Journal of Zhejiang University-SCIENCE C (Computers & Electronics)
ISSN 1869-1951 (Print); ISSN 1869-196X (Online)
www.zju.edu.cn/jzus; www.springerlink.com
E-mail: jzus@zju.edu.cn

Optimal placement of distributed generation units in distribution systems via an enhanced multi-objective particle swarm optimization algorithm*

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Received Sept. 11, 2013; Revision accepted Dec. 29, 2013; Crosschecked Mar. 17, 2014

Abstract: This paper deals with the optimal placement of distributed generation (DG) units in distribution systems via an enhanced multi-objective particle swarm optimization (EMOPSO) algorithm. To pursue a better simulation of the reality and provide the designer with diverse alternative options, a multi-objective optimization model with technical and operational constraints is constructed to minimize the total power loss and the voltage fluctuation of the power system simultaneously. To enhance the convergence of MOPSO, special techniques including a dynamic inertia weight and acceleration coefficients have been integrated as well as a mutation operator. Besides, to promote the diversity of Pareto-optimal solutions, an improved non-dominated crowding distance sorting technique has been introduced and applied to the selection of particles for the next iteration. After verifying its effectiveness and competitiveness with a set of well-known benchmark functions, the EMOPSO algorithm is employed to achieve the optimal placement of DG units in the IEEE 33-bus system. Simulation results indicate that the EMOPSO algorithm enables the identification of a set of Pareto-optimal solutions with good tradeoff between power loss and voltage stability. Compared with other representative methods, the present results reveal the advantages of optimizing capacities and locations of DG units simultaneously, and exemplify the validity of the EMOPSO algorithm applied for optimally placing DG units.

Key words: Distributed generation, Multi-objective particle swarm optimization, Optimal placement, Voltage stability index, Power loss

doi:10.1631/jzus.C1300250 **Document code:** A **CLC number:** TM715

1 Introduction

Distributed generation (DG) has attracted special attention all over the world. Its potential to serve as an alternative distribution planning option is now well recognized and its estimated share in power systems will increase significantly in the near future (Ayres *et al*., 2010; Devi and Geethanjali, 2013). However, conventional distribution systems (DSs) are constructed without considering interconnection of DGs. Accordingly, the placement of DG units can impact the current DSs, including power quality, voltage conditions, and system reliability (Tanaka *et al*., 2010; Gopiya Naik *et al*., 2013). Meanwhile, an appropriate placement of DG in the DSs can result in active loss reduction as well as other operational, environmental, and economic benefits (Atwa *et al*., 2010). Thus, the optimal placement of DG units in the DS is fundamental to ensure its positive effects.

Optimal placement of DG can be regarded as an optimization problem. Conventionally, the problem was described mostly by a single objective to

* Project supported by the Science & Technology Innovation Team of Outstanding Youth of Hubei Provincial Universities (No. T201319) and the Scientific Research Foundation for Talents of China Three Gorges University (No. 0620130076)

determine the optimal location(s) of DG units with a given capacity, or the optimal capacity with given location(s). Considering the minimization of the total real power loss, Lee and Park (2009) proposed a Kalman filter algorithm to determine the optimal locations of multiple DGs. To obtain the optimal capacity of installed DG at each given bus, Mistry and Roy (2014) employed particle swarm optimization (PSO) to minimize the total system power loss without violating system constraints.

Two aspects of optimizing the DG placement must be addressed. Firstly, to guarantee the best use of the DG, the key is that DG units with appropriate capacity should be placed at optimal location(s) in the DS. Secondly, to ensure the positive effects of the installed DG, it is insufficient for decision-making with only one index being considered as a criterion. Hence, a multi-objective analysis with consideration of technical, economic, and environmental constraints should be employed (Sheng *et al.*, 2012; Dehghanian *et al.*, 2013). In terms of multi-objective optimization (MOO) of the optimal location and capacity of the DG in the DSs, there has been much research in which more than one objective was considered. Akorede *et al*. (2011) proposed an optimization model to maximize the system loading margin and the distribution companies' returns. Moradi and Abedini (2012) developed a model to minimize network power loss, better voltage regulation, and improve voltage stability. Li *et al*. (2013) aimed to reduce system power loss and minimize the investment on DG. Yu *et al*. (2013) established a multi-objective model by considering the construction and operation fees, network loss, reliability, and the environmental factor. What is common to such research is that a multi-objective problem (MOP) is converted to a single-objective problem with a set of weighting factors. Although the weighted function can be used to handle MOPs, in a sense, these are still single-objective optimization methods and the only one best solution fails to provide the designer with alternative options. Furthermore, the corresponding weighting factors are difficult to determine due to the lack of enough information about the problem. In fact, generally, objectives to be optimized are non-comparable and even conflict with each other, which means the solution to such MOPs is a set of different solutions (so-called Pareto-optimal solutions) representing the best possible compromises among the objectives (Sierra and Coello, 2006). MOO is able to identify such Pareto-optimal solutions and has been testified to be an efficient method to solve MOPs by tackling multiple conflict objectives concurrently. Such MOO algorithms have been employed to deal with placement of the DG units. Chen and Cheng (2012) and Hu *et al.* (2013) presented MOO methods for optimizing the capacity and locations of DG units, considering loss reduction, voltage promotion, emission decrease, and reliability improvement. They employed NSGA-II (Deb *et al.*, 2002) to solve the specific MOPs and essentially realized the MOO of optimally placing DG units. Although NSGA-II is a milestone in the history of MOO, its performance needs to be further explored. Thus, it is desirable to apply MOO algorithms of better performance to the complex problem of optimally placing DG units.

