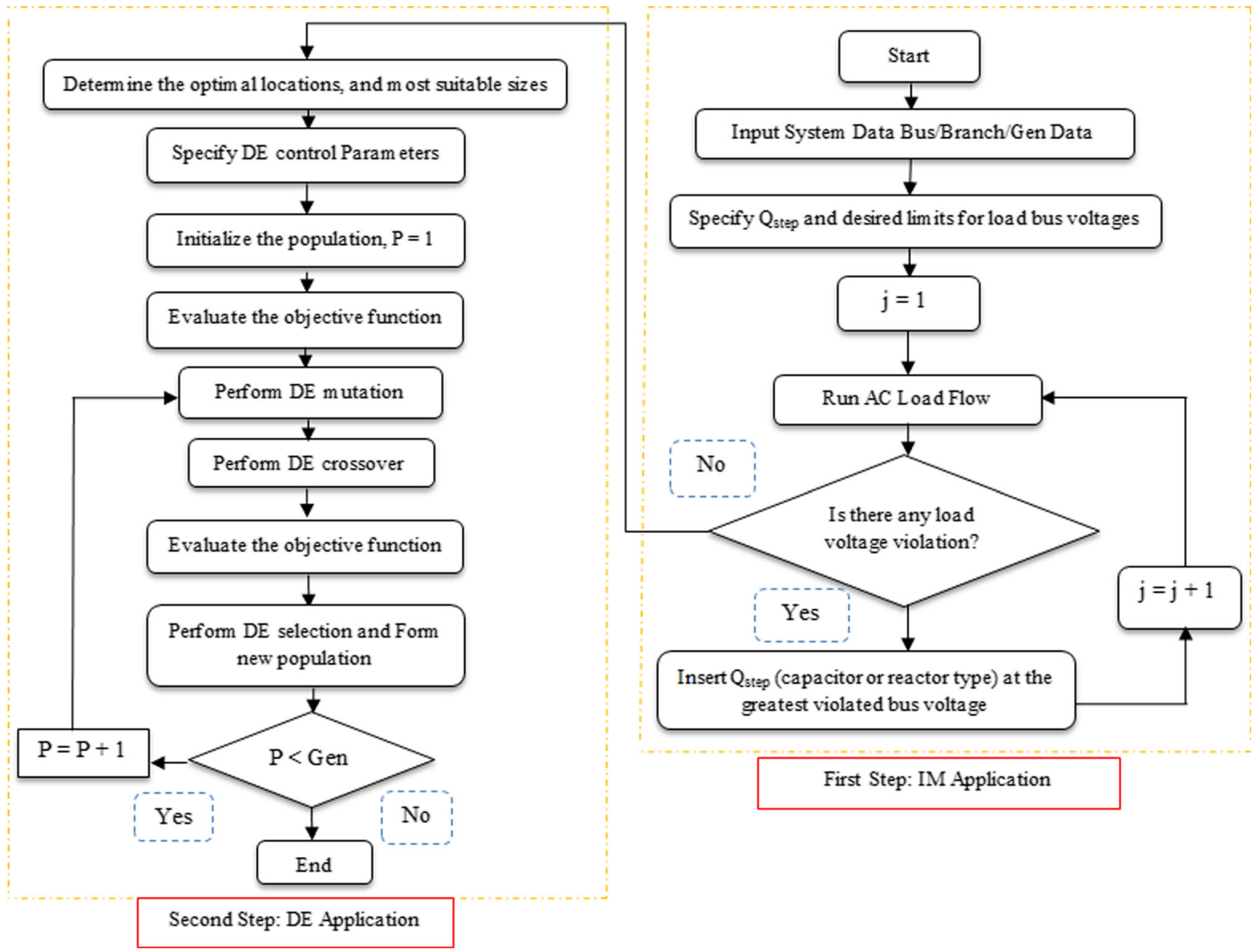

Fig. 1 Flowchart of the proposed two-step procedure

steps are reiterated until the maximum number of iterations is achieved or other stopping method is applied.

3.2 DE strategies

In Table 1, a summary is presented to define the basic difference of different DE strategies from the DE algorithm stated above. These strategies differ from each other based on mutation operator. Each one is addressed as DE/*a*/*b*/*c*. *a* indicates the kind of perturbation, *b* indicates the number of difference individuals, and *c* indicates the kind of crossover.

In Table 1, $r1$–$r5$ are random integers within the range [1, *NP*], and they are unlike the vector *i*. X_{best} refers to the vector with best objective value. These DE strategies are worked with the binomial crossover operator as Eq. 15. Added to that, the individual is reinitialized randomly if any dimensional variable is exceeded its limits, while the dependent variables augmented as penalty terms inside the objective function as follows:

$$f = F + \mathrm{K}_v \sum_{Nv_V} \Delta V_{\text{Load}}^2 + \mathrm{K}_q \sum_{Nv_Q} \Delta Q_g^2 + \mathrm{K}_{Ps} \Delta P_s^2 + \mathrm{K}_{Sf} \sum_{Nv_{Sf}} \Delta S_f^2 \quad (16)$$

Table 1 Table summary of the different DE strategies [30]

No.	DE strategy	Kind of mutation
DE 1	DE/rand/1	$V_{i,j}(I+1) = X_{r1,j}(I) + F.(X_{r2,j}(I) - X_{r3,j}(I))$
DE 2	DE/rand to best/1	$V_{i,j}(I+1) = X_{i,j}(I) + F.(X_{r1,j}(I) - X_{r2,j}(I)) + F.(X_{\text{best},j}(I) - X_{i,j}(I))$
DE 3	DE/best/1 [48]	$V_{i,j}(I+1) = X_{\text{best},j}(I) + F.(X_{r1,j}(I) - X_{r2,j}(I))$
DE 4	DE/best/2	$V_{i,j}(I+1) = X_{\text{best},j}(I) + F.(X_{r1,j}(I) - X_{r2,j}(I)) + F.(X_{r3,j}(I) - X_{r4,j}(I))$
DE 5	DE/rand/2	$V_{i,j}(I+1) = X_{r1,j}(I) + F.(X_{r2,j}(I) - X_{r3,j}(I)) + F.(X_{r4,j}(I) - X_{r5,j}(I))$

where K_v, K_q, K_{Ps}, K_{Sf} are the penalty factors, Nv_V refers to the set of violated load voltages, Nv_Q refers to the set of violated reactive outputs of generators, Nv_{Sf} refers to the overflow set of branches, ΔV_{Load}, ΔQ_g, ΔP_s and ΔS_f are defined as follows:

$$\Delta V_{\text{Load}} = \begin{cases} V_{\text{Load}}^{\min} - V_{\text{Load}} & \text{if} \quad V_{\text{Load}} < V_{\text{Load}}^{\min} \\ V_{\text{Load}}^{\max} - V_{\text{Load}} & \text{if} \quad V_{\text{Load}} > V_{\text{Load}}^{\max} \end{cases} \tag{17}$$

$$\Delta Q_g = \begin{cases} Q_g^{\min} - Q_g & \text{if} \quad Q_g < Q_g^{\min} \\ Q_g^{\max} - Q_g & \text{if} \quad Q_g > Q_g^{\max} \end{cases} \tag{18}$$

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

$$\Delta S_f = S_f^{\max} - S_f \quad \text{if} \quad S_f > S_f^{\max} \tag{20}$$

where superscripts “min” and “max” indicate the minimum and maximum of a variable.

3.3 Proposed procedure

A two-step procedure is proposed to handle the RPP. An IM is introduced to place the additional sources of reactive power and their associated maximum sizes in the first step as depicted in Fig. 1. As shown, an AC load flow is performed and if there are any violations of load buses voltage out of the desired specified limits, the bus with the exceeded/lowest voltage is determined. Subsequently, an identified step size of a reactor/capacitor is added to that violated, respectively. An AC load flow is performed again and so until the voltage of the load buses is to be inside the desired identified limits. This IM is flexible that it can find different strategies for the RPP which is helpful for various trends to operate the power system. This can be achieved based on identifying the step size and the desired voltage limits. The output of this IM is the candidate VAR buses and their associated maximum sizes to be utilized in the second step. For this purpose, the compensation step and the minimum desired voltage are specified at 0.1 MVAR and 1 p.u., respectively, while $I^{\max}$ is 1000.

In the second step, various DE strategies are suggested for handling the RPP. To assess the single-step optimization procedure, only the second step of the two-step optimization procedure is employed to obtain the RPP solution considering all buses as candidate buses.

4 Applications

To estimate the performance and efficiency of the suggested strategies to handle the RPP, IEEE 30 bus and the WDN are used. These power systems are considered at their peak loads, while the active power outputs are predefined. Additional case study is applied for IEEE 354-bus test network [49, 50] as a large-scale power system.

For simulation studies, GA with crossover factor = 0.80 and mutation factor = 0.20 [7], DE/rand/1, and PSO with learning factors = 2, and inertia factors ($\omega_{\max} = 0.90$ and $\omega_{\min} = 0.40$) are utilized. The velocities related to PSO are reinitialized if they are violated 80% of their concerned particles. The DE’s crossover and mutation factors are 0.90 and 0.60, respectively. h, e_i and C_{ci} (Eq. 1) have been considered equal to 60 \$/MWh, 1000 \$ and 30,000 \$/MVAR, respectively, as taken in most articles [8–10, 13, 15, 17, 18, 22, 26–28]. $NP = 50$ and $I^{\max} = 300$. To show the capability of the proposed strategies, three cases have been studied as follows:

Case 1: Minimization of system power losses.
Case 2: Minimization of total costs of operation and VAR investment.
Case 3: Voltage profile improvement.

Added to that, a comparative to the single-step optimization procedure is presented. The effects of discrete model are discussed compared to the continuous model of decision variables.

