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Co-Evolutionary Multi-Swarm PSO Based Optimal Placement of Miscellaneous DGs in a Real Electricity Grids Regarding Uncertainties

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Abstract- *Distributed generators (DGs) facilitate minimizing a monetary objective for controlling overload or low-voltage obstacles. In conjunction with controlling such complications, a DG unit can be allocated for maximum reliability or efficiency. This study presents a new method based on a new index for locating and sizing DGs in electricity distribution systems. Stable node voltages which are known as power stability index (PSI) are considered in developing the index. An analytical method is applied in visualizing the effect of DG on losses, voltage profile, and voltage stability of the system. In this study, a new approach using co-evolutionary multi-swarm particle swarm optimization (CMPSO) algorithm is purposed for locating DGs in radial electrical distribution systems considering the uncertainty of solar power as well as load and wind power. In this paper, the optimal locations and sizes of DG units are calculated by considering the active power loss, reliability index, and PSI as objective functions. The presented algorithm is tested on 33-bus and 274-bus real distribution networks. The results of the simulation show the effectiveness of the proposed method.*

Keyword: Distributed generators (DGs); Co-evolutionary multi-swarm particle swarm optimization (CMPSO); Uncertainty; Power stability index; Real distribution network.

NOMENCLATURE

CMPSO	Co-evolutionary multi-swarm particle swarm optimization
DG	Distributed generation
MCS	Monte Carlo simulation
RDS	Radial distribution system
P_{loss}	Active power losses
Q_{loss}	Reactive power losses
P_{Gi}	Real power injection in the bus *i*
Q_{Gi}	Reactive power injection in the bus *i*
R	The resistance of the bus impedance matrix
X	The reactance of the bus impedance matrix
Z	Impedance matrix
δ_i	Voltage angle of the Bus *i*
V_s	Voltage of the reference bus
P_G	Generated active power
Q_G	Generated reactive Power
R_{ij}	Line resistance between bus i and j
θ	The angle of the line impedance
V_i	The voltage of the Bus *i*
u_i	Annual outage duration at *i*th load point
N_i	Number of customers at *i*th load point
l_i	The average load connected at *i*th load point
P_{DG}	Active power of DG
Q_{DG}	Reactive power of DG
X_i^m	Position of the *i*th particle in the *m*th Swarm
V_i^m	The velocity of the *i*th particle in *m*th Swarm
P_{La}	The active power loss after DG installation
P_{Lb}	The active power loss before DG installation
P_i	The active power of the bus *i*
Q_i	The reactive power of the bus *i*
n	Number of buses
P_{slack}	The active power in slack bus
Q_{slack}	The reactive power in slack bus
$P_d(k)$	The demand active power in load k

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$Q_d(k)$	The demand reactive power in load k
k	Number of demands
v_{min}, v_{max}	The minimum and maximum of voltage magnitude
$I(l)$	The current flow in line *l*
λ	Failure rate
r	The repair time (h)
n_{pv}	The number of panels
A_{pv}	The area of PV panel
$I(t)$	The Irradiation
$T_0(t)$	The temperature
P_{pv}	The output power of the PV
c_1, c_2, c_3	The acceleration coefficients
r_1, r_2, r_3	The random value between 0 and 1
ω	The inertia weigh
V_i^m	Velocity vector of objective *m* and particle *i*
X_i^m	Position vector of objective *m* and particle *i*
U	Annual outage

1. INTRODUCTION

The high increasing demand of electricity has resulted in the continuous depletion of the traditional power generation sources. The traditional sources are operated centrally and are not appropriate for cost and environmental issues in today's electricity network. The main goal of the utilities is to provide electricity to their customers in a decent, reliable and cost effective manner. In this prospect, DGs offer the solution of these issues up to some extent. Because DGs need less area for installation, possess smaller unit size and can be powered by non renewable and renewable source, they are gradually becoming integral parts of the distribution network.