Based on the above comments, in this paper we propose an improved multi-objective PSO (MOPSO) algorithm for optimally placing DG units to decrease the total active power loss of the DS and reinforce system reliability. The contributions and characteristics of this paper are:

1. An MOO model is constructed for optimally placing DG units, taking into account economic issues (reducing the total power loss) and technical aspects (decreasing the voltage stability index, VSI). In addition, various constraints have been considered in the model.

2. An enhanced MOPSO (EMOPSO) algorithm is proposed to solve the MOP with non-linear constraints and objectives. A dynamic inertia weight, acceleration coefficients, and circular crowding sorting applied to the selection of particle swarm for the next iteration, have been integrated to guarantee the algorithm performance.

3. Both locations and capacities of dispersed DG units are optimized, instead of locations or capacities alone. The optimization method can also be used to optimize either locations or capacities.

2 Multi-objective optimization model

To realize the optimal development and operation of the power system, engineering aspects of system planning require various objectives to be simultaneously accomplished (Sheng *et al.*, 2012). Furthermore, because integration of DG to DS brings about both technical and economic effects, the resulting placement of DG units has conflicting objectives and an MOO model can efficaciously replicate different perspectives of the DG placement. In this study, unlike the conventional way to place emphasis on economic benefit, the main goal of installing DG units is supposed to result in both economic benefit and improvement in the security, stability, and quality of the DS. Accordingly, reducing the total active power loss and maximizing the voltage stability of the system are chosen as the two main objectives.

Fig. 1 illustrates the radial DS model penetrated with DG located at bus i. The following assumptions are integrated to establish the MOO model:

1. DG is regarded as a negative power load in case of being installed at some bus (Lee and Park, 2009; Akorede *et al.*, 2011).

2. Candidate of DG units' locations can be any bus, except the slack bus.

3. The power factor of the installed DG is unity.

4. Capacity of DG units is a set of discrete values, which are integral multiples of DG-unit capacity.

5. The maximum permitted total capacity of integrated DG units is given.

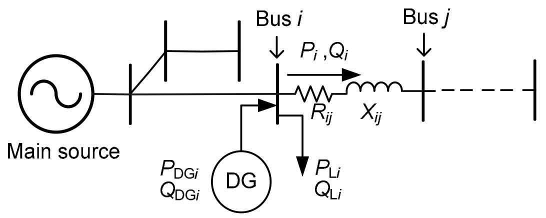

Fig. 1 Radial distribution system model with DG located at bus *i*

2.1 Objective function

Because improper allocation can result in excessive loss and cause the feeders to overheat, power loss is a key and greatly concerned consideration for the placement of DG units (Gopiya Naik *et al.*, 2013). Minimizing the power loss of DS is propitious to alleviate the feeders, lower the voltage drop, promote the voltage profile, and possess other environmental and economic benefits (Atwa *et al.*, 2010). Therefore, the first objective is to minimize the power loss of the system. The mathematical formulation of the active power loss can be expressed as

$$\min f_{\text{P loss}} = \sum_{k=1}^{N_{\text{bra}}} G_k (V_i^2 + V_j^2 - 2V_i V_j \cos\theta_{ij}), \quad (1)$$

where N_{bra} denotes the total number of branches in the system, G_k indicates the conductance of branch k which connects buses i and j, and V and θ represent the bus voltage magnitude and angle, respectively. $\theta_{ij}=\theta_i-\theta_j$.

Obviously, integrating DG into DS has a strong effect on the security and reliability of the system, and the effect varies in accordance with the type, location, capacity, and load of the DG. The reliability of the system could be harmed by the improperly placed DG. Specifically, the modern load level of the DS changes distinctly from low to high every day, and the DS may experience voltage collapse under certain critical loading conditions. Thus, considering the security and reliability of the system, minimization of the voltage stability index (VSI) of the DS is selected to be the second objective-function of the MOO model. VSI in a DS has been analyzed by Liu *et al.* (2002), and a modified VSI is adopted.

The VSI of branch k can be expressed as

$$\text{VSI}_k = \frac{4}{V_i^4}[(X_{ij}P_j - R_{ij}Q_j)^2 + (X_{ij}Q_j + R_{ij}P_j)V_i^2], \quad (2)$$

where R_{ij} and X_{ij} denote the resistance and reactance of branch k, respectively, and P_j and Q_j indicate the total active and reactive power injected to the receiving bus j of branch k, respectively.

Note that $\text{VSI}_k \le 1.0$ and the branch whose VSI value close to 1.0 is more likely to experience voltage collapse. Thus, the second objective-function can be represented by

$$\min f_{\text{VSI}} = \max\{\text{VSI}_1, \text{VSI}_2, ..., \text{VSI}_{N_{\text{bra}}}\}. \quad (3)$$

2.2 Constraints

DG units in the DS must be installed with operating conditions being kept within given limits. The multi-objective functions (1) and (3) are minimized subject to technical and operational constraints to meet the electrical requirements for the DS. These constraints include:

Power balance constraints: the power balance constraints with DG, which are equality constraints and include two nonlinear recursive power flow equations, can be formulated as follows:

$$\begin{cases} P_i + P_{\mathrm{DG}i} - P_{\mathrm{L}i} = V_i \sum_{j=1}^{N_{\mathrm{bus}}} V_j (G_k \cos\theta_{ij} + B_k \sin\theta_{ij}), \\ Q_i - Q_{\mathrm{L}i} = V_i \sum_{j=1}^{N_{\mathrm{bus}}} V_j (G_k \sin\theta_{ij} + B_k \cos\theta_{ij}). \end{cases} \quad (4)$$

Herein N_{bus} indicates the total number of buses in the DS; P_i, $P_{\mathrm{DG}i}$, and $P_{\mathrm{L}i}$ denote the active power, active power of installed DG, and active power load at bus i, respectively; Q_i, $Q_{\mathrm{DG}i}$, and $Q_{\mathrm{L}i}$ represent reactive power, reactive power of installed DG, and reactive power load at bus i, respectively; B_k represents the susceptance of branch k.