4.1 Simulation results for IEEE 30-bus system

It comprises of 30 buses, 6 generators, 41 lines, 4 on-load tap change transformers and 2 existed VAR sources at buses 10 and 24. The generator, load voltages and tap changing of transformer are bounded between 0.90 and 1.10. The data of IEEE 30-bus system are taken from MATPOWER 5.0b1 [50].

In the first step, the proposed IM is carried out. Initially, the weakest location is node 30 with lower voltage of 0.901 p.u. Thus, node 30 is firstly chosen and injected by a VAR step (Q_{step}) equals 0.1 MVAR step (0.1 MVAR). Then, power flow program is run again and so until the voltage of the load buses is inside the desired identified limits. Finally, the VAR candidate buses are identified at 18, 19, 21, 23, 24, 26, 27, 29 and 30 and their associated maximum sizes are 0.70, 7.10, 7.70, 1.30, 11.40, 4.70, 2.10, 2.40 and 8.10 MVAR, respectively.

In the second step, GA, PSO and the proposed DE strategies are employed. Tables 2 and 3 show the corresponding results for Cases 1 and 2, respectively. In these tables, P_{save} and C_{save} denote the percentage saving of the power losses and the costs of energy loss and investment, respectively, with respect to the initial condition. For minimizing the power losses, DE 2 and DE 3 achieved the highest reduction of losses with 18.98 and 18.99%, respectively, where DE 1 and DE 4 attained reductions of

Table 2 Simulation results of the compared approaches to minimize the losses for IEEE 30-bus test system (Case 1)

Variables	Initial	GA	PSO	DE 1	DE 2	DE 3	DE 4	DE 5
Vg_1	1.050	1.0995	1.0968	1.0999	1.10	1.10	1.0999	1.0998
Vg_2	1.040	1.0914	1.0862	1.0935	1.0943	1.0943	1.0941	1.0940
Vg_5	1.010	1.0732	1.0712	1.0734	1.0748	1.0748	1.0746	1.0753
Vg_8	1.010	1.0758	1.0651	1.0756	1.0765	1.0765	1.0763	1.0762
Vg_{11}	1.050	1.0742	1.0944	1.0967	1.0992	1.10	1.0963	1.057
Vg_{13}	1.050	1.0949	1.0903	1.0999	1.10	1.10	1.0996	1.0905
$Tap_{6–9}$	1.0780	1.0221	1.0562	1.0232	1.0758	1.0917	1.0423	1.0345
$Tap_{6–10}$	1.0690	0.9658	0.9483	0.981	0.9162	0.9	0.963	0.9517
$Tap_{4–12}$	1.0320	1.03	1.0134	0.9778	0.9703	0.9713	0.9716	0.9765
$Tap_{28–27}$	1.0680	1.0295	1.0013	0.9832	0.9777	0.9765	0.9835	0.9991
Qc_{10}	19	4.2988	8.5474	15.6831	16.2137	15.4389	17.1797	17.4024
Qc_{18}	0	0.44	0.4482	0.5981	0.6123	0.6967	0.6932	0.2393
Qc_{19}	0	1.0764	6.0428	4.8124	4.6191	4.5177	4.7244	6.2288
Qc_{21}	0	6.1826	4.6433	7.6331	7.6919	7.6953	7.4614	6.8622
Qc_{23}	0	1.0165	1.2123	1.1742	1.2955	1.2992	1.2626	0.9219
Qc_{24}	4.3	8.4129	3.966	6.6863	6.8881	6.8805	7.4917	6.2272
Qc_{26}	0	0.5696	4.035	2.0887	1.9447	1.9799	2.1608	2.6655
Qc_{27}	0	0.3889	1.8509	0.9593	0.4954	0	0.7964	1.9901
Qc_{29}	0	1.6845	2.1499	0.7637	0.7517	0.8575	0.9511	1.6535
Qc_{30}	0	4.5385	2.9974	1.7331	1.9242	1.8829	1.6739	2.4318
P_{losses} (MW)	5.596	4.638	4.6652	4.5371	4.5336	4.5333	4.5363	4.5726
P_{save} %	–	17.11%	16.63%	18.92%	18.98%	18.99%	18.93%	18.28%

18.92 and 18.93%, respectively. DE 5, GA and PSO accomplished lower costs reduction of 18.28, 17.11 and 16.63, respectively.

For minimizing the costs of energy loss and investment (Case 2), the obtained results by the proposed strategies of DE algorithm are compared with other MOs such as

Table 3 Simulation results of the compared approaches to minimize the costs of energy loss and investment for IEEE 30-bus test system (Case 2)

	P_{losses} (MW)	I_c ($)	O_c ($)	Total costs ($)
Initial	5.596	0	2,941,300	2,941,300
MOs				
GA	4.7621	164,783	2,503,000	2,667,800
PSO	4.9263	8221	2,589,300	2,597,500
DE 1	4.6842	8147	2,462,000	2,470,200
DE 2	4.6694	0	2,454,236	2,454,236
DE 3	4.6690	0	2,453,990	2,453,990
DE 4	4.6855	5096	2,462,700	2,467,796
DE 5	4.7512	8134	2,498,000	2,506,134
EP [17]	4.6835	0	2,461,600	2,461,600
EP [18]	4.963	0	2,608,500	2,608,500
DE [21]	4.6835	0	2,469,600	2,469,600
RGA [21]	4.6987	0	2,461,600	2,461,600
Improved GA [8]	4.963	0	2,608,815	2,608,815
DE [28]*	4.545	0	2,421,600	2,421,600
CMAES [13]	4.946	0	2,600,085	2,600,085
COMs				
BFGSM [18]	5.736	1,000,000	3,013,280	4,013,280
SQP [13]	4.951	0	2,602,106	2,602,106
LP [8]	5.68	0	2,985,408	2,985,408

* Refers to infeasible operating point

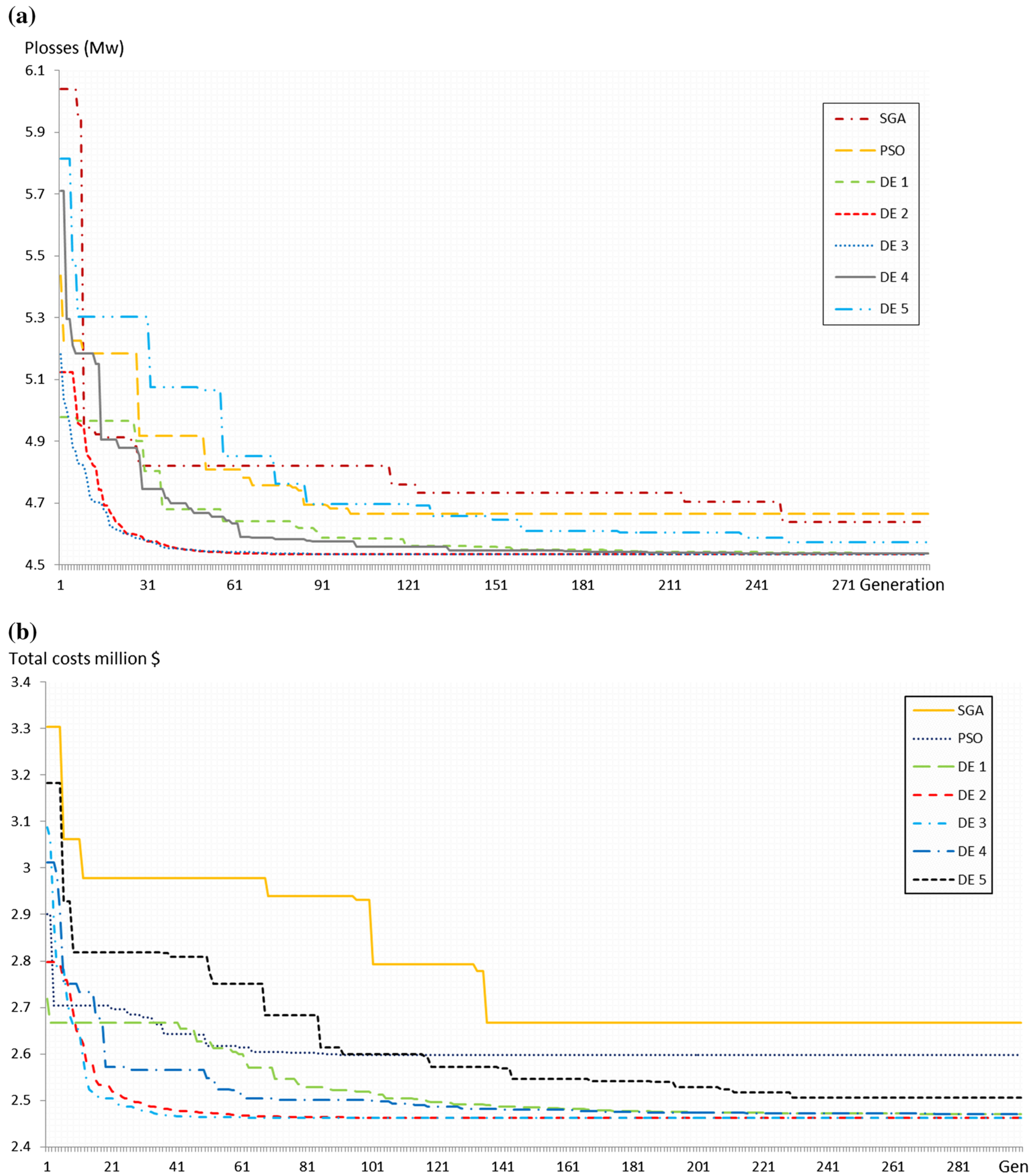

Fig. 2 Convergence characteristics of the compared approaches for solving the RPP (IEEE 30-bus test system). **a** Case 1, **b** Case 2

evolutionary programming (EP) [18, 19], DE [22, 29], improved GA [8], RGA [22], improved GA [8] and CMAES [14] and COMs such as Broyden–Fletcher–Goldfarb–Shanno method [19], sequential QP (SQP) [14] and LP [8] in Table 3. From this comparison, the greatest costs reduction is acquired using DE 2 and DE 3 except the best solution that got hold of DE [29], but it is an infeasible solution that the reactive outputs at generator buses 2 and 4 were −25.25 and 85.6914 MVAR, respectively, which exceeded their corresponding limits [49]. Thus, the proposed algorithm outperforms these MOs and COMs which establish the efficacy of the proposed RPP methodology.