1.1. Motivation

Nowadays, the usage of conventional power generation units that are covering the growth of load demand has diminished. The distributed generation (DG) units generate limited power. They are classified into two types of renewable and non-renewable [1-2]. The optimal location of DG units outcome as power loss reduction, the betterment of voltage profile, and system reliability. Furthermore, DG installation in the radial distribution system (RDS) reduces the total harmonic distortion (THD) and voltage sags. There are various issues about the integration of power grids and DGs [3-5]. The penetration of DGs could change the grid from passive to active, which affects the operation and reliability of a power grid [4]. Further, the random location of DG can alter a decrease of the voltage profile and an increase of the system losses [6]. An optimum location of DG is required due to minimizing system total loss and improving voltage profiles.

One of the vital objective functions to the allocation of DGs in the RDS is reliability indexes assessment. Besides, power system stability is a very momentous subject. This paper proposes a stability index as one of the objective functions. The expanded index is employed to recognize the most critical bus in the power grid that can lead to instability when the load exceeds the defined range. In this work, the multi-objective function which includes the reliability, power loss reduction, and power stability indexes for the allocation of different types of DGs that have random characteristics (wind turbine and photovoltaic) are considered. To have an all-inclusive evaluation, the wind generation, load demand, and PV power are modeled with considering uncertainty. Doing so, the Monte Carlo Simulation (MCS) method is applied for uncertainty modeling. This method typically is applied to complex and nonlinear problems.

1.2. Literature review

As mentioned earlier, DG units have various benefits. Achieving these benefits requires the optimal sitting and sizing of DGs in the RDS. The different techniques to solve the optimal DG sizing and sitting problem in the previous literature were presented [7]. The common approaches to solve this problem are analytical, numerical, and heuristic methods [8]. For instance, an analytical method for optimal DG allocation in the power system was presented in Ref. [9]. According to this method, first, the DG placement in a radial feeder was investigated. Then, the optimal location for the DG installation was obtained theoretically. Finally, a method that considers bus admittance matrix, generation, and load data for optimal DG placement, was used. On the other hand, another analytical method that does not need a bus impedance matrix to specify the optimal sizing and sitting of the DG unit was suggested in Ref. [10]. It introduced the concept of the PV and PQ buses. The ordinal optimization technique which has three major parts has been used to ascertain the place and capacities of DG units [11]. It considered the candidate locations of DG unit installation. Then, effective linear programming obtains the amount of objective function. Finally, the optimal size and site of DG units are determined by optimal power flow programming. From the heuristic point of view, optimal placement of DG units in the RDS drives a heuristic method called the cuckoo search algorithm whose presents the betterment of the voltage profile and power loss reduction [12]. Besides, the grey wolf optimization algorithm has exerted to detect the optimal place and size of numerous DG units in the RDS [13]. Applying the grey wolf algorithm leads to improvement of voltage profile and RDS loading significantly as well as reduce the active and reactive power losses. Next, the composition of analytical and heuristic techniques to the optimal allocation of numerous DG units in RDS was tested in Ref. [14]. These composition results confirm convergence correctness and velocity in the numerous DG unit allocation problem. Authors in Ref. [15] present a novel opposition-based tuned-chaotic differential evolution technique for the optimal sizing and placement of multiple DG units. Ref. [16] used a differential evolution algorithm to optimize the location, size, and power factor setting each distributed generation source to minimize network losses and maximize distributed generation integration. Ref. [17] proposed an analytical index to determine the optimal size and siting of DGs in a distribution network. The proposed index has consisted of loss sensitivity factor, voltage stability index, and reliability based factors. Recently, a comprehensive learning-based optimization technique for finding the optimal placement and size of DG units in the RDS was proposed [18]. This method is used for mixed-integer variables. To attain the optimal location of the DG units, the local minimums in the objective function were eliminated. DG resources could drive improved reliability and superior power quality at load points. When DG units are applied nearby the loads, the time duration and number of outages are decreased [19]. First, an objective function that includes the reliability indices was selected. The repair time and failure rate of each section in the RDS have an important role in indices determination. Then, the differential evolution and bare-bones PSO algorithm for RDS reliability assessment have used [20].

