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Multi-objective placement and sizing of DGs in distribution networks ensuring transient stability using hybrid evolutionary algorithm

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ABSTRACT

Distributed generation (DG) units are increasing their popularity around the world. Considering the low inertia constant of DGs, the transient stability of them in the network is one of the major issues. In this paper, a new Pareto-based multi-objective problem is proposed for the placement and sizing of multiple micro-turbines in a distribution network to improve the transient stability index in addition to the losses and voltage profile. To calculate the transient stability index, the rates of fault occurrence in the different locations are considered. Also, the loads are modeled as both constant power and voltage dependent cases. In order to identify Pareto optimal solutions of the optimization problem, a novel hybrid evolutionary algorithm based on the Particle Swarm Optimization (PSO) and Shuffled Frog-Leaping (SFL) algorithm is presented. A 33-bus distribution test system is used to demonstrate the performance of the proposed method in DIgSILENT® PowerFactory software which can be used for practical applications in power systems.

Contents

1. Introduction

Distributed generation will play an important and crucial role in emerging power systems. Studies show that DG will be a significant percentage of all new installed generations [1].

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Increasing DG penetration in distribution system causes a significant impact on the power flow, voltage profile, losses, stability, continuity, short circuit level, and quality of power supply for customers and electricity suppliers. Therefore, it is necessary to consider some aspects in optimization problem for the best placement and sizing of DG units. Many interesting works have been developed to deal with this problem. The main differences among these studies refer to the formulation, solution methodology and assumptions of the problem. In [2,3], only the optimum DG placement was investigated in the distribution system. Several factors were studied in these works such as the overall system efficiency, system reliability, load variation, voltage profile, system losses and DG loss adjustment factors. Both DG placement and sizing in one optimization problem were performed in [4–11]. The location and size of a single DG unit is determined in [4] to only minimize the network losses. The authors of [5] integrate a comprehensive optimization model and planner's experience in different scenarios for optimum distribution planning. The aim of this model is to minimize the investment risk and different costs according to the alternative scenarios. A new analytical method and a fuzzy logic approach are used in [6] to calculate the optimal DG size and location. The investigated factors are the active and reactive power losses and voltage stability index. Effect of different load models on a single objective and a multi-objective distributed generation planning is investigated in [7,8], respectively. It is shown that the load models can significantly affect the problem of DG placement and sizing in distribution networks. In [9], the PSO algorithm was employed to optimize a multi-objective index. This index contains active and reactive power losses, voltage profile, MVA capacity, and short circuit level. Different load models have been considered in [9]. In [10], a combined PSO and genetic algorithm is presented and then a multi-objective index considering active power losses, voltage regulation and voltage stability is optimized by this algorithm. In [11], improved honey bee mating optimization (HBMO) algorithm has been proposed in a Pareto-based multi-objective framework to calculate sitting and sizing of multiple DGs while the competing objective functions of the study refer to minimize costs, emission and losses of distributed system and to enhance voltage profile. Eventually, the review of the relevant aspects related to DG planning notably DG placement are provided in [12–14], where their challenges, trends and latest developments are presented.

Among the various issues related to the network operation, the transient stability is one of the major aspects which should be investigated [15–19]. In [15] the stability of a distribution system is studied in the presence of Distributed Synchronous Generator (DSG) and Distributed Induction Generators (DIG), while [16] focused on dynamic behavior of the network considering the impacts of high DSGs penetration. The [17] considered the impact of distributed generation penetration levels on the transmission system transient stability with applying a fault at all branches. Also, [18] investigated the power system stability considering large number of micro-turbines and fuel cells as DGs. A comparative analysis was presented in [19] between the DSG and DIG for distributed generation applications and it is shown that DSGs have significant advantages from the aspects of voltage profile, voltage and transient stability and DG penetration levels. Moreover, [20,21] described that the short-circuit current in the case of inverter connected generators or DIGs is less than its value in the case of DSGs. However, it is noted that this issue should not prevent careful assessment of power systems and if necessary appropriate setting of protection schemes should be done. The [22] presents some analysis, including steady state and transient studies, on an existing Italian distribution network in the presence of a DSG in different locations and different scenarios. In [23], Critical Clearing Times (CCTs) of DGs were calculated for a real 10-kV distribution network with wind generators, diesel units and micro-turbines while applying three-phase faults at different network locations. The CCT value was determined when the first DG becomes unstable. The general conclusion of [23] is that with the connection of new DG units to the distribution networks, the transient stability issue of DGs may be important and should be taken into account. It is also shown that for some types of DG units, e.g., split-shaft micro-turbines, these problems are more serious and for some others are less, e.g., diesel units and wind turbines. Moreover, it is noted that DG under voltage protection can be set based on transient stability analysis to prevent unnecessary DG disconnections.