Voltage operational tolerance constraints: they include the lower and upper voltage magnitudes. For bus i, the voltage limits can be expressed as

$$V_{i\min} \le V_i \le V_{i\max}. \quad (5)$$

Feeder transmission capacity constraints: power flow through any distribution feeder must comply with the thermal capacity of the line, that is,

$$S_k \le S_{k\max}. \quad (6)$$

The total capacity of DG integrated into the DS should be within a given penetration level, which can be expressed by

$$\sum_{i=2}^{N_{\mathrm{bus}}} P_{\mathrm{DG}i} \Big/ P_{\mathrm{load}} \le \eta, \quad (7)$$

where P_{load} indicates the total active power load of the DS, and $\eta\in[0, 1]$ denotes the penetration rate.

Constraints on the sizing of DG installed at each bus: the capacity of DG can be represented by its active power and capacity of the DG installed at each bus should not be larger than the allowed maximum:

$$P_{\mathrm{DG}i} \le P_{\mathrm{DG}\max}, \quad (8)$$

where P_{DGmax} indicates the allowed maximum active power of DG to be allocated at bus i.

2.3 Variables

From Eqs. (1)–(8), it can be seen that the state variables include the voltage, active power, and reactive power at each bus, all of which can be obtained by power flow computation, and that the decision variables include both the capacities and locations of the DGs to be installed at the candidate buses, which can be denoted as $[P_{\mathrm{DG2}}, P_{\mathrm{DG3}}, ..., P_{\mathrm{DG}N_{\mathrm{bus}}}]^{\mathrm{T}}$. If $P_{\mathrm{DG}i}$=0 (i=2, 3, ..., N_{bus}), it means that there is no DG unit to be accommodated at bus i.

For the determination of optimal capacity of the DG with a settled location, the decision variable is one dimension, while for optimal location of the DG with a given capacity, the decision variable is the location. Let x and y denote the position of the particle and the optimal location, respectively, in which x is a real number in [0, 1]. Candidate locations range from bus n_1 to bus n_2. Then, the mapping relation must be conducted. y is expressed as y=round((n_2−n_1)x)+n_1, where round(·) is an operator to round the number in the parentheses to the nearest integer. The optimal decision variable(s) can be determined by the EMOPSO algorithm introduced in Section 3.

3 Enhanced multi-objective particle swarm optimization algorithm

PSO is a population-based global optimization technique. It has been successfully employed to deal with various problems relating to a power system and has been proven to be a powerful optimizer. Each particle flies through the problem space and it is regarded as a potential solution to the problem. Particle i (i=1, 2, …, N) is associated with its velocity $\boldsymbol{v}_i=[v_{i1}, v_{i2}, …, v_{iD}]^{\mathrm{T}}$ and position $\boldsymbol{x}_i=[x_{i1}, x_{i2}, …, x_{iD}]^{\mathrm{T}}$, where D stands for the dimensionality of the solution space. PSO is initialized with a population of particles with random positions and velocities in the problem space. During the evolutionary process, the best position achieved so far by particle i is recorded as $\boldsymbol{p}_i=[p_{i1}, p_{i2}, …, p_{iD}]^{\mathrm{T}}$, whose corresponding fitness value is called the particle's best, denoted as p_{best}. Moreover, the best position found by any particle is recorded as $\boldsymbol{p}_g=[p_{g1}, p_{g2}, …, p_{gD}]^{\mathrm{T}}$, and its fitness value is called the global best, denoted as g_{best}. In each iteration, the velocity and position of particle i on dimension d (d=1, 2, ..., D) are updated according to Eqs. (9) and (10), respectively:

$$v_{id}(t+1) = wv_{id}(t) + c_1 r_1 (p_{id} - x_{id}(t)) + c_2 r_2 (p_{gd} - x_{id}(t)), \quad (9)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1), \quad (10)$$

where t denotes the current iteration, w indicates the inertia weight, c_1 and c_2 represent positive acceleration coefficients, and r_1 and r_2 are random numbers with a uniform distribution in [0, 1].

3.1 Special techniques introduced to MOPSO

To improve the performance of PSO for MOPs, special techniques have been introduced and an EMOPSO algorithm has been proposed. The inertia weight controls the convergence behavior and provides a balance between global exploration and local exploitation of the PSO algorithm. Instead of a constant or linearly changing one, a dynamic inertia weight (Chen *et al.*, 2009) is used that can adjust dynamically according to

$$w(t) = w_0 + r_3(1 - w_0), \quad (11)$$

where r_3 is a random number with uniform distribution in [0, 1], and $w_0 \in [0, 0.5]$ is a constant. Eq. (11) is used to keep a dynamic balance between global and local search.