Figure 2 shows the convergence features of the GA, PSO and the proposed DE strategies for both studied cases. It was explicated that DE 2 and DE 3 converged to the minimum objective at the 80th and 70th iteration for both Cases 1 and 2, respectively. DE 1 and DE 4 continued through the 300 iterations and remained minimizing the objective, while PSO got stuck in a local minimum at the

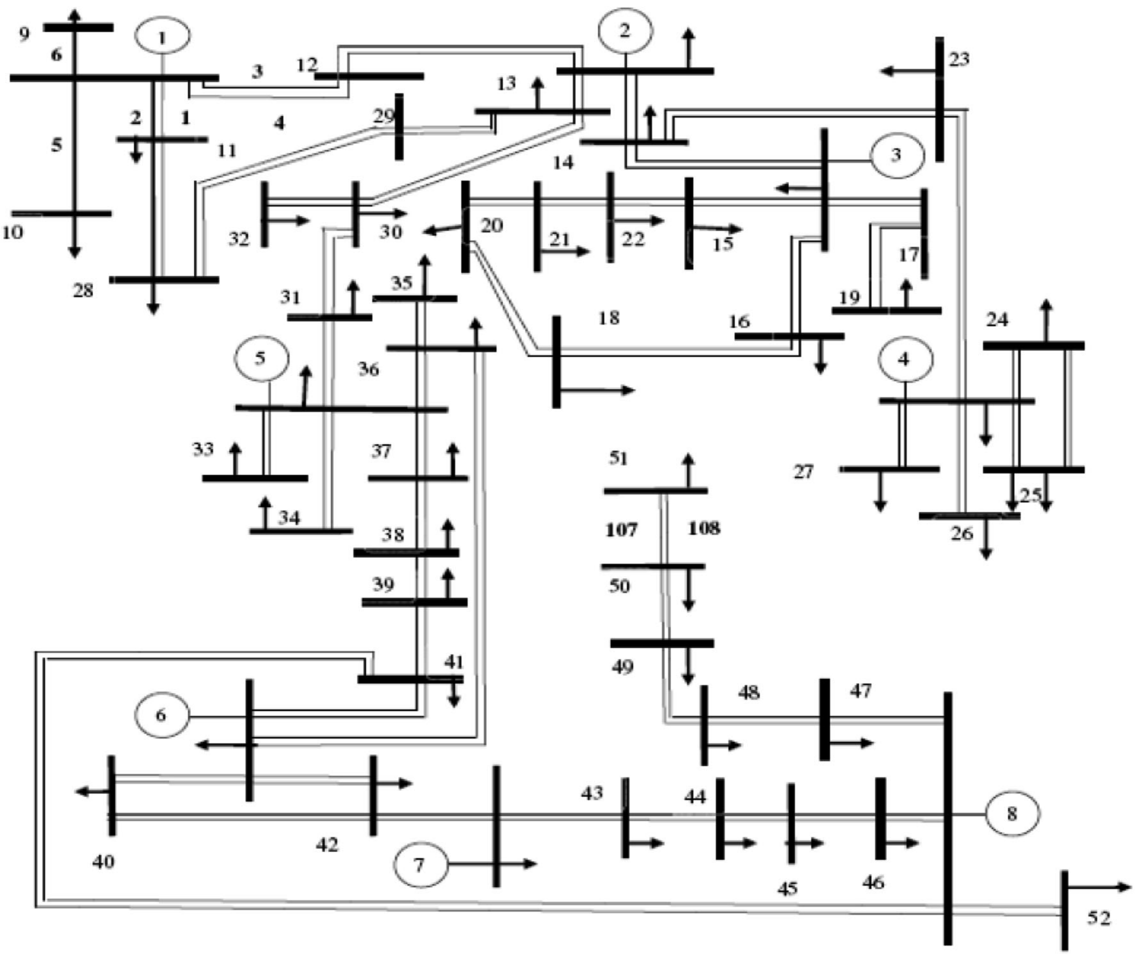

Fig. 3 Single-line diagram of West Delta network [12]

100th and 80th iteration for both Cases 1 and 2, respectively.

4.2 Results for West Delta network

This second network comprises of 52 bus, 8 generator buses and 108 lines [12] as illustrated in Fig. 3. The generator and load voltages are bounded between 0.94 and 1.06, while tap changing of transformer is between 0.9 and 1.1 p.u. Its nominal power demand equals (889.75 + j539.98) MVA. The voltages at load buses 18 and 20–22 exceeded their minimum value.

Similarly, the VAR candidate buses are identified at 18, 19, 20, 21, 24, 32, 33, 35, 49 and 50 and their associated maximum sizes are 13.70, 0.80, 24.20, 12.70, 0.10, 10, 26.50, 3, 4.20 and 4.70 MVAR, respectively. Tables 4 and 5 represent the simulation results of GA, PSO and DE strategies for Cases 1 and 2, respectively.

For Case 1, the minimal power losses are obtained by the proposed strategies DE 2 and DE 3 with 23.29% (from 19.015 to 14.586 MW) and 23.25% (from 19.015 to 14.5936 MW), respectively. Very close results are accomplished by DE 1 and DE 4 which attained real losses reduction of 23.13 and 23.09%, respectively. DE 5, PSO and GA achieved less reduction of 21.93, 20.93 and 20.63%, respectively.

For Case 2, the greatest costs reduction is attained by DE 3 and DE 2 that procured reduction of 15.41 and 15.408%, respectively. On the other hand, DE 1 and DE 4 acquired a relative reduction of 15.406 and 15.403%, respectively, while DE 5 and PSO achieved a significant reduction of 15.09 and 14.491%, respectively.

In this case, although the IM is developed to identify the candidate buses, DE 2 and DE 3 acquired the minimal losses without installing additional VAR sources compared to other algorithms for IEEE 30 bus and WDN. This illustrates that the optimal solutions found by proposed DE 2 and DE 3 strategies are achieved via controlling the generator voltages and tap settings of transformers which are sufficient for Case 2.

Figure 4 displays the convergence features of GA, PSO and DE strategies which illustrates that DE 2 and DE 3

Table 4 Simulation results of the compared approaches to minimize the losses for WDN (Case 1)

	Initial	GA	PSO	DE 1	DE 2	DE 3	DE 4	DE 5
Vg_1	1	1.0581	1.0528	1.0598	1.06	1.06	1.0598	1.0564
Vg_2	1	1.0552	1.0552	1.0598	1.06	1.06	1.0596	1.0561
Vg_3	1	1.0593	1.0579	1.0597	1.06	1.06	1.0586	1.0577
Vg_4	1	1.0562	1.0323	1.0574	1.0587	1.0594	1.0582	1.0436
Vg_5	1	1.0569	1.0574	1.0587	1.0591	1.0591	1.0587	1.0585
Vg_6	1	1.0317	1.0174	1.0326	1.0327	1.0337	1.0331	1.0298
Vg_7	1	1.017	1.0016	1.025	1.0253	1.0263	1.0248	1.0216
Vg_8	1	1.017	1.0155	1.0407	1.0393	1.0402	1.0426	1.0433
$Tap_{4\text{-}7}$	1	1.0134	0.985	1.0018	0.9991	0.9991	1.0013	0.9979
$Tap_{4\text{-}9}$	1	0.9913	0.9988	0.9956	0.9952	0.9952	0.9921	0.9854
Qc_{18}	0	9.3191	13.0552	12.0245	13.26	13.71	13.5022	7.5621
Qc_{19}	0	0.2424	0.0383	0.4152	0.4018	0.7899	0.7063	0.3064
Qc_{20}	0	16.4477	16.7512	19.2924	21.6338	19.1607	21.3964	19.505
Qc_{21}	0	10.1998	10.0679	10.8568	9.1628	11.6034	10.5964	8.4218
Qc_{24}	0	0.0985	0.0906	0.0465	0.055	0.1	0.0523	0.0576
Qc_{32}	0	8.5058	9.0403	10.0972	10.0999	10.1	9.6193	9.3802
Qc_{33}	0	20.2297	25.6712	26.0819	26.4359	26.4999	25.93	26.1455
Qc_{35}	0	1.9774	2.8604	2.6533	2.992	3	2.5851	1.0033
Qc_{49}	0	0.596	3.3041	3.3961	4.198	4.1989	4.065	0.8298
Qc_{50}	0	4.6367	4.0813	4.1546	4.1077	4.1908	3.3134	4.1364
P_{losses} (MW)	19.015	15.0914	15.0338	14.6159	14.5936	14.586	14.6243	14.8456
P_{save} %	0	20.63%	20.93%	23.13%	23.25%	23.29%	23.09%	21.93%

Table 5 Simulation results of the compared approaches to minimize the costs of energy loss and investment for WDN (Case 2)

	Initial	GA	PSO	DE 1	DE 2	DE 3	DE 4	DE 5
P_{losses} (MW)	19.015	16.1189	16.215	16.0854	16.0851	16.0849	16.086	16.1456
I_c ($)	0	627,497	23,182	0	0	0	0	0
O_c ($)	9,994,284	8,472,103	8,522,818	8,454,486	8,454,328	8,454,223	8,454,802	8,486,127
Total costs ($)	9,994,284	9,099,600	8,546,000	8,454,486	8,454,328	8,454,223	8,454,802	8,486,127
C_{save} %	–	8.95%	14.491%	15.406%	15.408%	15.4095%	15.403%	15.09%

converge to the minimum objective at the 70th and 50th iteration for Cases 1 and 2, respectively. DE 1, DE 4 and DE 5 take the 300 iterations still reducing the objective. PSO achieves similar costs reduction; nevertheless, it remains stuck within a local minimum, while GA's solution remains unchanged for a large number of iterations and obtained higher objective value compared to other approaches.