Besides, different DG locations as well as different DG power operation in the network can influence transient stability and CCT of DGs due to following reasons:

– Changing the short circuit impedance with placing DG in different buses of the network.
– The interaction effects of DGs with placing them in different buses of the network.
– Different rates of fault occurrence in the buses of the network.
– Different load models in the buses of the network.
– Effect of output power of DGs on the acceleration torque during the fault.

In this regard, in order to improve transient stability of DGs in distribution networks, maximization of the CCT can be added to the DG placement and sizing optimization problem as an extra objective function.

Most of the optimization problems in power systems have been implemented in the MATLAB software environment which is suitable software for power system modeling. This modeling may be degraded the result of optimization problems due to some restrictions of modeling. Therefore, the DIgSILENT® PowerFactory, as one of the most powerful softwares in the area of power system studies, has been implemented in this work. Moreover, dynamic and static modeling of power systems in DIgSILENT® to yield accurate results has been investigated in some papers [24,25]. In [24] only the IEEE 34-node radial network is simulated in DIgSILENT® and several static analyses is performed. A multi-objective approach based on the Bellman–Zadeh algorithm and fuzzy logics is used to determine suitable DG site in [25]. DG location is determined and then the optimized network is simulated in DIgSILENT®.

Based on the above mentioned explanations, the contributions of this paper with respect to the previous ones can be summarized as follows:

– A multi-objective optimization problem for placement and sizing of multiple micro-turbines as DGs in a distribution networks is performed in which the objective functions are minimizing the power losses, improving voltage profile and improving the CCT of DGs in the network. In order to calculate the CCT function, the rates of fault occurrence in the different buses of the network are considered. Also, the simulation is performed considering different voltage-dependent load models.
– To solve the optimization problem, a hybrid technique is proposed which uses the advantages of both PSO and SFL algorithms by combination of them. The Pareto method have been used for multi-objective approach and finally a fuzzy decision making tool is adopted to select the most preferred Pareto optimal solution among the generated efficient solutions.
– For precise dynamic modeling of the network and obtaining accurate value of CCT, the simulation is executed in DIgSILENT®

software and optimization algorithm is implemented using DIgSILENT Programming Language (DPL).

The main structure of the rest of paper is: Section 2 presents problem formulations, in Section 3 solution approach is explained in detail, in the next section numerical results are presented, and the research will be concluded in Section 5.

2. Problem formulations

The best location and size of multiple micro-turbines is determined in this work by minimizing three competing objective functions. The formulations of these three objective functions and the practical system constraints as well as load models are presented in the subsequent subsections.

2.1. Objective functions

2.1.1. Minimizing the power losses

Minimizing the real power loss is an important issue in the optimization problem of DG placement and sizing which consider in the most previous work. Therefore the first objective function is represented as follows:

$$f_1 = P_{loss} = P_{loss}^{lines} + P_{loss}^{transformers}$$

$$OF_1 = \mathbf{min}\, f_1 \tag{1}$$

where, P_{loss} is the total active power losses in the distribution systems including the power losses of lines and the copper losses of DG transformers.

2.1.2. Improving the voltage profile

One of the most significant security and power quality indices is the voltage deviation of the buses which used as the second objective function in this work. Minimizing this function can be described as follows:

$$f_2 = \sum_{bi=1}^{bi=NB} (V_{bi} - V_{rated})^2$$

$$OF_2 = \mathbf{min}\, f_2 \tag{2}$$

where NB is the number of system buses, V_{rated} is the nominal voltage of buses which is equal to 1 p.u. and V_{bi} is the voltage of the *bi*th bus of the system. By minimizing this objective function, the voltage of busses is propelled to the rated voltage (1 p.u.) which causes voltage profile improvement [10].