In this paper, optimal multi-objective allocation of DG units in the 33-bus and real distribution network to achieve more power loss reduction and reliability betterment is carried out by co-evolutionary multi-swarm particle swarm optimization (CMPSO) algorithm. Due to Simplicity, the powerful and extremely rapid convergence of the PSO algorithm, it is selected to design the evolutionary multi-swarm algorithm. According to the framework of multiple populations for multiple objectives (MPMO), an information-subscribe strategy through an outwardly shared archive in the CMPSO algorithm is applied. Two solutions exist for the improvement of the presented algorithm performance. The initial solution is the modification of the particle velocity updating equation. The stored information in the outwardly shared archive updates each particle velocity. The infeasible results are also hoarded in a shared archive. It is to be noted that the shared archive is updated every population generation. Each particle’s position and velocity of their individual experience and data brought from the archive must be updated. Hence, all swarms search information could subscribe through the shared archive. The current algorithm by accelerating the estimation of all Pareto front is improved. Usage of elitist learning strategy (ELS) for archiving update is introduced as the next solution to the improvement of PSO performance. This strategy results in avoiding the incidence of local Pareto fronts. Both solutions could be applied to solve multi-objective problems with multimodal objective functions. The CMPSO algorithm superiority could be listed as:

- Easiness in implementation of the CMPSO algorithm for DGs allocation in the RDS
- Optimizing each swarm by just one objective function and their cooperation to estimate the all Pareto front
- Storing the undesirable solutions in the external archive and using of all swarms information for better approximate of Pareto front
- Updating the external archive and avoiding local Pareto front selection in the multiple objectives.

1.3. Contributions

The principal contributions of this paper can be presented as follows:

- A fast and accurate technique considering the system’s uncertainties is presented.
- CMPSO algorithm based DG units’ allocation is proposed in a real distribution network.
- Multi-objective formulation is expressed by considering reliability index, power loss and power stability improvement.
- The proposed CMPSO is demonstrated high accuracy, robustness and reliability.

2. PROBLEM FORMULATION

For achieving the maximum profit from the DGs locating, it is essential to consider the effect of DGs on a grid. The factors in the following are considered in the siting and sizing of DGs.

- Reducing line losses
- Improving voltage profile and voltage stability
- Improving reliability index.

The power loss exact formulation which contains active and reactive power losses is given in Ref. [21, 22].

$$P_{loss} = \sum_{i=1}^{n}\sum_{j=1}^{n}[\alpha_{ij}(P_iP_j + Q_iQ_j) + b_{ij}(Q_iP_j - P_iQ_j)] \quad (1)$$

$$Q_{loss} = \sum_{i=1}^{n}\sum_{j=1}^{n}[c_{ij}(P_iP_j + Q_iQ_j) + d_{ij}(Q_iP_j - P_iQ_j)] \quad (2)$$

Where,

$$\alpha_{ij} = \frac{R_{ij}}{V_iV_j}\cos(\delta_i - \delta_j),\ b_{ij} = \frac{R_{ij}}{V_iV_j}\sin(\delta_i - \delta_j) \quad (3)$$

$$c_{ij} = \frac{X_{ij}}{V_iV_j}\cos(\delta_i - \delta_j),\ d_{ij} = \frac{X_{ij}}{V_iV_j}\sin(\delta_i - \delta_j) \quad (4)$$

The below mentioned indices apply to the optimal location of the DG units.

2.1. Optimization Process

In this paper, the proposed optimal DG algorithm is developed using real power loss reduction index, power stability index, SAIDI, and average energy not supplied index as objective functions which are described in the following.

- Real power loss reduction index (PLRI)

The main aim of optimal allocation of DG units is minimizing the RDS power loss. Real PLRI as a first objective function could be expressed as:

$$f_1 = PLRI = \frac{P_{Lb} - P_{La}}{P_{Lb}} \quad (5)$$

P_{Lb} and P_{La} represent the active power loss before and after DG installation.

- Power stability index (PSI)

The power stability index is proposed by Aman et al. [23]. This stability index determines the critical buses which could face the voltage drop during load demand increment. As explained, the most optimum location of DG depends on the system critical buses. The PSI value can be computed as follows:

$$f_2 = PSI = \frac{4r_{ij}(P_L - P_G)}{[|V_i|Cos(\theta - \delta)]^2} \leq 1 \quad (6)$$

This value must be less than one, under stable operation, the system will be more stable when the value of PSI is closer to zero. The index is applied to detect the optimum site of DGs. For multi DG placement, the site of the second DG unit will be based on the impact of the first DG on PSI using Eq. (6).