Taking into consideration the evolution of the system, the annual growth rate of peak load in the Egyptian system is approximately 6–8% in the previous year's [51]. For this purpose, the proposed algorithm (DE 3) is performed for three-year plan with 8% annual growth rate of peak load. Therefore, the active and reactive power loads are increased with 8% and consequently the active power generations are increased with the same percentage. As planning for installing fixed capacitors, their values are considered optimally fixed for the three-year plan, while the generator bus voltages and tap ratio of transformers are optimally varied with increasing loading level. Table 6 shows the corresponding results for handling Case 1 which demonstrates the capability of the proposed algorithm to obtain savings of 22.93, 22.87 and 24.06% for the consecutive three years, respectively. Besides that, the initial voltages are improved and become within the acceptable range since the minimum voltages after installing the new VAR sources are recorded at bus 44 with values of 1.001, 0.996 and 1.000 p.u. for the consecutive 3 years, respectively.

To discuss the sensitivity of the optimal sizing and positioning of the VAR sources for the system state

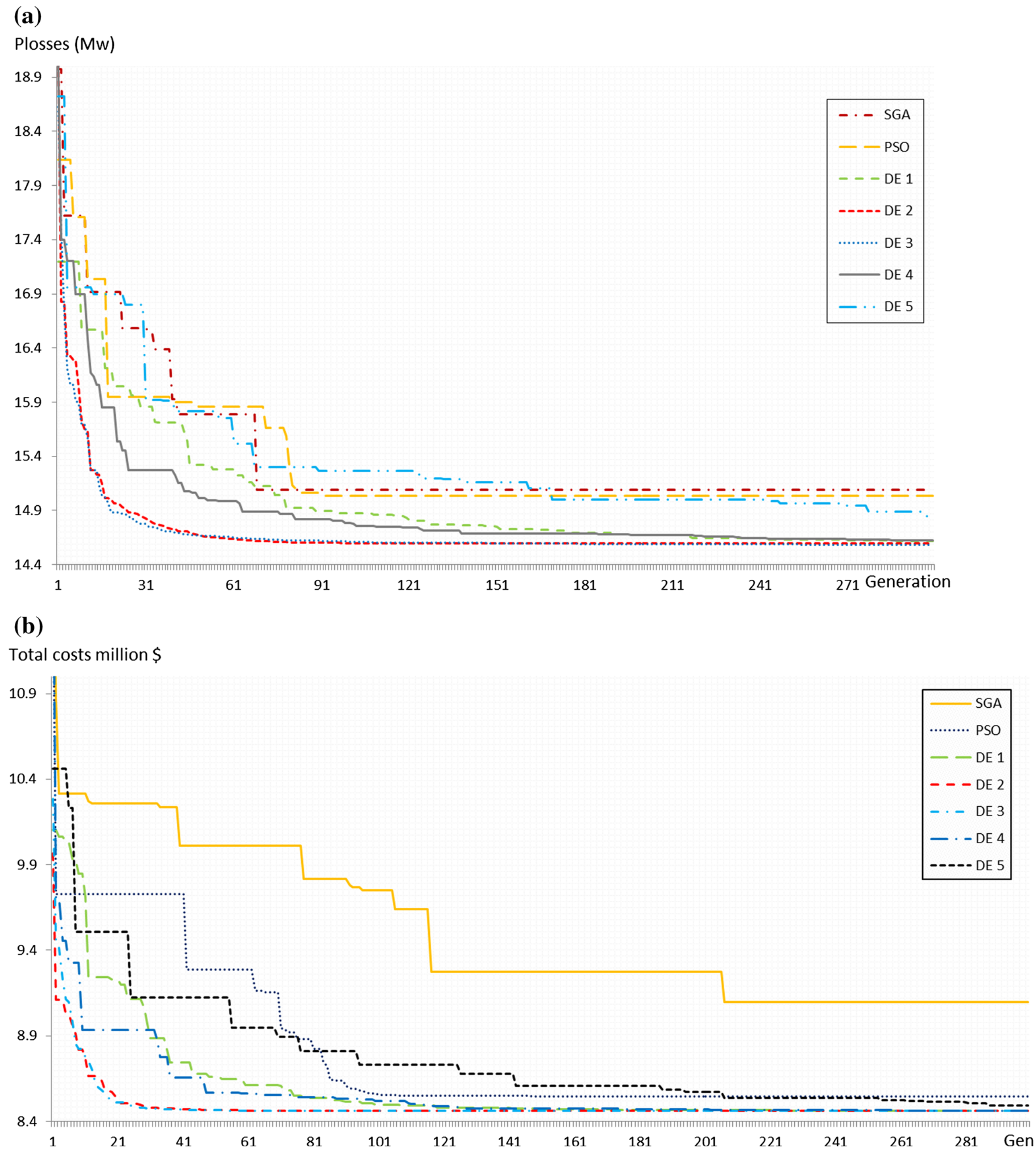

Fig. 4 Convergence characteristics of the compared approaches for solving the RPP (WDN). **a** Case 1, **b** Case 2

changes due to different loading situations and considering the annual growth rate of these loading, three loading conditions are taken into account as shown in Table 7.

Table 8 shows the related simulation results for WDN for handling Case 1. Great savings are obtained using the proposed algorithm at each loading situation through the consecutive three years, respectively. This proves the ability of the proposed procedure to deal with different loading situations and considering the annual growth rate which provide some kind of dynamic optimization on a larger set of system states instead of implementing on a static state of the power system.

4.3 Statistical analysis

In evolutionary optimization, the definition of robustness is not uniform, but a solution is commonly defined as a robust solution if it behaves well with slightly diverse situations [52]. Therefore, the algorithm that provided a robust solution against diverse initial populations due to the randomization existed in evolutionary optimization is considered a robust one.

For this purpose, the compared approaches have been applied for 30 runs in each case study and the statistics of best, worst, mean, standard deviation (Std) and standard

Table 6 Simulation results for WDN considering its evolution by 8% annual growth rate (Case 1)

	Year 1 Peak loading	Year 2 +8% increase	Year 3 +8% increase
Sum (P_{load}) MW	889.75	960.93	1037.804
Sum (Q_{load}) MVAr	539.984	583.1827	629.8373
Sum (P_{g}) MW	908.7651	983.6002	1064.898
Initial P_{losses} (MW)	19.01507	22.67018	27.09315
Initial related costs (million $)	9.99432	11.91545	14.24016
Initial total costs (million $)	36.14992		
Initial minimum voltage (p.u.)	0.903 @ bus 20	0.892 @ bus 20	0.880 @ bus 20
Vg_1	1.059997	1.059861	1.059921
Vg_2	1.059975	1.059816	1.059998
Vg_3	1.059993	1.05992	1.059497
Vg_4	1.05805	1.057371	1.05939
Vg_5	1.059109	1.046503	1.059129
Vg_6	1.027697	1.021775	1.029387
Vg_7	1.018484	1.014528	1.019645
Vg_8	1.027485	1.027051	1.037043
$Tap_{4\text{–}7}$	1.000069	1.000328	0.999393
$Tap_{4\text{–}9}$	0.99451	0.99451	0.99451
Qc_{18}	13.67722		
Qc_{19}	0.773036		
Qc_{20}	23.32679		
Qc_{21}	12.49209		
Qc_{24}	0.043632		
Qc_{32}	8.685839		
Qc_{33}	26.49966		
Qc_{35}	2.994285		
Qc_{49}	4.056532		
Qc_{50}	4.642492		
Optimized P_{losses} (MW)	14.65439	17.48457	20.57423
Optimized related costs (million $)	7.70235	9.18989	10.81381
Optimized total costs (million $)	27.70605		
Saving %	22.93%	22.87%	24.06%
Optimized minimum voltage (p.u.)	1.001 @ bus 44	0.996 @ bus 44	1.000 @ bus 44

Table 7 RPP for different loading conditions and their duration for WDN

	Peak loading condition	Medium loading condition (80% of the peak)	Light loading condition (60% of the peak)
Sum (P_{load}) MW	889.75	711.8	533.85
Sum (Q_{load}) MVAr	539.984	431.9872	323.9904
Sum (P_{g}) MW	908.7651	723.3396	540.0058
d_{L} (h)	2920	2920	2920

error (Ste) are listed in Table 9 to solve the RPP for IEEE 30-bus test system and WDN. Added to that, the convergence frequency in obtaining the minimal losses or total costs is recorded in Tables 10 and 11 for IEEE 30 bus and WDN, respectively. Moreover, statistical tests to judge the significance of the obtained results by the proposed method are carried out in Table 12 using a parametric test of paired *t* test and a nonparametric test of Wilcoxon's rank-sum test [53].