2.1.3. Improving the transient stability

The third objective function of the optimization problem is to improve the transient stability of DGs using the CCT index. CCT is defined as maximal fault duration for which the system remains transiently stable. Mathematically, CCT is a complex function of pre-fault system conditions (operating point, topology, system parameters), fault structure (type and location) and post-fault conditions that themselves depend on the protective relaying plan employed. For this purpose, different contingencies related to the various fault locations have been considered. Indeed, a three phase short circuit fault (as the most severe fault) is individually applied to all buses, and in each case the CCT is calculated as the first DG begins to be unstable. The DG begins to be unstable when the rotor speed and angle continue to increase, leading to loss synchronism. Note that, in the simulation phase, the stability of the system is examined based on this fact if the pole slipping phenomenon is occurred or not. Then, the calculated CCTs are aggregated according to the normalized rates of fault occurrence (normalized fault occurrence probabilities) in the different buses as follows:

$$f_3 = \frac{\sum_{bi=1}^{NB} p_{bi}.CCT_{bi}}{\sum_{bi=1}^{NB} p_{bi}}$$

$$OF_3 = \mathbf{min} \left\{ \frac{f_{\min,3}}{f_3} \right\} \tag{3}$$

where, CCT_{bi} is the calculated CCT for applied fault to bith bus and p_{bi} is the fault occurrence rate in the bith bus. f_3 and $f_{\min,3}$ are the aggregated value and its minimal value, respectively. To improve the transient stability, we minimize the defined index OF_3.

2.2. Constraints

The proposed multi-objective optimization problem consisting three defined objective functions is solved subject to the following constraints:

2.2.1. Voltage limit

Voltage of all buses should be kept within the allowable range:

$$V_{\min} \le V_{bi} \le V_{\max} \tag{4}$$

where, V_{bi} is the voltage magnitude at *bi*th bus and V_{min} and V_{max} are the allowable higher and lower values of voltage.

2.2.2. DG technical constraints

Due to the capacity of each DG depending on its type and operation conditions is different, it is necessary to constrain the capacity within the permissible levels.

$$P_{\min,gi} \le P_{gi} \le P_{\max,gi} \tag{5}$$

where, P_{gi} is the output active power of *gi*th DG, and $P_{min,gi}$ and $P_{max,gi}$ are their boundary limits.

2.2.3. Branch power flow limits

The power flow over the lines is limited based on the capacity of lines:

$$S_{li} \le |S_{\max,li}| \tag{6}$$

where, S_{li} is the power flow through the *li*th line and $S_{max,li}$ is the related line capacity.

2.3. Load models

The load models can be mathematically expressed as [8]:

$$P_{bi} = P_{0bi} V_{bi}^{\alpha} \tag{7}$$

$$Q_{bi} = Q_{0bi} V_{bi}^{\beta} \tag{8}$$

where, P_{0bi} and Q_{0bi} are the active and reactive load of *bi*th bus at the nominal voltage, P_{bi} and Q_{bi} are the active and reactive power injections of *bi*th bus, V_{bi} is the voltage magnitude of *bi*th bus, and α and β are active and reactive power exponents.

3. Solution approach

To explain the solution approach, at first, a fuzzy based multi-objective formulation of problem is presented, and then, the proposed algorithm using combination of PSO and SFL is described in detail.

3.1. Fuzzy based multi-objective formulation

Multi-objective optimization problems have several objective functions with different single optimal solutions and we cannot have a single solution that simultaneously optimizes all the objective functions. In these cases, the efficient (or Pareto optimal, non-dominated) solutions should be calculated which are the solutions that cannot be improved in one objective function without worsening their performance in at least one of the rest. In the mathematical definition, If we assume that all the objective functions OF_n, $n=1\ldots p$ should be minimized, a point $x^*\in\Omega$ is efficient solution of the multi-objective problem if and only if there is no $x\in\Omega$ such that $OF_n(x)\le OF_n(x^*)$ for all $n=1,2,\ldots,p$ with at least one strict inequality.