Ratnaweera *et al*. (2004) advocated that c_1 changing from 2.5 to 0.5 and c_2 changing from 0.5 to 2.5 during the search process can provide an improved optimal solution for most of the benchmarks. Thus, to enhance the global exploration capability, a time-decreasing c_1 expressed by Eq. (12) and a time-increasing c_2 formulated by Eq. (13) have been integrated into the EMOPSO algorithm:

$$c_1 = 2.5 - t / M_t, \quad (12)$$

$$c_2 = 0.5 + t / M_t, \quad (13)$$

where M_t indicates the maximum number of iterations.

The acceleration coefficients c_1 and c_2 control the amount of 'tension' of PSO to guide each particle towards $\boldsymbol{p}_i$ and $\boldsymbol{p}_g$, respectively. As Eqs. (12) and (13) show, at the beginning c_1 is set to be a larger value and c_2 a smaller one, and they are gradually decreasing and increasing with each iteration, respectively. Such a mechanism not only provides a high diversity during the early stage of the evolutionary process for global exploration of the search space, but also allows for more accuracy in the optimum solution via local exploitation in the last stage.

How to maximize the distribution of identified non-dominated solutions is another issue that should be addressed for MOPSO. Conventionally, the non-dominated crowding distance sorting (NCDS) technique was commonly used to maintain a good spread of Pareto-optimal solutions. This method computes the CD of each non-dominated solution in the set **ND** identified at the current iteration and then selects the solutions with the larger CDs as the current final Pareto-optimal solutions. The main disadvantage of such a method is that the selected solution does not have a uniform distribution. To avoid this disadvantage, an improved NCDS (INCDS) technique is presented and integrated to select the particles for the next iteration. Set **Temp**=**ND** and INCDS can be described as follows. Firstly, compute the CD of each solution in **Temp**. Secondly, sort the non-dominated solutions based on their CDs and delete the solution with the least CD from **Temp**. Thirdly, check the number of solutions left in **Temp**. If it is smaller than the required number, go to the first step; else, output the solutions in **Temp** as the current final Pareto-optimal solutions. The scheme for the selection of particles for the next iteration integrated with INCDS can be illustrated in Fig. 2, where $\boldsymbol{D}$, $\boldsymbol{P}_{\text{new}}$, and $N_{\mathbf{ND}}$ represent the dominated solutions at the current iteration, the population for the next iteration, and the number of solutions in **ND**, respectively.

Selecting leader particle(s) is a key component for MOO. There are a variety of equally good non-dominated solutions, and just one or more can be assigned as $\boldsymbol{p}_g$ to update each individual's position. Traditionally, NCDS was used to evaluate the non-dominated solutions and one was selected as each particle's leader. Unlike the conventional way, a dynamic weighted aggregating approach is used to evaluate non-dominated solutions and assign each particle with a different leader to update its position. Although the aggregating function (Chen *et al.*, 2009) is defective in producing the Pareto-optimal set, it can be applied to the non-dominated solutions produced and guide the selection of the personal and global best. For each particle, randomly generate a set of weights and use Eq. (14) to evaluate each non-dominated solution:

$$\text{fit}=1\Big/\sum_{i=1}^{M}w_i f_i,\quad w_i=\lambda_i\Big/\sum_{i=1}^{M}\lambda_i,\quad \lambda_i=U(0,1),\quad (14)$$

where M is the number of objectives and f_i is the ith objective. Then sort the non-dominated solutions based on their fit values and select the solution with the largest fit value as this particle's $\boldsymbol{p}_g$. The apparent advantage of such an approach is that all the non-dominated solutions have the same opportunity to be selected as leader, which promotes the diversity of the swarm and strengthens the global exploration.

Finally, the mutation strategy is applied to the EMOPSO algorithm to avoid premature convergence.

3.2 Algorithm procedure

In light of the above introduced special techniques, the procedure of the proposed EMOPSO algorithm can be summarized as follows:

Step 1: Initialization. Set the population size N and iteration number M_t, initialize the population $\boldsymbol{P}$ via initializing the position $\boldsymbol{x}_i$ and velocity $\boldsymbol{v}_i$ of particle i (i=1, 2, …, N). Moreover, set $\boldsymbol{p}_i=\boldsymbol{x}_i$ and $V_{d\max}=k\, x_{d\max}$, $0.1\le k\le 1.0$, where $x_{d\max}$ indicates the upper bound of the decision variable on the dth dimension.

Step 2: Evaluation. Compute the fitness of each particle, and update $\boldsymbol{p}_i$ and $\boldsymbol{p}_g$.

Step 3: Generate $\boldsymbol{P}$'s offspring $\boldsymbol{P}_{\text{new}}$ with velocity $\boldsymbol{v}_{i\text{new}}$ and position $\boldsymbol{x}_{i\text{new}}$ based on the current position $\boldsymbol{x}_i$ (i=1, 2, …, N), and compute the objective-function values of the newly generated particles. Then, combine $\boldsymbol{P}$ and $\boldsymbol{P}_{\text{new}}$ and store them in $\boldsymbol{R}$.

Step 4: Distinguish the non-dominated solutions and dominated ones from $\boldsymbol{R}$ based on non-domination, and store them in matrices **ND** and $\boldsymbol{D}$, respectively.

Step 5: Select particles for the next iteration according to the scheme illustrated in Fig. 2.

Step 6: Mutating. If all $|\boldsymbol{v}_i(t)|<0.2V_{\max}$, carry out the Gaussian mutation operator; else, go to step 7.