From Tables 9, 10, 11 and 12, it can be concluded as follows:

Table 8 Simulation results considering different loading conditions and their growth rate for WDN (Case 1)

	Year 1 initial loading			Year 2 +8% increase			Year 3 +8% increase		
	Light	Medium	Peak	Light	Medium	Peak	Light	Medium	Peak
Vg_1	1.003327	1.059001	1.044841	1.000844	1.007662	1.041258	1.01893	1.03285	0.998631
Vg_2	1.013691	1.052474	1.019076	1.019415	1.048132	1.046111	1.003856	1.009216	1.016361
Vg_3	0.999185	1.049687	1.008645	1.00476	1.043563	1.052043	1.00011	1.005091	1.006948
Vg_4	1.002999	1.014184	1.018945	0.994329	1.052525	1.00954	0.986676	1.005909	0.992227
Vg_5	0.998609	1.022524	1.04059	1.013018	1.031471	1.055854	1.025011	1.023726	1.019537
Vg_6	0.971396	0.987684	1.013359	0.995816	1.006811	1.017252	1.017673	0.98894	0.979445
Vg_7	0.967014	0.983714	1.00224	0.995371	0.991763	1.009055	1.017627	0.98045	0.97297
Vg_8	0.968662	0.993187	1.018917	1.001226	1.014278	1.017874	1.034156	1.00678	0.988831
Tap_{4-7}	0.999621	0.995599	0.999887	0.998955	0.992926	1.01911	1.000467	0.995499	0.998962
Tap_{4-9}	0.997938	0.997938	0.997938	0.997938	0.997938	0.997938	0.997938	0.997938	0.997938
Qc_{18}	8.090666								
Qc_{19}	0.618159								
Qc_{20}	21.3202								
Qc_{21}	11.57566								
Qc_{24}	0.024828								
Qc_{32}	10.04242								
Qc_{33}	25.3419								
Qc_{35}	2.91543								
Qc_{49}	3.952814								
Qc_{50}	3.501348								
Initial MW P_{losses}	6.155764	11.53958	19.01507	7.273149	13.68864	22.6701	8.600984	16.26191	27.09315
Initial costs (million $)	1.07849	2.021734	3.33144	1.274256	2.398251	3.971815	1.506893	2.849087	4.746719
Optimized MW P_{losses}	5.70696	9.577911	15.85409	6.58833	11.53652	18.14835	7.850915	14.04829	23.46187
Optimized costs (million $)	0.99986	1.67805	2.777636	1.154277	2.021199	3.179592	1.37548	2.461261	4.11052
Saving %	7.29%	17%	16.64%	9.41%	15.72%	19.94%	8.72%	13.61%	13.4%

Table 9 Comparison between the compared approaches to solve the RPP

Case study	Test system	Index	GA	PSO	DE 1	DE 2	DE 3	DE 4	DE 5
Case 1	IEEE 30-bus test system	Best	4.638	4.6652	4.5371	4.5336	4.5333	4.5363	4.5726
Real power losses (MW)		Mean	4.7434	4.8162	4.5949	4.5757	4.5333	4.6072	4.758
		Worst	5.0141	4.8673	4.6475	4.6017	4.5339	4.6614	4.8158
		Std	0.0799	0.0585	0.0346	0.0234	1.12E−04	0.0393	0.0773
		Ste	0.0146	0.0107	0.0063	0.0043	2.05E−05	0.0072	0.0141
	WDN system	Best	15.0914	15.0338	14.6159	14.5936	14.586	14.6243	14.8456
		Mean	15.5504	15.9533	14.8783	14.6182	14.5864	14.9246	15.7568
		Worst	15.9051	16.3018	15.0654	14.627	14.5869	15.1448	16.1577
		Std	0.1851	0.3485	0.1296	0.0097	3.23E−04	0.1584	0.3695
		Ste	0.0338	0.0636	0.0237	0.0018	5.89E−05	0.0289	0.0675
Case 2	IEEE 30-bus test system	Best	2,667,800	2,597,500	2,462,000	2,454,236	2,453,900	2,467,796	2,506,200
Total costs range ($)		Mean	2,827,000	2,610,900	2,465,500	2,454,500	2,453,900	2,470,700	2,533,900
		Worst	3,015,300	2,819,000	2,515,000	2,454,940	2,454,000	2,503,700	2,680,800
		Std	71,100	39,480	7892	231.4356	19.2179	5795	29,587
		Ste	13,000	7208	1441	42.2542	3.5087	1058	5402
	WDN system	Best	9,099,600	8,546,000	8,454,486	8,454,328	8,454,223	8,454,802	8,486,127
		Mean	9,413,100	8,680,600	8,467,400	8,464,480	8,456,500	8,470,000	8,515,600
		Worst	9,633,000	9,699,000	8,569,600	8,498,200	8,472,300	8,631,100	8,925,000
		Std	138,500	198,280	19,394	6357.8	1654.8	30,557	79,697
		Ste	25,300	36,201	3541	1161	302.1317	5578.9	14,551

Table 10 Convergence frequency of IEEE 30-bus test system

Solution algorithms	Case 1 Real power losses (MW)				Case 2 Total costs range (million $)			
Range	4.5–4.6	4.6–4.7	4.7–4.8	Greater than 4.8	2.3–2.5	2.5–2.7	2.7–2.9	2.9–3.1
GA	–	30%	60%	10%	–	3.33%	83.33%	13.33%
PSO	–	6.67%	16.67%	76.66%	–	96.67%	3.33%	–
DE 1	53.33%	46.67%	–	–	96.67%	3.33%	–	–
DE 2	80%	20%	–	–	100%	–	–	–
DE 3	100%	–	–	–	100%	–	–	–
DE 4	40%	60%	–	–	96.67%	3.33%	–	–
DE 5	6.67%	13.33%	36.67%	43.33%	–	100%	–	–

- The proposed DE 3 strategy is the most robust algorithm to handle the RPP compared to the other approaches.
- DE 3 achieved trivial Std and Ste in Case 1 with 1.12E−04 and 2.05E−05 for IEEE 30-bus system and 3.23E−04 and 5.89E−05 for the WDN system, respectively. This states the high potency of the proposed DE 3 strategy to find the global minimal regardless of the initial guesses.
- Moreover, its superiority over the compared approaches is proven as the DE 3 strategy always obtains mean objective very near to its obtained best and lower than the achieved best of the other compared approaches except DE 2 best of WDN for Case 2.

Table 11 Convergence frequency of WDN

Case 1 Real power losses (MW)						
Range	14.5–14.6	14.6–14.7	14.7–14.8	14.8–14.9	14.9-15	Greater than 15
GA	–	–	–	–	–	100%
PSO	–	–	–	–	–	100%
DE 1	–	13.33%	13.33%	22.34%	30%	20%
DE 2	10%	90%	–	–	–	–
DE 3	100%	–	–	–	–	–
DE 4	–	13.33%	13.33%	16.67%	16.67%	40%
DE 5	–	–	–	3.33%	3.33%	93.34%
Case 2 Total costs range (million $)						
Range	8.4–8.5	8.5–8.6	8.6–8.7	8.7–8.8	8.8–9	Greater than 9
GA	–	–	–	–	–	100%
PSO	–	3.33%	86.67%	3.33%	3.33%	3.33%
DE 1	96.67%	3.33%	–	–	–	–
DE 2	100%	–	–	–	–	–
DE 3	100%	–	–	–	–	–
DE 4	96.67%	–	3.33%	–	–	–
DE 5	76.67%	20%	–	–	3.33%	–

Table 12 *t* test and Wilcoxon's rank-sum test between DE 3 and the compared approaches to solve the RPP (Case 2) for IEEE 30-bus test system

Index	GA-DE 3	PSO-DE 3	DE 1-DE 3	DE 2-DE 3	DE 4-DE 3	DE 5-DE 3
t value	28.10594	20.6375725	8.2211523	8.647397	10.914177	13.2926443
Related *p* value	Less than 0.001	Less than 0.001	Less than 0.001	Less than 0.001	Less than 0.001	Less than 0.001
z value (Wilcoxon)	4.78213	4.78213	4.78213	4.4622	4.78213	4.78213
Related *p* value	0.0001	0.0001	0.0001	0.00015	0.0001	0.0001