In this paper, there are three conflicting objective functions OF_1, OF_2 and OF_3, formulated in (1), (2) and (3), respectively. A fuzzy approach is used to solve the proposed multi-objective problem. For this purpose, the above-mentioned objective functions should be modeled by fuzzy membership functions as follows:

$$\mu_n(x)=\begin{cases}1 & , \quad OF_n(x)\le OF_n^{\min}\\ 0 & , \quad OF_n(x)\ge OF_n^{\max}\\ \frac{OF_n^{\max}-OF_n(x)}{OF_n^{\max}-OF_n^{\min}} & , \quad OF_n^{\min}\le OF_n(x)\le OF_n^{\max}\end{cases} \tag{9}$$

where, OF_n and μ_n are the value of the nth objective function and its membership function, respectively. Also, x refers to the vector of decision variables. For properly applying this method, the ranges of objective functions ($OF_n^{\min}$ and $OF_n^{\max}$) are needed. For this purpose calculation of the payoff table is the most common approach. To calculate the payoff table, the single optimizations of problem for all three objective functions are performed. In each case, the individual optimal solution of the one objective function is calculated and the value of the other objective functions is obtained, too. Each case constructs one row of the payoff table as follows:

$$\Phi=\begin{pmatrix}OF_1^*(x_1^*) & OF_2(x_1^*) & OF_3(x_1^*)\\ OF_1(x_2^*) & OF_2^*(x_2^*) & OF_3(x_2^*)\\ OF_1(x_3^*) & OF_2(x_3^*) & OF_3^*(x_3^*)\end{pmatrix} \tag{10}$$

where, $OF_n{}^*(x_n^*)$ is the individual optimal solution of OF_n. The minimum and maximum values of the nth column of the payoff table indicate the range of the objective function OF_n for the implemented fuzzy approach. Membership functions which are used here are continuous and monotonic functions. Further detail about payoff table can be found in our paper [26].

Evolutionary based algorithms generate a population and search in an objective space to find the optimum solution. In multi-objective problems, there is a set of efficient solutions which will be saved in the repository space, iteratively. After finding these efficient solutions, the decision makers are looking for the "most preferred" solution among them. For this purpose, the normalized membership function is evaluated as follows:

$$\mu^k=\frac{\sum_{n=1}^{N_{obj}} w_n\times\mu_n(x_k)}{\sum_{k=1}^{N_{rep}}\sum_{n=1}^{N_{obj}} w_n\times\mu_n(x_k)} \tag{11}$$

where, N_{obj} is the number of objective function and N_{rep} is the number of efficient solutions which is saved in the repository space. Also μ^k is the normalized membership function of kth efficient solution. This membership function is implemented to sort the efficient solutions based on the decision maker priority over objective functions which is mentioned by w_n in (11) [11].

3.2. Proposed hybrid evolutionary algorithm

In this paper, a new modified hybrid algorithm (combining SFL [27] and PSO [28] algorithms) is used to optimize the objective functions. The original SFL and PSO algorithms and their concepts can be found in [27,28].

The major advantages of the SFL algorithm compared to mathematical algorithms and other evolutionary optimization techniques are its simple context and minimal storage requirements [27]. Besides, PSO [28] is known as an optimization algorithm which has the ability to possibly escape from local optima by accepting non-improving energy solution during the first and middle stage of the algorithm. Also, the PSO is widely-used algorithm in the literature of power systems due to its simple implementation. Based on the above mentioned reasons we have chosen these evolutionary algorithms to combine as hybrid algorithm. Moreover, the motivation of combining PSO and SFL can be described as follows.

The main deficiency of the PSO algorithm is its premature convergence. One reason is that all particles have the tendency to fly to the current best solution that may be a local optimum or a solution near local optimum. Therefore, all particles may concentrate to a small region and the global exploration ability may be weakened. As a matter of fact, the most significant character of the SFL [27] is to divide frogs into several memplexes, and search in different parts of the solution space. Consequently, with combining the PSO and the SFL algorithms, the SFL can remedy the PSO drawback by dividing particles into several memplexes. In other words, by this method, several PSO algorithms will search in different parts of the search/solution space. It is proved that, the optimum solution obtained by the proposed algorithm is better than those obtained by PSO and SFL algorithms in the simulation results.