Step 7: Return to step 2 until the maximum iteration M_t is met.

Step 8: Output the current non-dominated solutions as the final Pareto-optimal solutions.

3.3 Performance of the EMOPSO Algorithm

To illustrate the effectiveness of the EMOPSO algorithm, four commonly recognized benchmark functions (ZDT1–ZDT4) and two metrics, namely the generational distance GD and the spread Δ (Deb *et al.*, 2002), are used here. Let Q and P^* denote an obtained and a known Pareto-optimal set, respectively. GD and Δ are defined as follows:

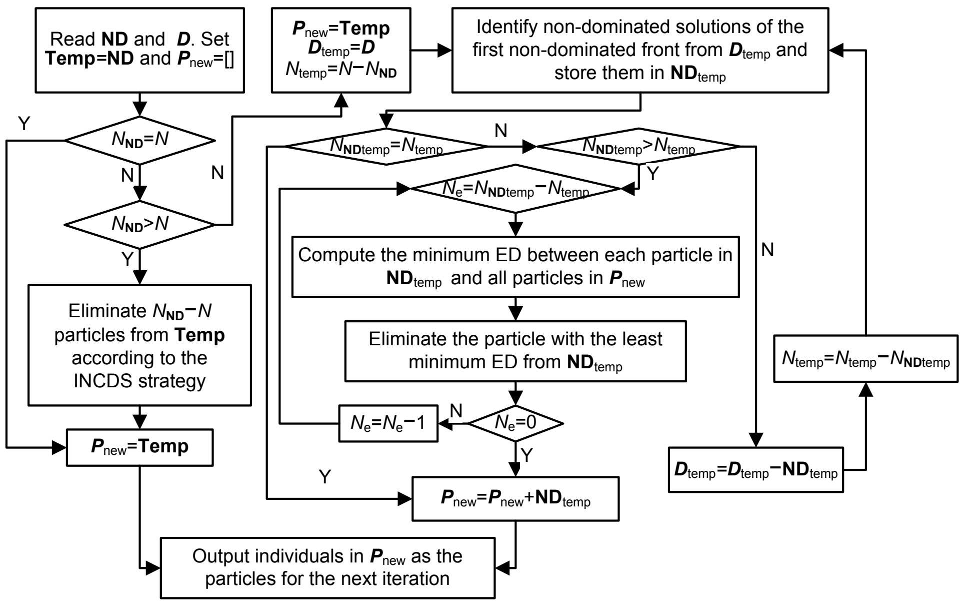

Fig. 2 Scheme for selection of the particles for next iteration integrated with improved non-dominated crowding distance sorting (INCDS)

$$\begin{cases} \mathrm{GD} = \left(\sum_{i=1}^{M} D_i^M \right)^{1/M} \Big/ |Q|, \\ \Delta = \dfrac{\sum_{m=1}^{M} d_m^{\mathrm{e}} + \sum_{i=1}^{|Q|} |d_i - \bar{d}|}{\sum_{m=1}^{M} d_m^{\mathrm{e}} + |Q| \bar{d}}. \end{cases} \tag{15}$$

GD and Δ evaluate the closeness of Q from P^* and the distribution of the Pareto-optimal solutions along the Pareto front, respectively. Considering a two-objective problem (M=2), D_i denotes the Euclidean distance between the solution $i\in Q$ and the nearest member of P^*. d_i and $\bar{d}$ represent the distance between consecutive solutions in Q and the average of all d_i's, respectively. d_m^{e} indicates the distance between the extreme solutions of Q and the nearest member of P^* in the mth objective space.

A set of $|P^*|$=500 true Pareto-optimal solutions of a uniform distribution is used to calculate GD. The performance metrics averaged over 10 iterations are compared with those of NSGA-II (Deb *et al.*, 2002), NSPSO (Li, 2003), MOPSO (Coello *et al.*, 2004), and LH-MOPSO (Jia *et al.*, 2012), as summarized in Table 1. Fig. 3 shows the Pareto-optimal solutions identified by the EMOPSO algorithm. From Table 1 and Fig. 3, it can be seen that the EMOPSO algorithm performs very well as far as convergence and diversity are concerned. It can identify a set of diverse Pareto-optimal solutions, which are close to the real Pareto front and capture the whole spectrum of the true Pareto front.

4 Simulation results and analysis

The encouraging results demonstrated in the previous section reveal that the EMOPSO algorithm enables to distinguish a variety of Pareto-optimal solutions, and gives more information on the trade-offs and correlations between the objectives. The comparison indicates it is competitive considering the convergence and distribution of Pareto-optimal solutions. Having established its effectiveness, EMOPSO is applied to the optimal placement of DG units and its feasibility is verified by the placement of the DG units in the IEEE 33-bus system (Baran and Wu, 1989) shown in Fig. 4. The system studied is a radial feeder system, which has an initial real power loss of 201.53 kW and the VSI is 0.0996. Three scenarios, including determination of the optimal location with a given capacity, optimal capacity with a settled location, and optimal capacities and locations of DG units, are simulated. Simulation results are also compared with those of other representative methods.