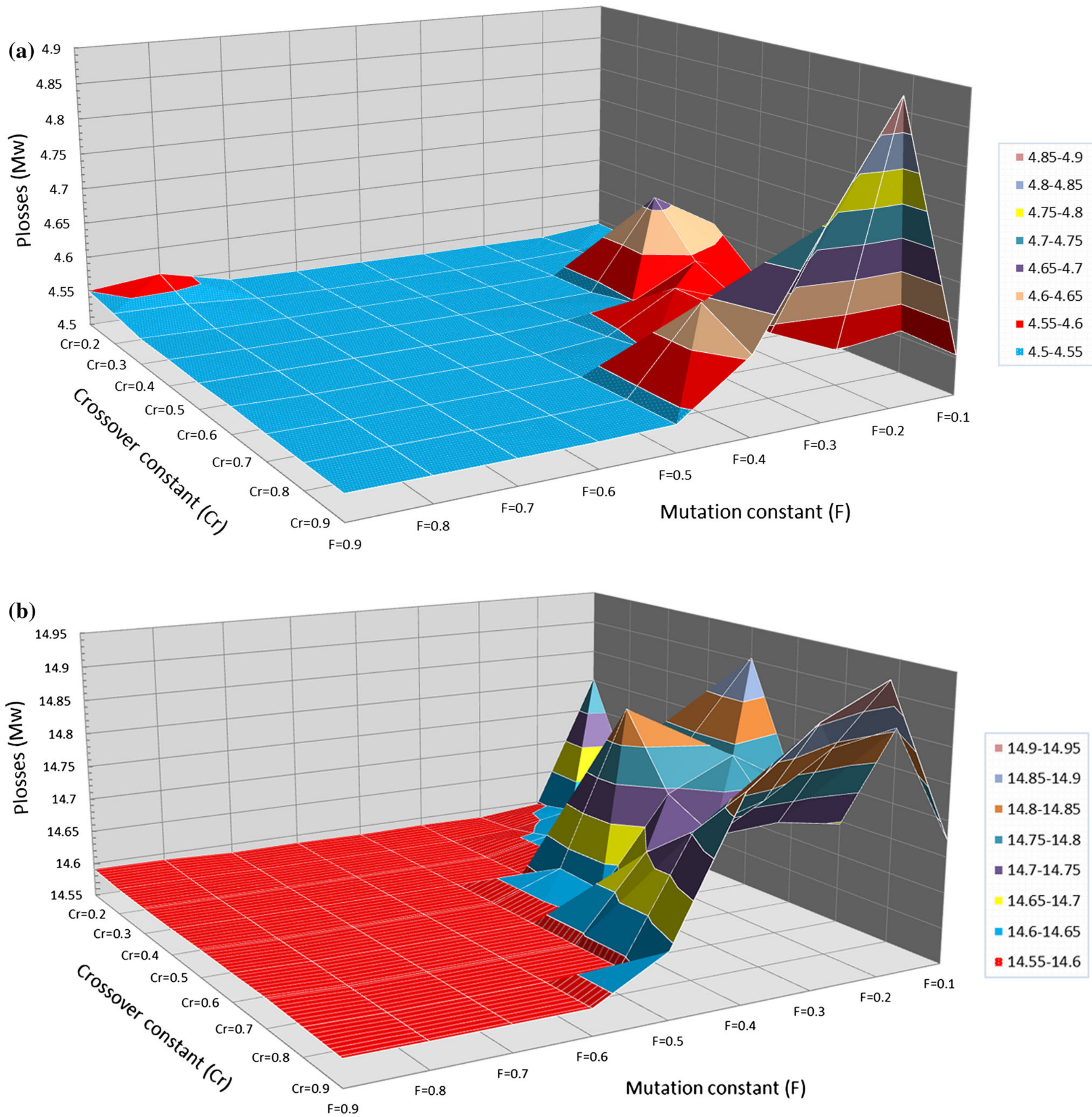

Fig. 5 Effects of varying Cr and F of DE 3 strategy on the power losses (Case 1). **a** IEEE 30-bus test system. **b** WDN

- The proposed DE 3 strategy is the most consistent algorithm to solve the RPP problem as its success rates compassed always perfect (100%) in the first range for both systems and higher than other methods. The nearest results are obtained by DE 2 strategy with perfect success rates (100%) in the first range for both systems in Case 2.
- In Table 12, z values are evaluated based on Wilcoxon's rank-sum test so it does not be varied except for DE 2–DE 3. This is due to that the obtained worst objective value using the proposed DE 3 is better than the best values of GA, PSO, DE 1, DE 4 and DE 5.
- Table 12 indicates that the p values of the statistical t test and Wilcoxon's rank-sum test prove that the obtained results of the proposed method do not happen by chance in spite of the stochastic nature of the meta-heuristic algorithms. Thus, the significance of the obtained results is verified.

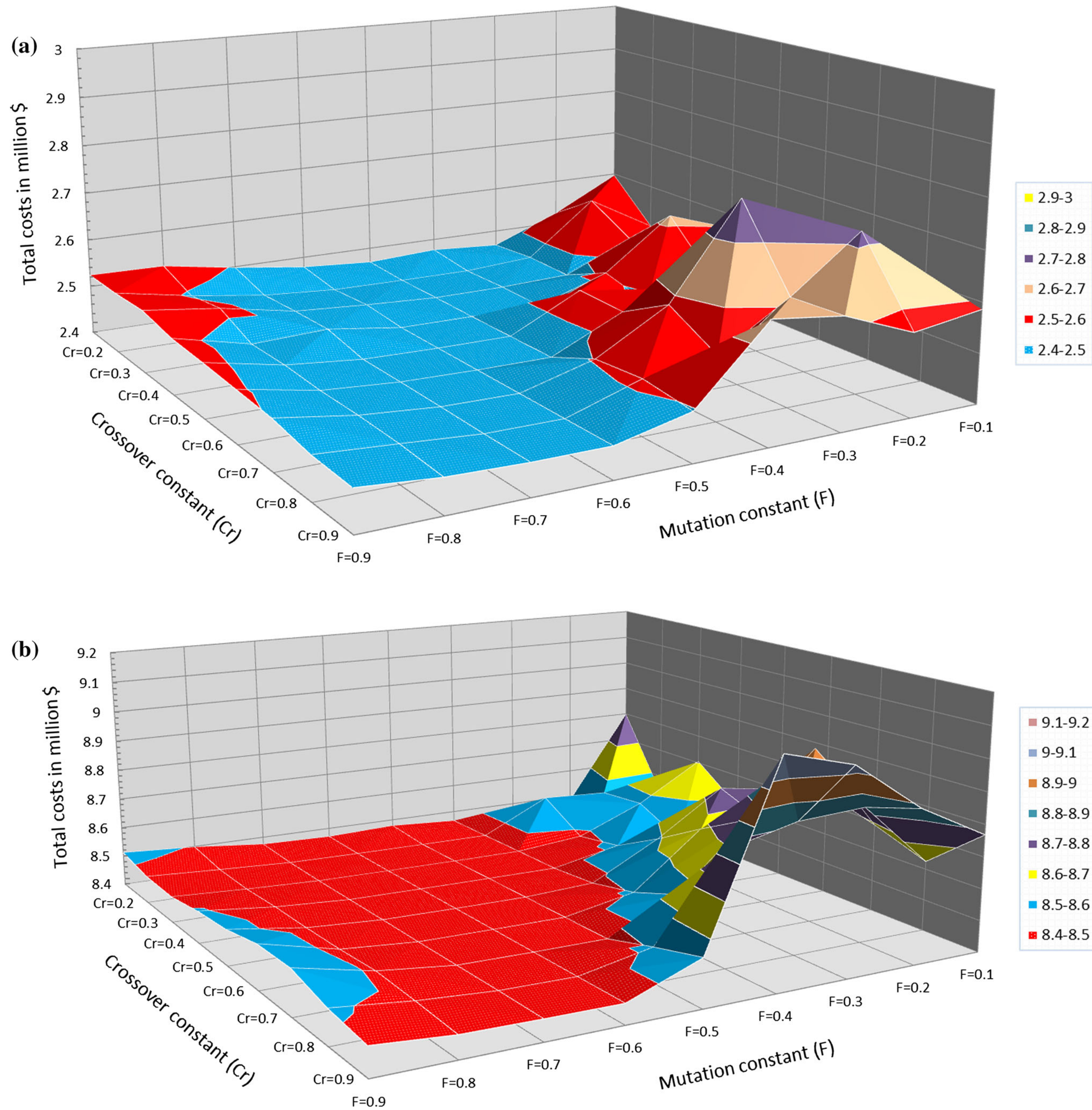

Fig. 6 Effects of varying Cr and F of DE 3 strategy on the total costs (Case 2). **a** IEEE 30-bus test system. **b** WDN

4.4 Parametric analysis of the suggested DE 3 strategy for solving the RPP

In DE algorithm, two parameters have to be adjusted which are Cr and F. The parameter Cr controls the number of individuals to be varied in each iteration, while F guides the directions and the appended values through the search space. In this section, a parametric analysis of the suggested DE 3 strategy by varying Cr and F on the costs of energy loss and investment is studied. Figures 5 and 6 show the effects of simultaneous varying Cr and F of the proposed DE 3 strategy for Cases 1 and 2 for IEEE 30 and WDN, respectively. For minimizing the power losses, the optimal ranges of F and Cr, as illustrated in Fig. 5, are inside [0.50, 0.90] and [0.10, 0.90] for IEEE 30-bus system and WDN. For Case 2, the optimal ranges of F and Cr, as illustrated in Fig. 6, are inside [0.50, 0.80] and [0.30, 0.90] for IEEE 30-bus system, respectively.

Table 13 Application of the proposed DE 3 strategy for voltage profile improvement for IEEE 30-bus test system

	Initial	Case 1	Case 2	Case 3
Vg_1	1.050	1.1	1.1	1.066671
Vg_2	1.040	1.0943	1.0943	1.056612
Vg_5	1.010	1.0748	1.0747	1.031714
Vg_8	1.010	1.0765	1.0766	1.03289
Vg_{11}	1.050	1.1	1.1	1.02776
Vg_{13}	1.050	1.1	1.1	1.046178
$Tap_{6–9}$	1.078	1.0917	1.085	1.085145
$Tap_{6–10}$	1.069	0.9	0.9	0.934431
$Tap_{4–12}$	1.032	0.9713	0.9925	1.031658
$Tap_{28–27}$	1.068	0.9765	0.9654	0.973567
Qc_{10}	19	15.4389	18.9998	18.65532
Qc_{18}	0	0.6967	0	0.000362
Qc_{19}	0	4.5177	0	2.89E−05
Qc_{21}	0	7.6953	0	9.31E−06
Qc_{23}	0	1.2992	0	9.11E−05
Qc_{24}	4.3	6.8805	4.2996	4.299604
Qc_{26}	0	1.9799	0	0.002299
Qc_{27}	0	0	0	0.000141
Qc_{29}	0	0.8575	0	0.001491
Qc_{30}	0	1.8829	0	0.00275
P_{losses} (MW)	5.596	4.5333	4.6690	5.102
Total costs ($)	–	2,957,578	2,453,990	2,689,718

Similarly for the WDN, the optimal ranges of F and Cr are inside [0.50, 0.80] and [0.10, 0.90], respectively. By crossing these ranges, F and Cr of the proposed DE 3 strategy are recommended to be within [0.50, 0.80] and [0.30, 0.90], respectively, to handle the RPP for any electrical network.