- *SAIDI*

The worth criteria to evaluate reliability are presented, especially for electricity service. One of the useful reliability indicators which are commonly employed by electric power utilities is the system average interruption duration. The total power outage duration for a customer during a certain period is determined by SAIDI. This index value is expressed as:

$$f_3 = SAIDI = \frac{\sum_{i=1}^{n} u_i \times N_i}{\sum_{i=1}^{n} N_i} \quad (7)$$

Where, u_i is annual outage duration at *i*th load point.

- *Average energy not supplied index*

Average energy not supplied (AENSI) could be used in the appropriate asset management of the power generation companies. AENSI is one of the most important indicators of reliability assessment. This index is defined as follows:

$$f_4 = AENSI = \frac{\sum_{i=1}^{n} l_i \times u_i}{\sum_{i=1}^{n} N_i} \quad (8)$$

Where, l_i is average of load connected at *i*th load.

2.2. Problem uncertainty

In this study, the MCS method is exploited to formulate the uncertainty of the system. The MCS is a statistical and stochastic approach that produced random numbers based on a distribution function for providing an approximate solution for a problem which includes a type of uncertainty [24]. A comprehensive description of this method is presented in Ref. [24]. The MCS steps can be shown as follows:

Step 1. Developing a parameter for the model.
Step 2. Determining the limits for numbers that are created randomly.
Step 3. Producing the random numbers as inputs based on the distribution function.
Step 4. Evaluating the model with the numbers.
Step 5. Repeating steps 3 and 4.
Step 6. Aggregating the result.

In this work, the uncertainties of wind power, solar PV, and load demand are considered.

2.3. Constraints

The constraints for the optimal site of DGs could be categorized as follows:

1) Equality constraints:

- Power balance

$$P_{slack} = \sum_{l=1}^{L} P_{line-loss}(l) + \sum_{k=1}^{K} P_d(k) - \sum_{n=1}^{n_{DG}} P_{DG}(n)$$
$$Q_{slack} = \sum_{l=1}^{L} Q_{line-loss}(l) + \sum_{k=1}^{K} Q_d(k) - \sum_{n=1}^{n_{DG}} Q_{DG}(n) \quad (9)$$

2) Inequality constraints:

- Bus voltage limitation

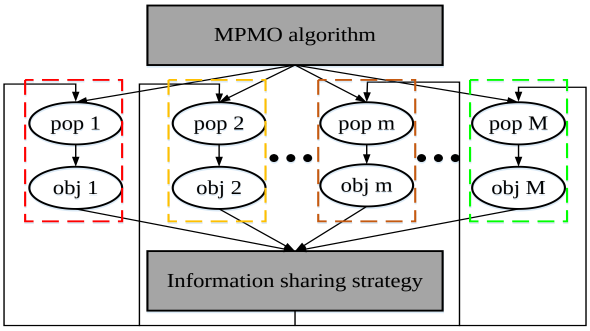

Fig. 1. MPMO approach to solving the multi-objective problems

The voltage magnitude of each bus should be held in the defined range.

$$v_{\min} \le v_i \le v_{\max} \qquad \forall i = 1,2,\ldots,N \tag{10}$$

- Line capacity constraint

Each line's maximum thermal limit restricts its current flow.

$$I(l) \le I_{\max}(l) \qquad \forall l = 1,2,\ldots,L \tag{11}$$

- DG capacity constraint

Due to the constraint of substation power generation, the installed DG capacity must be restricted in limitation to prevent reverse power flow in the RDS [25].

$$\begin{gathered} \sum_{n=1}^{N_{DG}} P_{DG}(n) \le {}^{3}\!/_{4} \times \left[\sum_{l=1}^{L} P_{line-loss}(l) + \sum_{k=1}^{K} P_d(k) \right] \\ \sum_{n=1}^{N_{DG}} Q_{DG}(n) \le {}^{3}\!/_{4} \times \left[\sum_{l=1}^{L} Q_{line-loss}(l) + \sum_{k=1}^{K} Q_d(k) \right] \\ P_{DG}^{\min} \le P_{DG}(i) \le P_{DG}^{\max}, \quad Q_{DG}^{\min} \le Q_{DG}(i) \le Q_{DG}^{\max} \end{gathered} \tag{12}$$

- Line capacity constraint

The complex power passage through each line shall be smaller than its nominal value.