The application of the proposed algorithm on the proposed DG placement and sizing problem is presented as following steps:

Step 1: Input required data of the problem (including, network data and algorithm parameters).
Step 2: Generate the initial population considering the defined information in the previous step.

$$X_i=\begin{bmatrix}x_{location} & x_{size}\end{bmatrix}$$
$$x_{location}=\begin{bmatrix}DG_1^{loc} & DG_2^{loc} & \ldots & DG_{N_{DG}}^{loc}\end{bmatrix}$$
$$x_{size}=\begin{bmatrix}DG_1^{size} & DG_2^{size} & \ldots & DG_{N_{DG}}^{size}\end{bmatrix} \tag{12}$$

$$initial\text{–}population=\begin{bmatrix}X_1\\ X_2\\ \vdots\\ X_{Npop}\end{bmatrix} \tag{13}$$

Step 3: Calculate the load flow and transient stability analysis; based on the decision variables.
Step 4: Calculate the objective functions. The objective functions are calculated by Eqs. (1)–(3).
Step 5: Check the problem constraints considering the results of load flow. If the problem constraints are satisfied, go to the next step, otherwise add penalty term to the objective functions. The penalty term is a big number in this work.
Step 6: Calculate the membership function of each objective function; Fuzzy approach, i.e., Eq. (9), is used to obtain μ_1, μ_2 and μ_3 corresponding to F_1, F_2 and F_3.
Step 7: Calculate the fitness function using Eq. (11). Steps 3–7 are repeated for all members of initial population.
Step 8: Sort the frogs in descending order of fitness values [27].
Step 9: Place frogs into q memplexes. Note that each memplex comprises of (F/q) frogs.where, q and F are the number of memplexes and populations, respectively.