Table 1 Mean values of the convergence and diversity

Algorithm	GD				Δ			
	ZDT1	ZDT2	ZDT3	ZDT4	ZDT1	ZDT2	ZDT3	ZDT4
NSGA-II	8.94e-4	8.24e-4	4.34e-2	2.92e-2	0.463	0.435	0.576	0.655
NSPSO	7.53e-4	8.05e-4	3.41e-3	7.82e-4	0.767	0.758	0.869	0.768
MOPSO	1.33e-3	0.89e-3	4.18e-3	7.374	0.681	0.639	0.832	0.962
LH-MOPSO	2.10e-3	2.70e-3	5.90e-3	4.81e-1	0.409	0.380	0.561	0.409
EMOPSO	9.75e-5	8.71e-5	6.01e-4	4.48e-4	0.714	0.682	0.844	0.618

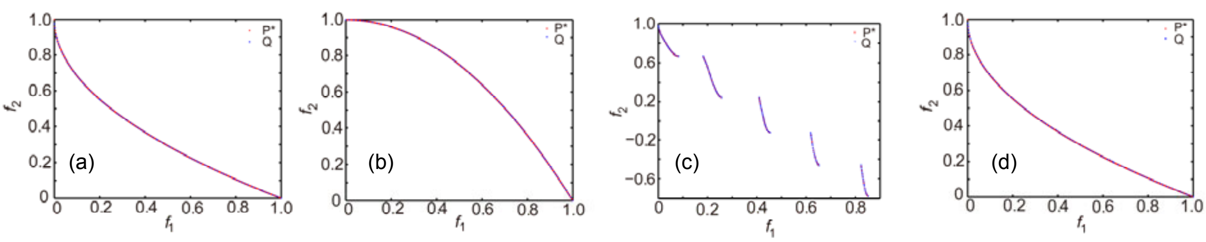

Fig. 3 Pareto-optimal solutions of ZDT1 (a), ZDT2 (b), ZDT3 (c), and ZDT4 (d) in the objective space

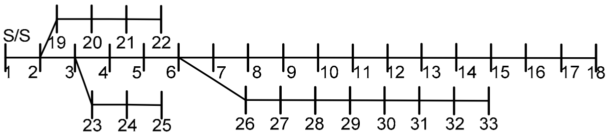

Fig. 4 Single-line diagram of the IEEE 33-bus system

4.1 Scenario I: determination of the optimal location with a given capacity

As the first case study, the EMOPSO algorithm is applied to determine the optimal location of DG units with a given capacity of 1 MW. The candidate locations range from buses 2 to 33. Fig. 5 demonstrates the Pareto-optimal solutions and the corresponding objective-function values. Clearly, the power loss is reduced and the VSI is improved after installing the DG units. It also indicates that the two objectives cannot be optimal at the same bus and the VSI decreases with increasing power loss. To illustrate the effect of integrating DG units at different buses on the voltage of each bus, five Pareto-optimal solutions are selected and the corresponding voltage magnitudes are illustrated in Fig. 6. The installation of DG units has a positive effect on the promotion of the voltage. On the other hand, the effect changes with the location of the installed DG units and the voltage magnitude of the bus, where DG units are installed and those of its nearby buses are greatly prompted.

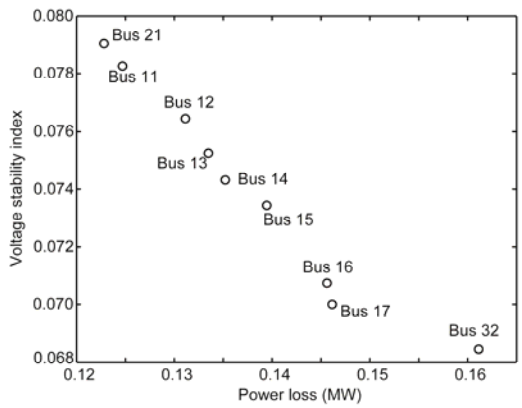

Fig. 5 Pareto-optimal solutions of scenario I in the objective space (optimal location of DG with a given capacity of 1 MW)

4.2 Scenario II: determination of the optimal capacity with a settled location

The variable of scenario I is the location of the DG units with a given capacity, while for scenario II, the DG units are supposed to be located at bus 12. EMOPSO is used to determine the optimal capacity. The variable is continuous during the iterations, and for objective-value computation it is approximated to be an integral multiple of 50 kW. The maximum capacity is equal to P_{load}. The optimal solutions and the corresponding objective-values are shown in Fig. 7. The voltage magnitudes with different capacities are shown in Fig. 8. As shown in Fig. 7, the total power loss of the studied system becomes less and the VSI becomes better after installing DG units with optimal capacity. Similar to Fig. 5, Fig. 7 clearly indicates that the considered objectives conflict with each other. Besides, bus 12, where the DG units are located, has a higher level of voltage magnitude after installing DG units, and a larger capacity implies a better promotion (Fig. 8).

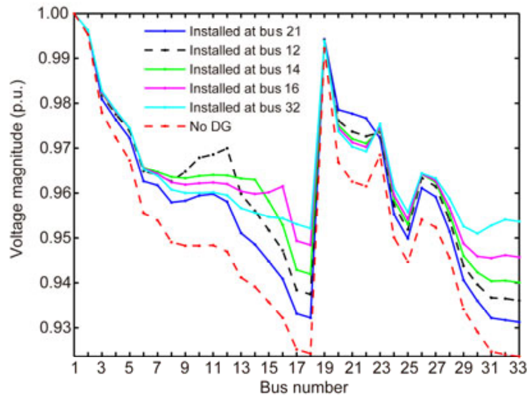

Fig. 6 Voltage magnitude of each bus with 1 MW DG units being installed at different buses