$$S_{li} \le S_{li}(\text{nominal}) \qquad \forall l = 1,2,\ldots,L \tag{13}$$

The multi-objective function is expressed to the optimal location of DG units in the RDS as follows:

$$\min \{ f_1(x), f_2(x), \ldots, f_m(x) \}$$

Subject to:

Equality Constraints $g_i(x) = 0$ where $1 \le i \le k$

Inequality Constraints $h_j(x) \ge 0$ where $1 \le j \le k$

3. CO-EVOLUTIONARY MULTI-SWARM PARTICLE SWARM OPTIMIZATION

In the multiple populations for multiple objectives (MPMO) technique based CMPSO algorithm, several swarms are used for distinct objectives optimization. The use of the MPMO approach for solving multi-objective problems is shown in Fig. 1.

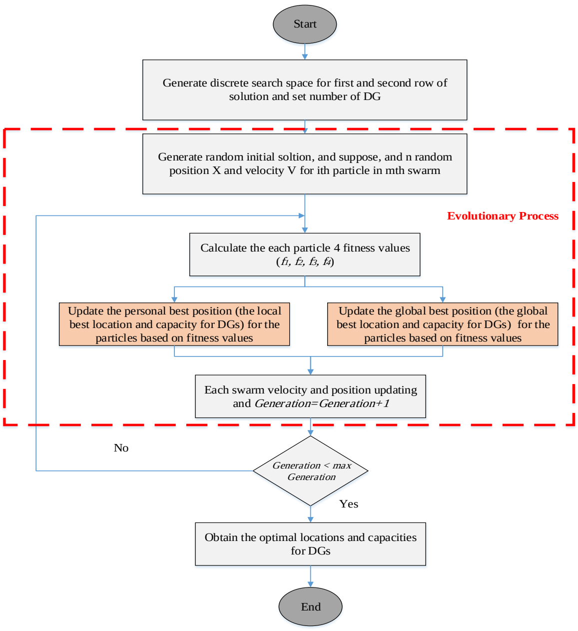

Fig. 2. The flowchart of CMPSO algorithm to solve the optimization problem

The evolutionary and archive update process for each swarm was presented in Ref. [26]. First, *M* swarms with *N* particles in each swarm are selected. Archive *A* must be set empty. The velocity and position of the ith particle in the mth swarm are calculated as:

$$V_i^m = \omega V_i^m + c_1 r_1 (P_i^m - X_i^m) + c_2 r_2 (G_i^m - X_i^m) + c_3 r_3 (A_i^m - X_i^m) \tag{14}$$

$$X_i^m = X_i^m + V_i^m \tag{15}$$

All objectives X_i^m are computed and stored $Pbest_i^m$. The whole of $Pbest_i^m$ being compared with the amount of *m*th objective function. Then, $gbest^m$ is obtained for the *m*th swarm. After updating archive *A*, the algorithm evolutionary process begins. In every generation, a subset of archive *A* by the *i*th particle in the *m*th swarm is randomly selected. Then, its velocity and position are updated. All objectives for the new position X_i^m are computed. When the fitness value of *m*th objective of X_i^m is less than the fitness value of *m*th objective of $Pbest_i^m$, X_i^m must be replaced instead of the previous best position. $Pbest_i^m$ which has the smallest fitness rate as $gbest^m$ is determined. Finally, archive *A* is updated. This procedure iterates until it reaches the end criterion. At the end of the algorithm, results are listed in archive *A*. The limitations of the available PSO algorithm in front of the complex optimization problems with multiple objectives are the motive for the CMPSO algorithm usage. Therefore, DG units are optimally allocated by the CMPSO algorithm. The flowchart of CMPSO is shown in Fig. 2.