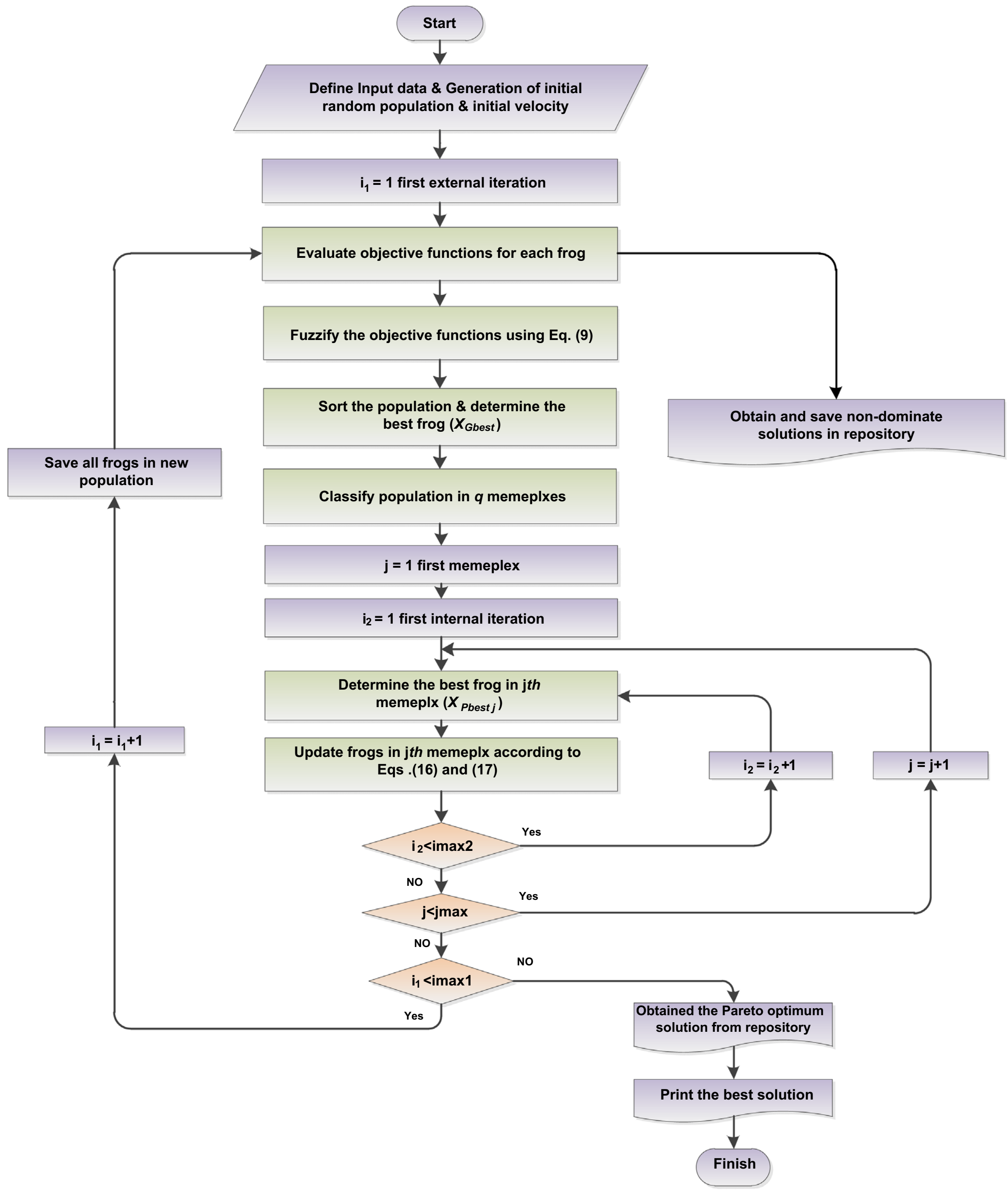

Fig. 1. The flowchart of the proposed algorithm for solving the DG placement and sizing problem.

Step10: Determine the $X_{Pbest\ j}$ and X_{Gbest}. where, $X_{Pbest\ j}$ and X_{Gbest} are the best solution for jth memplex and global best solutions in all populations, respectively [28].

Step 11: Update the ith frog of jth memplex based on the PSO algorithm using (14) and (15) [28]. This step is repeated until predetermined iteration number is reached.

$$D_{i,j}^{iter+1} = \omega \cdot D_{i,j}^{iter} + c_1 \cdot rand_1(\cdot)(X_{Pbest_j} - X_{i,j}^{iter}) + c_2 \cdot rand_2(\cdot)(X_{Gbest} - X_{i,j}^{iter}) \quad (14)$$

$$X_{i,j}^{iter+1} = X_{i,j}^{iter} + D_{i,j}^{iter+1} \quad (15)$$

where, D is analogous to the velocity of particles in PSO algorithm.

Note: It is noted that this procedure should be iterated for all memplexes.

Step 12: Shuffle the memplexes. In this step information is exchanged among all memplexes. To do this, all memplexes are mixed together and resorted. From the existing frogs, all the non-dominated solutions are extracted and saved in the repository based on the definition of Pareto optimality.

Step 13: Check the convergence criteria. In this work, a pre-specified number of iteration is adopted for stopping criteria. If the convergence criteria are satisfied, optimization trend is finished and the last repository contents are considered selected as Pareto solutions, otherwise return to Step 9.

Step 14: Finally, after obtaining the Pareto solutions, the decision-maker can select one best compromised solution according to the specific preference for different conditions. Therefore, for each individual solution in the repository, the normalized membership function is calculated using Eq. (11). This membership function is implemented to sort the non-dominated solutions based on the decision maker priority over objective functions. The solution which has the highest normalized membership function is the best compromised (most efficient) solution.

The flowchart of the proposed algorithm for solving the proposed DG placement and sizing problem is depicted in Fig. 1.

4. Numerical results

The proposed problem is studied on the 33-node radial distribution system which its data can be found in [29]. The single-line diagram of the network has been illustrated in Fig. 2. Total load of this system is 3.27 MW and 2.3 MVAr. In Table 1, the rates of fault occurrence in the different buses are presented. In this work, five split-shaft micro-turbines with the rated power of 400 kW are applied as DGs. The split-shaft micro-turbines use a power turbine rotating at 3600 rpm and a conventional generator (synchronous or induction machine) connected via a gearbox. Here, the synchronous split-shaft design is used, and the synchronous machine is 6th order [30] (four rotor windings, rotor speed and rotor angle). Detailed information concerning the dynamic models of split-shaft micro-turbines can be found in [31].