4.5 Solving the RPP problem including the voltage profile improvement for IEEE 30-bus system

For solving the RPP problem including the voltage profile improvement (Case 3), a robust DE variant (DE/best/1) is employed with high ability of global exploitation and fast convergence as proven previously. Table 13 tabulates the related results for IEEE 30-bus system where the system voltage profile obtained by the proposed DE variant in all studied cases compared to the initial case is shown in Fig. 7. It is evident that the voltage profile distribution is quite improved compared to the initial case and Cases 1–2.

4.6 Application of the proposed DE 3 strategy for the RPP on large-scale power system

In order to show the efficiency of the proposed approach in solving the RPP for large-scale systems, a 354-bus system [49, 50] is used. The concerned results using the proposed DE 3 strategy to minimize the total costs of both of system operational losses and VAR investment are illustrated in Table 14. As shown, 57 new VAR sources are installed where the power losses are 390.82 MW. All the bus voltages are within its bounds where the minimum voltage is 0.95597 p.u. at bus 1091 and the maximum one is 1.04359 p.u. at bus 2041.

4.7 Application of single-step optimization procedure

The RPP problem could be solved using single- step optimization procedure for searching for the optimal solution considering all load buses as candidate VAR locations. Table 15 shows a comparison between single-

Fig. 7 Voltage profile using the DE strategy for all studied cases with IEEE 30-bus test system

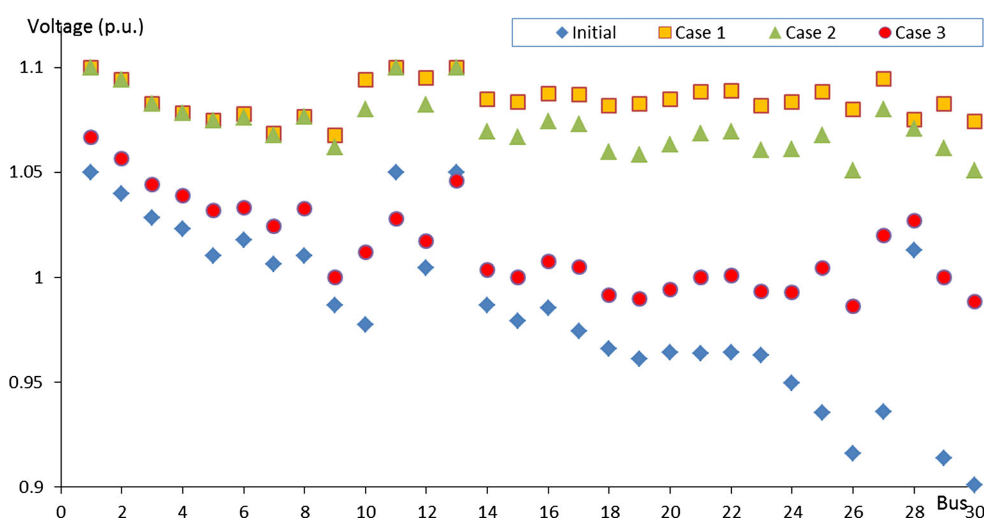

Table 14 Application of the proposed DE 3 strategy to solve the RPP for 354-bus test system (Case 2)

Variables	Value	Variables	Value	Variables	Value	Variables	Value	Variables	Value
Vg_{1}	0.978389	Vg_{1010}	0.979125	Vg_{2019}	0.980837	$Tap_{1038-1037}$	0.941676	Qc_{1046}	1.040947
Vg_{4}	1.034174	Vg_{1012}	1.012883	Vg_{2024}	1.043997	$Tap_{1063-1059}$	0.965119	Qc_{1048}	0.058911
Vg_{6}	1.007828	Vg_{1015}	0.994315	Vg_{2025}	1.04182	$Tap_{1064-1061}$	0.951955	Qc_{1053}	1.786993
Vg_{8}	1.036198	Vg_{1018}	0.997196	Vg_{2026}	1.000175	$Tap_{1065-1066}$	0.988739	Qc_{1057}	0.018859
Vg_{10}	1.01174	Vg_{1019}	0.992303	Vg_{2027}	1.044524	$Tap_{1068-1069}$	1.02891	Qc_{1058}	0.073653
Vg_{12}	1.002316	Vg_{1024}	0.984823	Vg_{2031}	1.006573	$Tap_{1081-1080}$	0.98325	Qc_{1063}	0.035175
Vg_{15}	0.986663	Vg_{1025}	1.021765	Vg_{2032}	1.030058	$Tap_{2008-2005}$	0.971542	Qc_{1074}	0.050398
Vg_{18}	0.988356	Vg_{1026}	0.98994	Vg_{2034}	1.000644	$Tap_{2026-2025}$	1.008889	Qc_{1079}	0.529278
Vg_{19}	0.981317	Vg_{1027}	1.018316	Vg_{2036}	0.993733	$Tap_{2030-2017}$	1.021518	Qc_{1082}	2.314376
Vg_{24}	0.990774	Vg_{1031}	0.97757	Vg_{2040}	0.990387	$Tap_{2038-2037}$	0.946139	Qc_{1083}	0.323715
Vg_{25}	0.989989	Vg_{1032}	1.003342	Vg_{2042}	0.995866	$Tap_{2063-2059}$	0.950788	Qc_{1105}	0.346983
Vg_{26}	1.016329	Vg_{1034}	1.011999	Vg_{2046}	0.996626	$Tap_{2064-2061}$	0.963045	Qc_{1106}	0.339573
Vg_{27}	1.012012	Vg_{1036}	1.010247	Vg_{2049}	1.02828	$Tap_{2065-2066}$	0.977063	Qc_{1107}	0.071593
Vg_{31}	1.023311	Vg_{1040}	1.006993	Vg_{2054}	1.03381	$Tap_{2068-2069}$	1.028477	Qc_{1108}	0.045308
Vg_{32}	1.007217	Vg_{1042}	0.993654	Vg_{2055}	1.023486	$Tap_{2081-2080}$	0.969011	Qc_{1109}	0.014927
Vg_{34}	0.973118	Vg_{1046}	0.978564	Vg_{2056}	1.026488	Qc_{3}	0.04048	Qc_{1110}	0.089978
Vg_{36}	0.966775	Vg_{1049}	1.021678	Vg_{2059}	1.028538	Qc_{13}	0.259425	Qc_{1114}	0.181218
Vg_{40}	1.020129	Vg_{1054}	0.965824	Vg_{2061}	1.00586	Qc_{20}	0.725036	Qc_{1115}	0.25974
Vg_{42}	1.028868	Vg_{1055}	0.963553	Vg_{2062}	0.998125	Qc_{21}	0.00343	Qc_{1118}	10.19201
Vg_{46}	0.997369	Vg_{1056}	0.965169	Vg_{2065}	0.994055	Qc_{28}	0.241155	Qc_{2001}	0.228235
Vg_{49}	1.013746	Vg_{1059}	0.973976	Vg_{2066}	1.01677	Qc_{29}	0.454858	Qc_{2013}	0.033572
Vg_{54}	1.018982	Vg_{1061}	1.000766	Vg_{2069}	1.039196	Qc_{34}	0.543943	Qc_{2020}	0.214447
Vg_{55}	1.00623	Vg_{1062}	0.992948	Vg_{2070}	1.011361	Qc_{38}	0.029644	Qc_{2021}	0.44543
Vg_{56}	1.009945	Vg_{1065}	1.006617	Vg_{2072}	0.999911	Qc_{39}	0.017285	Qc_{2028}	0.011023
Vg_{59}	0.98997	Vg_{1066}	1.010828	Vg_{2073}	1.029656	Qc_{41}	0.611687	Qc_{2029}	0.059316
Vg_{61}	0.982329	Vg_{1069}	1.032513	Vg_{2074}	0.973197	Qc_{44}	0.838182	Qc_{2034}	1.5284
Vg_{62}	0.981633	Vg_{1070}	0.987779	Vg_{2076}	0.957823	Qc_{45}	0.278498	Qc_{2038}	1.328001
Vg_{65}	0.996852	Vg_{1072}	0.999569	Vg_{2077}	0.996846	Qc_{46}	0.564884	Qc_{2039}	0.032945
Vg_{66}	1.013648	Vg_{1073}	0.994514	Vg_{2080}	1.024485	Qc_{48}	1.05418	Qc_{2041}	0.01401
Vg_{69}	1.052652	Vg_{1074}	0.963448	Vg_{2085}	0.986769	Qc_{53}	0.15561	Qc_{2044}	0.371456
Vg_{70}	0.997182	Vg_{1076}	0.953707	Vg_{2087}	0.985823	Qc_{57}	0.028255	Qc_{2045}	0.365617
Vg_{72}	0.992049	Vg_{1077}	1.004459	Vg_{2089}	1.000596	Qc_{58}	0.336388	Qc_{2046}	0.299192
Vg_{73}	0.971064	Vg_{1080}	1.036629	Vg_{2090}	0.994592	Qc_{63}	0.142534	Qc_{2048}	0.180828
Vg_{74}	0.987432	Vg_{1085}	0.991013	Vg_{2091}	1.040313	Qc_{74}	2.821826	Qc_{2053}	0.084318
Vg_{76}	0.9913	Vg_{1087}	1.039902	Vg_{2092}	1.005607	Qc_{79}	1.317698	Qc_{2057}	0.018818
Vg_{77}	1.022196	Vg_{1089}	0.990027	Vg_{2099}	1.029972	Qc_{82}	2.158411	Qc_{2058}	0.022566
Vg_{80}	1.048509	Vg_{1090}	0.998419	Vg_{2100}	1.036241	Qc_{83}	0.142051	Qc_{2063}	0.390924
Vg_{85}	1.008714	Vg_{1091}	0.951714	Vg_{2103}	1.026851	Qc_{105}	1.347197	Qc_{2074}	0.154108
Vg_{87}	0.991093	Vg_{1092}	0.983192	Vg_{2104}	1.009076	Qc_{106}	1.184674	Qc_{2079}	1.745292
Vg_{89}	1.032207	Vg_{1099}	1.041672	Vg_{2105}	1.008059	Qc_{107}	0.012585	Qc_{2082}	2.744744
Vg_{90}	1.00297	Vg_{1100}	1.022333	Vg_{2107}	1.035414	Qc_{108}	0.082858	Qc_{2083}	0.606731
Vg_{91}	0.987905	Vg_{1103}	1.015946	Vg_{2110}	0.996874	Qc_{109}	0.009363	Qc_{2105}	2.074437
Vg_{92}	1.018664	Vg_{1104}	1.004841	Vg_{2111}	0.988119	Qc_{110}	0.568476	Qc_{2106}	0.266277
Vg_{99}	1.040078	Vg_{1105}	1.003617	Vg_{2112}	1.014903	Qc_{114}	0.05159	Qc_{2107}	0.074188
Vg_{100}	1.047415	Vg_{1107}	1.013315	Vg_{2113}	1.014589	Qc_{115}	0.058387	Qc_{2108}	0.109816
Vg_{103}	1.024962	Vg_{1110}	1.005877	Vg_{2116}	0.962435	Qc_{118}	43.52831	Qc_{2109}	0.071822
Vg_{104}	1.00954	Vg_{1111}	1.034215	Tap_{8-5}	1.010062	Qc_{1003}	0.377127	Qc_{2110}	0.130525
Vg_{105}	1.005052	Vg_{1112}	0.996806	Tap_{26-25}	1.037109	Qc_{1013}	0.187193	Qc_{2114}	0.00113