Table 1. Characteristics of the DGs in the first case study

DG type	Minimum power per hour (kW)	Maximum power per hour (kW)
Wind turbine	0	150
PV	0	150

Table 2. Zones characteristics

Zone	λ (failure/yr)	r (h)	U (h/yr)
A	1.052	0.131	0.138
B	1.052	0.053	0.055

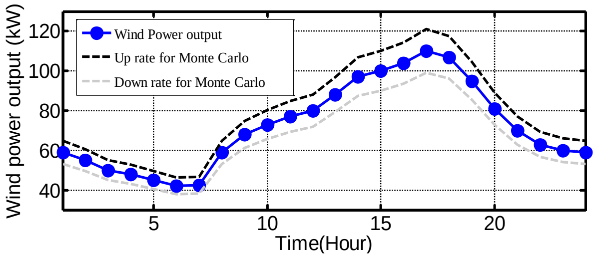

Fig. 3. The forecasted output power of the wind with uncertainty

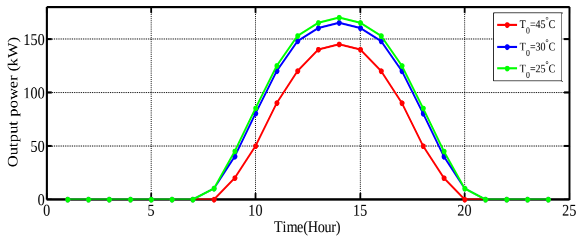

Fig. 4. The PV power in various temperatures

4. UNCERTAINTY MODEL FOR WIND POWER AND SOLAR SOURCES

The wind power generated depends on the wind speed. The power of the wind is calculated in Ref. [29]. The Beta and Weibull probability density functions as presented in Ref. [29] are used to model the probability factor of the wind speed. The power of the wind turbine is not stable. Therefore, in this paper, it is assumed that the power of the wind turbine changes in a zone with a ±10% deviation from the nominal wind speed. The power of the wind turbine is illustrated in Fig. 3. The PV power depends on the irradiation of solar, PV array efficiency, incidence angle, and temperature. It is supposed that a maximum power point tracker (MPPT) is fixed to follow the maximal of available power. The PV power generated can be calculated by using the following equation. The output power of the PV varies with the weather condition.

$$P_{pv}(t) = \eta_{pv} A_{pv} I(t)(1 - 0.005(T_0(t) - 25)) \quad (16)$$

The output power of PV at various temperatures is brought in Fig. 4. In this study, we supposed that the PV power varies between 1±10% of the nominal average amount [28].

5. SIMULATION RESULTS

To confirm the effectiveness of the presented method two test systems are studied. The first case is a 33-bus distribution grid with an active and reactive load of 3.72 MW and 2.3 MVAr respectively [27]. The second case is a real distribution grid, with 274 buses. The algorithm has been run in MATLAB 2010(a) environment on an Intel core™ 3duo PC with 2.66-GHz speed and 4 GB RAM.

Case 1: IEEE 33-Bus Test Network

The single-line diagram of the grid is illustrated in Fig. 5. More details about loads and branches are given in [27]. In this case, we suppose that we have two types of DG (wind and PV). The PV unit in this study is connected to the DC-to-AC converter while the wind unit is connected to the AC-to-AC inverter. The characteristics of these units are shown in Table 1. The grid is assumed as two zones so the characteristics of each zone varied from one another (illustrated in Table 2). The load profiles considering uncertainty are brought in Fig. 6. The load profiles are achieved based on the probabilistic model [28]. The CMPSO parameters selected for optimization are given in Table 3. The power flow analysis is applied to the 33-bus system and the PSI is calculated for each line using Eq. (13) considering no DGs. The value of PSI for each line is demonstrated in Fig. 7. It could be seen that the 12th line connecting bus 12 and bus 13 have a higher value than the others. So the installation of DG will be expected as one of the optimum places.

Table 3. The CMPSO parameters

Parameters	Value
Swarm size	100
Iterations	200
C_1 , C_2	2
X_{min}	0.4
X_{max}	0.9