The problem includes two sets of decision variables. The first set of decision variables refers to the locations of DGs which is discrete number within the range 2–32. The first bus feeds the network and there is no load on it. The second set of decision variables is the amount of active power of DG which is injected to the system. It is

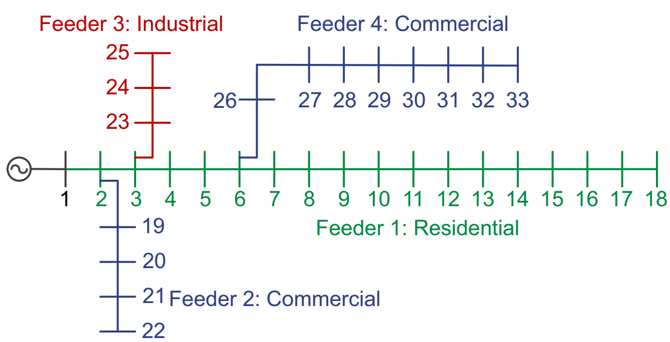

Fig. 2. The single line diagram of the 33-bus system.

Table 1
The rates of fault occurrence in the buses.

Bus no.	Rates of fault occurrence	Bus no.	Rates of fault occurrence	Bus no.	Rates of fault occurrence
1	0.02	12	0.03	23	0.025
2	0.025	13	0.04	24	0.025
3	0.02	14	0.02	25	0.04
4	0.03	15	0.035	26	0.035
5	0.04	16	0.035	27	0.02
6	0.02	17	0.02	28	0.035
7	0.035	18	0.04	29	0.04
8	0.035	19	0.03	30	0.02
9	0.025	20	0.02	31	0.03
10	0.02	21	0.03	32	0.025
11	0.03	22	0.02	33	0.035

Table 4
Load types of feeders and exponent values.

Feeder no.	Bus no.	Load type	α	β
Feeder 1	2–18	Residential	0.92	4.04
Feeder 2	19–22	Commercial	1.51	3.4
Feeder 3	23–25	Industrial	0.18	6
Feeder 4	26–33	Commercial	1.51	3.4

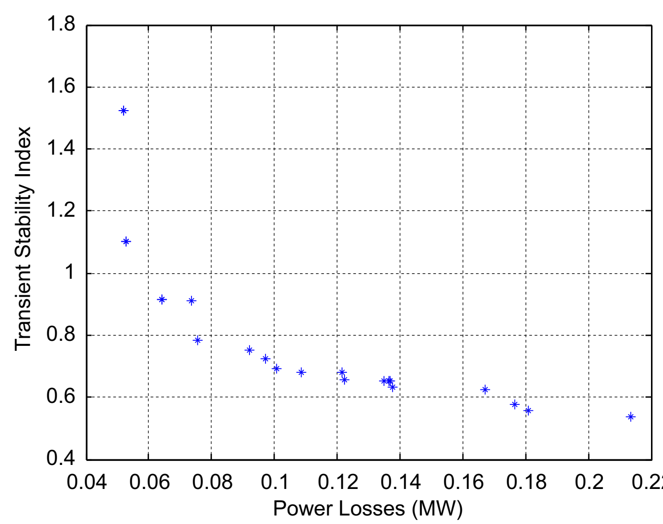

Fig. 3. Pareto front obtained from simultaneous optimization of OF_1 and OF_3 for Case I.

Table 2
Parameter settings of algorithms.

Method	Number of population	Number of memplexes	Iteration$_{max1}$	Iteration$_{max2}$	Learning factors		
PSO	40	–	60	–	$C_1=2$	$C_2=2$	$W=0.4$–0.9
SFL	40	5	6	10	–	–	–
Hybrid PSO & SFL	40	5	6	10	$C_1=2$	$C_2=2$	$W=0.4$–0.9

Table 3
Comparison of three algorithms for 10 trials (total power losses is the objective function).