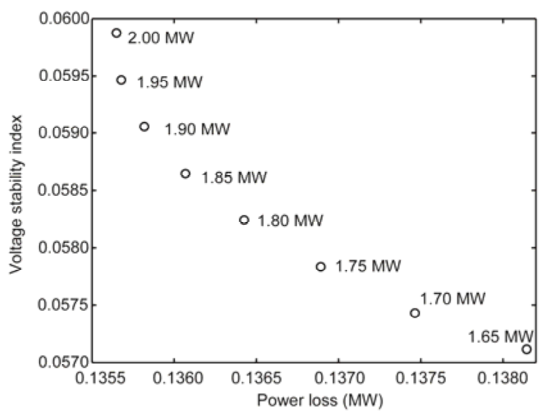

Fig. 7 Pareto-optimal solutions of scenario II in the objective space (optimal capacity of DG with a given location at bus 12)

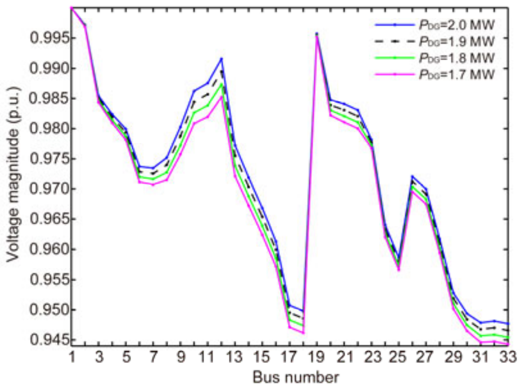

Fig. 8 Voltage magnitudes with different capacities of DG installed at bus 12

4.3 Scenario III: determination of the optimal capacities and locations of DG units

From scenarios I and II, it can be seen that the power loss and VSI of the system in the presence of DG depend on the capacities and locations of the DG units. Therefore, the optimal locations and capacities of the DG units should be determined simultaneously. The variables in scenario III include the capacities and locations of the DG units. Fig. 9 illustrates the VSI values against the power loss values according to the identified Pareto solutions, where η=0.50. Each is a possible solution for the placement of the DG units, but each has a different power loss and VSI. Some solutions have low power loss, but high VSI, and vice versa. Fig. 9 clearly indicates that VSI decreases with an increase in the power loss; that is to say, the objective function of power loss conflicts with that of VSI.

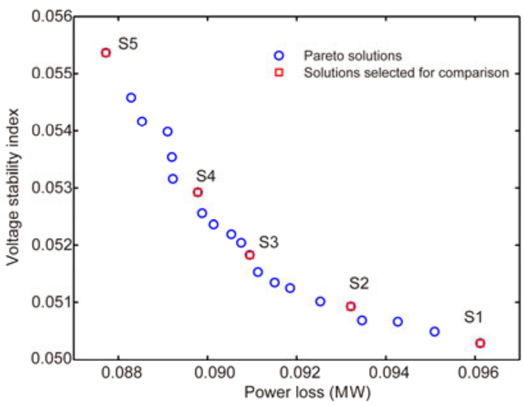

Fig. 9 Pareto-optimal solutions of scenario III in the objective space

Another advantage of proper locations and capacities of the DG units is the improvement in the voltage profile. Different solutions, even with the same total capacity, have different effects on the bus voltage. Five solutions shown in Fig. 9 are chosen from the Pareto-optimal solutions and their exact information is illustrated in Fig. 10a. Fig. 10b shows the corresponding voltage magnitudes. As shown in Fig. 10, the voltage magnitude of the bus where DG units are installed and those of its nearby buses, gain significant promotion, and the larger capacity has the better promotion (buses 21 and 33).

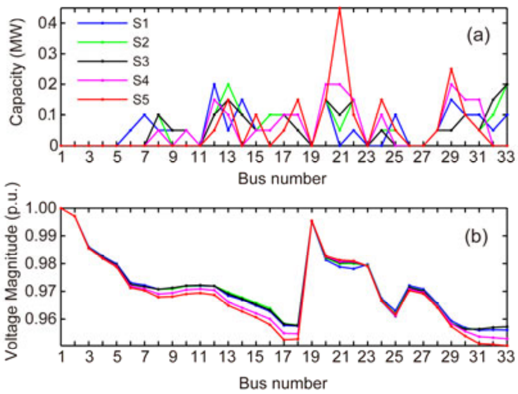

Fig. 10 Effects of installed DG on the bus voltage under the same capacity and different installation information: (a) installation information; (b) corresponding voltage magnitudes

4.4 Comparison and discussion

An inspection of the results presented about the three scenarios shows the advantages of optimizing the capacities and locations of the DG units simultaneously. To validate the completeness of the proposed method, Table 2 gives the simulation results obtained using the methods proposed by Kumar and Selvan (2009), Abu-Mouti and El-Hawary (2011), Moradi and Abedini (2012), and Mistry and Roy (2014). Note that Kumar and Selvan (2009) aimed to minimize the network power loss and maximize the voltage regulation in a given radial distribution network. Moradi and Abedini (2012) also proposed a multi-objective optimization model to minimize the total power loss, and improve the voltage regulation and voltage stability. Both studies converted MOO formulation into a single one via a set of weighting factors. The objectives of the other three studies are minimization of the total system power loss.