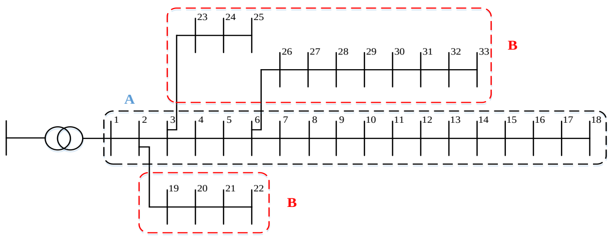

Fig. 5. IEEE 33-bus distribution system

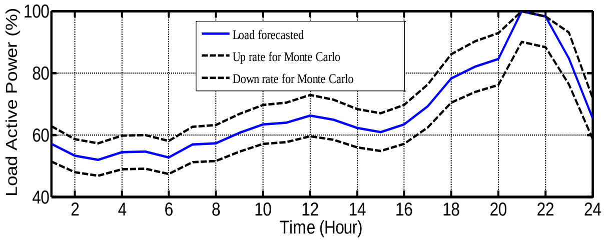

Fig. 6. Active power of load profiles with uncertainty

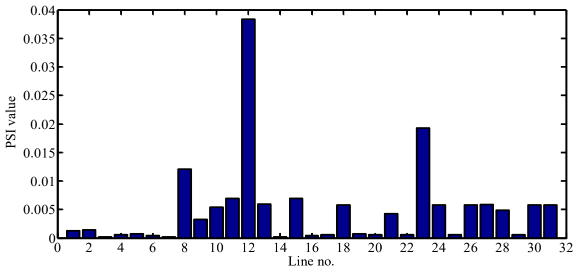

Fig. 7. The value of PSI for each line in the 33-bus distribution network

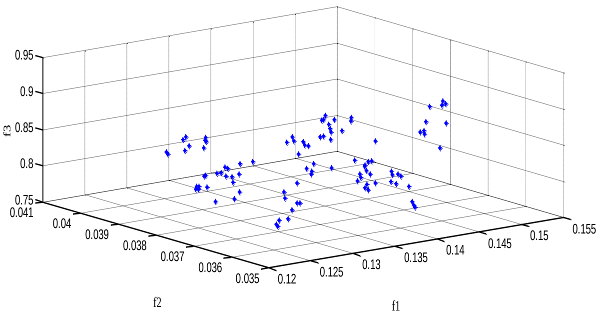

Fig. 8. The crowding distance grap for case 1

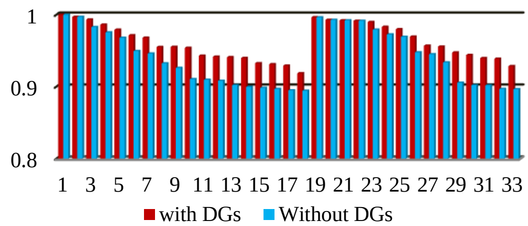

Fig. 9. The voltage profile before and after DGs placement

Table 4. The optimal size of DGs and values of the objective functions in 33-bus

DG type	Location (Bus no)	Capacity (kW)	f_1	f_2	f_3 (hour/yr)	f_4 (kWh/costomer.yr)
Wind turbine	12	65	0.14201	0.03891	0.82652	0.85278
	23	130				
PV	8	90				
	32	120				

Table 5. The characteristic of the real network

Characteristic	Value
Total active power (MW)	2.27
Total reactive power (MVAr)	1.12
Total active loss (kW)	195.5947
Number of buses	274

Table 6. Reliability data of the real network

λ (1/km)	r (TTR)	Number of disconnectors	Number of cut-out switches
0.025	78 min	5	8

The optimum size and locations obtained for different DGs with considering uncertainty are shown in Table 4. Also Fig. 8 shows the crowding distance graph for this case study when the f4 fixed to 0.85278. The ENS and the SAIDI have been decreased by the DGs. The profiles of voltage before and after the DGs placement are shown in Fig. 9.

Case 2: Real distribution network

In the second test system, the technique is tested on a 274-bus distribution grid. The real network is related to a part of Iran's electricity distribution network that is located in the Miandrood region of Mazandaran. The single line diagram of the system without DG is shown in Fig. 10. The electrical data of this real distribution network with associated reliability data are presented in Tables 5 and 6, respectively. The location of the switches in the real system is shown in the Fig. 11. In this case, ten DGs (different types) have been located in the distribution network. The characteristics of these DGs are shown in Table 1. The hourly wind speed and solar radiation data are the same as the data in case I. PSI graph for each line, in this case, is shown Fig. 12. From Fig. 12, it could be observed that the 140th line in the real distribution system has the highest PSI value. Hence, one of the optimum locations of DG is at bus 140.