Table 14 continued

Variables	Value	Variables	Value	Variables	Value	Variables	Value	Variables	Value
Vg_{107}	1.028899	Vg_{1113}	1.013075	Tap_{30-17}	0.967105	Qc_{1020}	0.160744	Qc_{2115}	0.269651
Vg_{110}	0.990007	Vg_{1116}	1.001558	Tap_{38-37}	1.0196	Qc_{1021}	0.180715	Qc_{2118}	7.166524
Vg_{111}	0.970908	Vg_{2001}	0.986788	Tap_{63-59}	0.929337	Qc_{1028}	0.154271	Losses	390.82 MW
Vg_{112}	0.997441	Vg_{2004}	1.020479	Tap_{64-61}	1.048542	Qc_{1029}	0.337263	Min voltage	0.95597 @ bus 1091
Vg_{113}	0.987633	Vg_{2006}	1.006994	Tap_{65-66}	0.961787	Qc_{1034}	0.020627		
Vg_{116}	0.989021	Vg_{2008}	1.018224	Tap_{68-69}	0.974792	Qc_{1038}	3.337642	Max voltage	1.04359 @ bus 2041
Vg_{1001}	0.984292	Vg_{2010}	1.04799	Tap_{81-80}	0.917687	Qc_{1039}	0.048806		
Vg_{1004}	1.018281	Vg_{2012}	1.008936	$Tap_{1008-1005}$	0.994568	Qc_{1041}	0.435884	Total costs million $	207.7806
Vg_{1006}	1.014141	Vg_{2015}	0.982506	$Tap_{1026-1025}$	0.960585	Qc_{1044}	0.243051		
Vg_{1008}	1.013849	Vg_{2018}	0.986228	$Tap_{1030-1017}$	1.014606	Qc_{1045}	0.113242		

Table 15 Comparison between single-step optimization and proposed two-step procedure using DE 3 to minimize the total costs for IEEE 30-bus system

Variables	Single step	Two step	Variables	Single step	Two step	Variables	Single step	Two step
Vg_1	1.0998	1.1	Qc_7	0.6888	–	Qc_{23}	0.0703	0
Vg_2	1.0931	1.0943	Qc_9	0.00211	–	Qc_{24}	3.4857	4.2996
Vg_5	1.0719	1.0747	Qc_{10}	7.972	18.9998	Qc_{25}	0.0041	–
Vg_8	1.0733	1.0766	Qc_{12}	0.0152	–	Qc_{26}	0.1882	0
Vg_{11}	1.0993	1.1	Qc_{14}	0.0872	–	Qc_{27}	0.0119	0
Vg_{13}	1.0999	1.1	Qc_{15}	0.0185	–	Qc_{28}	0.0529	
Tap_{6-9}	0.9693	1.085	Qc_{16}	0.0029	–	Qc_{29}	0.0138	0
Tap_{6-10}	1.02038	0.9	Qc_{17}	0.0013	–	Qc_{30}	0.212	0
Tap_{4-12}	1.0467	0.9925	Qc_{18}	0.0064	0	P_{losses} (MW)	4.725	4.669
Tap_{28-27}	0.9687	0.9654	Qc_{19}	0.0076	0	I_c ($)	77,557	0
Qc_3	0.0326	–	Qc_{20}	0.0049	0	O_c ($)	2,483,352	2,453,990
Qc_4	0.0053	–	Qc_{21}	0.0023	0	Total costs ($)	2,560,909	2,453,990
Qc_6	0.02524	–	Qc_{22}	0.3967	–	C_{save} %	12.93%	16.57%

step and two-step procedures using DE 3 to minimize the total costs for IEEE 30-bus system. As shown the two-step procedure achieved more reduction of the total costs (16.57%) where the single-step method recorded 12.93%. Thus, it is evident that reducing the search space with the effective VAR buses enables the optimization algorithm to find the optimal results.

4.8 Effect of discretizing the noncontinuous variables

DE algorithm can be adjusted to handle the discrete variables using a rounding operator which is involved after the initialization and mutation process [51]. Thus, the capacitor banks step is chosen of 0.1 MVAR, while 32 steps of on-load tap changers are considered as it generally provides ±10% automatic adjustment regulation [54]. Table 16 shows the discretization effect compared to its continuous considerations for Cases 1 and 2. As shown, the optimal settings and results are slightly changed and so the optimization process is influenced to a small degree.

5 Conclusions

This paper proposes a two-step procedure for handling the reactive power planning problem. The candidate locations for installing new VAR sources and their concerned maximum sizes are identified by employing a proposed iterative method. In addition, various strategies of DE algorithm are suggested as solution tools in order to solve the RPP optimization problem. A performance comparison with

Table 16 Optimal RPP solution considering discrete and continuous variables for Cases 1 and 2

Case 1			Case 2		
Variables	Continuous	Discrete	Variables	Continuous	Discrete
Vg_1	1.1	1.1	Vg_1	1.1	1.1
Vg_2	1.0943	1.0946	Vg_2	1.0943	1.0944
Vg_5	1.0748	1.0754	Vg_5	1.0747	1.0748
Vg_8	1.0765	1.0774	Vg_8	1.0766	1.0768
Vg_{11}	1.1	1.0937	Vg_{11}	1.1	1.1
Vg_{13}	1.1	1.1	Vg_{13}	1.1	1.1
$Tap_{6–9}$	1.0917	1.0313	$Tap_{6–9}$	1.085	1.0313
$Tap_{6–10}$	0.9	0.975	$Tap_{6–10}$	0.9	0.9625
$Tap_{4–12}$	0.9713	0.9813	$Tap_{4–12}$	0.9925	1
$Tap_{28–27}$	0.9765	1	$Tap_{28–27}$	0.9654	0.9688
Qc_{10}	15.4389	15.9	Qc_{10}	18.9998	19
Qc_{18}	0.6967	0.7	Qc_{18}	0	0.2
Qc_{19}	4.5177	4.5	Qc_{19}	0	0.2
Qc_{21}	7.6953	7.6	Qc_{21}	0	0
Qc_{23}	1.2992	1.3	Qc_{23}	0	0
Qc_{24}	6.8805	7.1	Qc_{24}	4.2996	4.3
Qc_{26}	1.9799	2.1	Qc_{26}	0	0
Qc_{27}	0	2.1	Qc_{27}	0	0
Qc_{29}	0.8575	0.8	Qc_{29}	0	0
Qc_{30}	1.8829	2.5	Qc_{30}	0	0
P_{losses} (MW)	4.5333	4.539	P_{losses} (MW)	4.669	4.6682
			I_c ($)	0	2,453,600
			O_c ($)	2,453,990	14000
			Total costs ($)	2,453,990	2467600

GA, PSO and the original DE variant DE/rand/1 is discussed and examined on the IEEE 30 bus and the WDN. An additional application to large-scale power system is implemented on IEEE 354-bus system.

The minimization of the power losses is considered as single objective function, while the minimization of both the VAR investment and costs of energy loss is handled using the mathematical sum approach. Additional technical objective is considered to enhance the voltage profile. Although DE/rand/1 strategy is exceedingly utilized for solving the RPP optimization that accomplished greater reduction in energy losses and costs, DE/rand to best/1 and DE/best/1 are able to obtain lesser values, but also they demonstrate more speedy convergence and the load voltages are ameliorated. While DE/rand/1 and DE/best/2 achieved a comparable reduction percentage of the power losses or the total costs, they recorded further reduction with more generations. DE and its strategies have better performance over PSO and GA. Also, robustness statistics are evaluated of the optimizing algorithms in solving the RPP problem which indicates that the suggested DE/best/1 strategy is frequently superior and highly robust than the other compared approaches for minimizing the real power losses or the total costs and its ability to converge near optimally values distinguishes DE/best/1 strategy over others. Though the DE/rand/2 performance shows worse than the other DE strategies, it is generally more robust and consistent than PSO and GA, especially for minimizing the total costs of VAR investment and operational power losses. Furthermore, a parametric analysis of the crossover and mutation factors related to the suggested DE/best/1 algorithm is studied and their optimal tuning is declared.

The proposed optimization procedure was checked for discrete and continuous models of decision variables. A comparative study between the single-step optimization procedure and the proposed two-step procedure was studied.

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