Table 2 Comparison of results obtained by different methods

Method	Location (Capacity, in MW)	L (%)	V (%)
Kumar and Selvan (2009)	14 (1.00), 18 (0.25), 33 (1.75)	27.78	6.67
Abu-Mouti and El-Hawary (2011)	6 (3.38)	44.83	–
Moradi and Abedini (2012)	11 (0.925), 16 (0.863), 32 (1.2)	50.97	29.44
Mistry and Roy (2014)	5 (0.8362), 10 (0.3122), 14 (0.1977), 15 (0.2123), 20 (0.2788), 23 (0.9544), 30 (0.6882)	68.76	–
Proposed-S1 in Fig. 10	12 (0.05), 13 (0.15), 15 (0.1), 17 (0.05), 18 (0.15), 20 (0.15), 21 (0.45), 22 (0.10), 24 (0.15), 25 (0.05), 28 (0.05), 29 (0.25), 30 (0.10), 31 (0.05)	52.30	49.51
Proposed-S5 in Fig. 10	6 (0.05), 7 (0.10), 8 (0.05), 9 (0.05), 10 (0.05), 12 (0.20), 13 (0.05), 14 (0.10), 15 (0.05), 16 (0.05), 17 (0.10), 18 (0.10), 20 (0.15), 22 (0.05), 24 (0.10), 28 (0.05), 29 (0.15), 30 (0.1), 31 (0.10), 32 (0.05), 33 (0.10)	56.47	44.41

L denotes the ratio of the total system power loss being reduced to that in case of no installed DG units; V indicates the ratio of the VSI value of the system being improved to that in case of no installed DG units

Firstly, the proposed method can result in better benefits of installing DG with less total capacity. The aim of the optimal placement is to find the optimal locations and capacities of DG units to obtain more benefits. Kumar and Selvan (2009) proposed to place DG units with a total capacity of 3.00 MW at buses 14, 18, and 33, and Moradi and Abedini (2012) proposed to install DG units with a total capacity of 2.988 MW at buses 11, 16, and 32. Such placements reduced power loss by 27.78% and 50.97%, and improved VSI by 6.67% and 29.44%, respectively. With a total capacity of 1.85 MW, the presented method can provide diverse solutions, whose corresponding reduction of power loss ranges from 52.30% to 56.47% and improvement of VSI ranges from 44.41% to 49.51%. Thus, applying the EMOPSO algorithm to optimally place DG units is rather effective.

Secondly, placing DG at multiple locations with a small capacity is more advantageous. As can be seen from Fig. 7 and Table 2, when DG units with a total capacity of 2.00 MW are installed at bus 12, the power loss is reduced by 31.45%, and the VSI is improved by 42.65%. Abu-Mouti and El-Hawary (2011) placed DG units with a capacity of 3.38 MW at bus 6, which reduces the power loss by 44.83%. If DG units with a total capacity of 1.85 MW are placed at buses 12, 13, 15, 17, 18, 20–22, 28–31, the system power loss and VSI are improved by 52.30% and 49.51%, respectively. Figs. 6, 8, and 10b illustrate the voltage profile without and with integration of the DG. As can be seen, integrating DG units with a larger capacity at one location significantly promotes the voltage at a certain area of the network, while placing DG units at multiple locations with a smaller capacity makes the voltage more uniform. Correspondingly, the effects on reduction of power loss and improvement of VSI are considerable. Hence, from the planning point of view, compared with placing DG units at a bus, optimally placing DG units disperse can result in more benefits.

Thirdly, the MOO algorithm provides a set of Pareto-optimal solutions for the decision maker to choose with preference, while the way converting the MOO formulations into a single one yields only one solution which is affected by the weighting factors dramatically. Kumar and Selvan (2009) and Moradi and Abedini (2012) set a larger weighting factor to the power loss. The resulting effect is that the power loss is reduced more than the other objective(s) being improved. Hence, such a trade-off solution is affected by the subjective weights, and in many cases, it is difficult to set appropriate weights to different objectives due to the lack of knowledge or information of the inner relations. The proposed MOO is non-subjective when identifying the Pareto-optimal solutions, because a set of weights reflecting the decision maker's preference for certain objectives is not necessary. After the Pareto-optimal solutions are found, a user can use a high-level qualitative method to make a decision. It is evident that how to use the specific problem preference information is the greatest difference between the MOO method and the method that converts the MOO formulations into a single one using weights. Consequently, MOO can provide the designer with alternative options, being methodical, practical, and less subjective (Deb, 2001).

5 Conclusions

In this paper, an EMOPSO algorithm was presented and employed to determine the optimal placement of DG units. The study mainly aims to determine the optimal capacities and locations of the integrated DG units for reducing the total power loss and VSI of the DS. To deal with such a non-linear problem with incompatible objectives, the EMOPSO algorithm adopts dynamic inertia weights and acceleration coefficients, dynamic aggregating functions, and the mutation operator for improving convergence. The introduction of the INCDS technique and its application to selection of particles for the next iteration ensures the uniform distribution of the Pareto-optimal solutions in the objective space. Application to four well-known benchmark functions shows that the proposed EMOPSO algorithm can identify a set of Pareto-optimal solutions that converge to the true Pareto front with high accuracy while keeping a good distribution. The EMOPSO algorithm has also been successfully tested on the IEEE 33-bus system and compared with the other optimization methods. The corresponding results have demonstrated that the EMOPSO algorithm is a feasible and effective way to solve the MOO of placing DG units in the DS. The numerical simulations also showed that installing DG can effectively reduce the power loss and improve the VSI if they disperse at various buses rather than locate at a stationary bus.

Future research includes using the proposed method in practical applications considering multiple DGs and adopting a high-level qualitative method to help make a decision from the Pareto-optimal solutions.

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