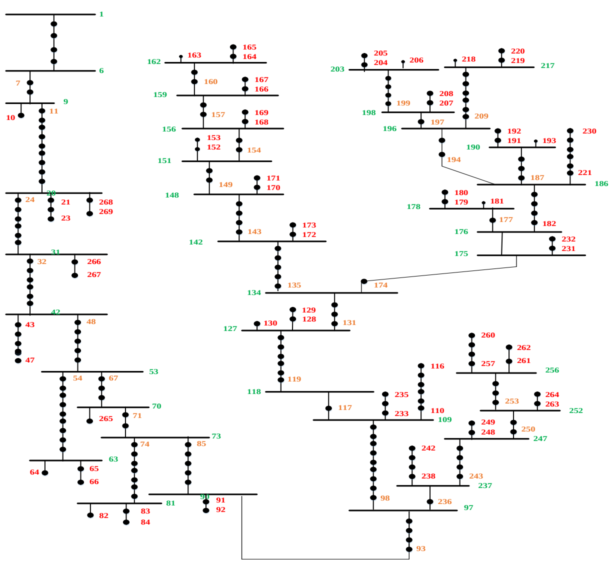

Fig. 10. Single line diagram of real distribution network

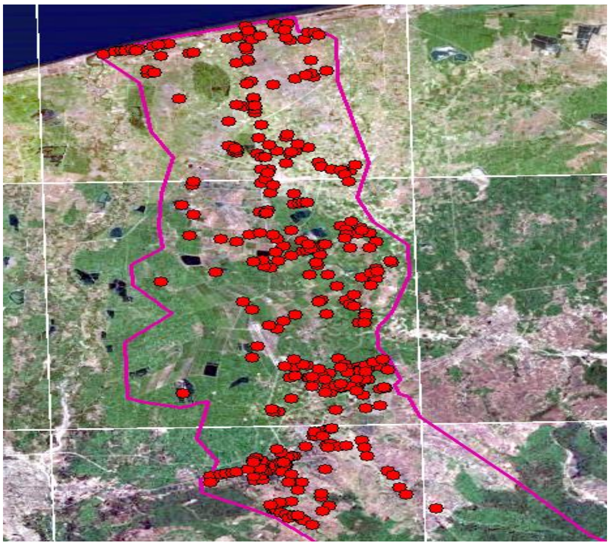

Fig. 11. Location of the switches in the real system

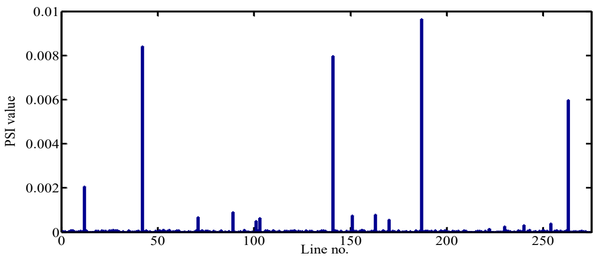

Fig. 12. PSI value for each line in the real distribution system

Table 7. The optimal size of DGs and values of the objective functions in the real network

DG Type	Location (bus no.)	Capacity (kW)	f_1	f_2	f_3 (hour/yr)	f_4 (kWh/costomer.yr)
Wind turbine	140	140	0.24133	0.009295	5.3199	4.5566
	41	45				
	15	115				
	180	110				
	5	60				
PV	94	90				
	46	35				
	265	40				
	87	80				
	146	120				

The optimum size and locations obtained for different DGs with considering uncertainty are shown in Table 7. The ENS and the SAIDI have been diminished by installing the DGs. From the simulation results presented in this section, the following list is concluded:

- The system voltage stability has raised and the voltage profile has improved and
- Losses of lines have decreased
- The capacity of the overall system has increased
- The reliability indexes have been improved.

6. CONCLUSIONS

Since one of the essential objectives of the optimal allocation of DG resources in distribution systems is improving network reliability. This paper aims to find the optimal size and site of different types of DGs in the presence of uncertainty in a real network considering the main index of reliability and loss reduction. For satisfying this purpose the index of reliability and loss reduction has been selected as objective functions. Doing so, for solving the non-linear multi-objective problem, a co-evolutionary method named multiple populations for multiple objectives is exploited. The proposed CMPSO method for optimal placement of multiple types of DGs decreases the line losses as well as the reliability index with the satisfaction of the permissible voltage limits. Eventually, these techniques are applied on real distribution networks, and simulation results prove the efficiency of this methodology.

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