Method	Best (kW)	Worst (kW)	Average (kW)	Standard deviation	Loss value for 10 trials (kW)
PSO	44.533	48.218	46.029	1.427	48.218, 47.975, 45.164, 47.583, 45.022, 45.029, 44.533, 45.09, 45.011, 46.668
SFL	44.69	47.275	45.647	0.946	45.268, 46.53, 47.275, 45.075, 45.304, 45.021, 44.69, 44.924, 47.088, 45.293
Hybrid PSO & SFL	44.533	45.184	44.649	0.198	44.533, 44.533, 44.686, 44.533, 45.184, 44.645, 44.534, 44.567, 44.683, 44.593

noted that the DG buses considered as PV buses. Therefore, their reactive injection is not constant. The range of injected active power of DGs is considered between 200 and 400 kW.

Modeling and simulations of the test case have been performed in DIgSILENT® Power Factory environment using DPL.

In the first step, we should evaluate the proposed algorithm compared with the original PSO and SFL algorithms.

4.1. Evaluation of proposed algorithm

For this purpose, three algorithms including SFL [27], PSO [28] and the proposed hybrid PSO & SFL are used to solve the DG placement and sizing problem. In this case, we only consider the first objective function, i.e., minimization of the power losses. The parameter settings of these algorithms are given in Table 2. In this table, the number of two iterations in the proposed algorithm (denoted by $imax_1$ and $imax_2$ in Fig. 1) has been shown. The value of the power losses in the base case is obtained as 0.210798 MW which is related to the power losses of lines. It should be noted that, in this work, the dynamic model of DGs is considered and therefore, in the presence of DG, the copper losses of DG transformers is added to the total losses.

To compare the results of the proposed hybrid algorithm with other methods in terms of computational efficiency and performance, the problem is solved in 10 trials for all three algorithms. Table 3 illustrates the obtained solutions as well as the related best, worst, and average solutions and standard deviation. It is observed that the obtained results by the proposed method are better than those obtained by the other methods. Note that the best solution for the PSO and proposed algorithm are equal (44.533 kW). However, the other values of the proposed algorithm (including worst solution, best solution and standard deviation) are better than PSO. As mentioned earlier, PSO has the ability to find a global or near-global optimum solution, but its global exploration ability may be weakened due to the premature convergence. As seen, this deficiency is significantly overcome using the proposed algorithm.

4.2. Implementation of the proposed multi-objective problem

In this subsection, the proposed algorithm is employed to solve the multi-objective problem which described in Sections 2 and 3. For load modeling, we consider two following cases:

Case I. Considering all loads as constant power

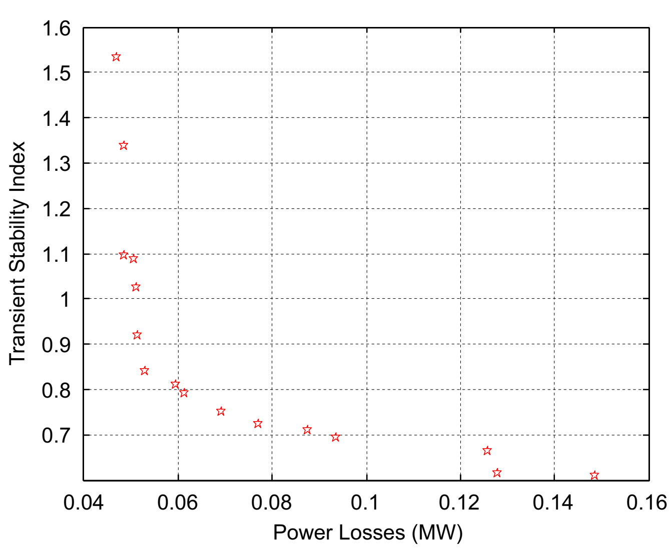

Fig. 4. Pareto front obtained from simultaneous optimization of OF_1 and OF_3 for Case II.

Case II. Considering the loads as different voltage-dependent models

In Case I, all loads of the 33-node distribution system are modeled as constant power which conventionally used in power

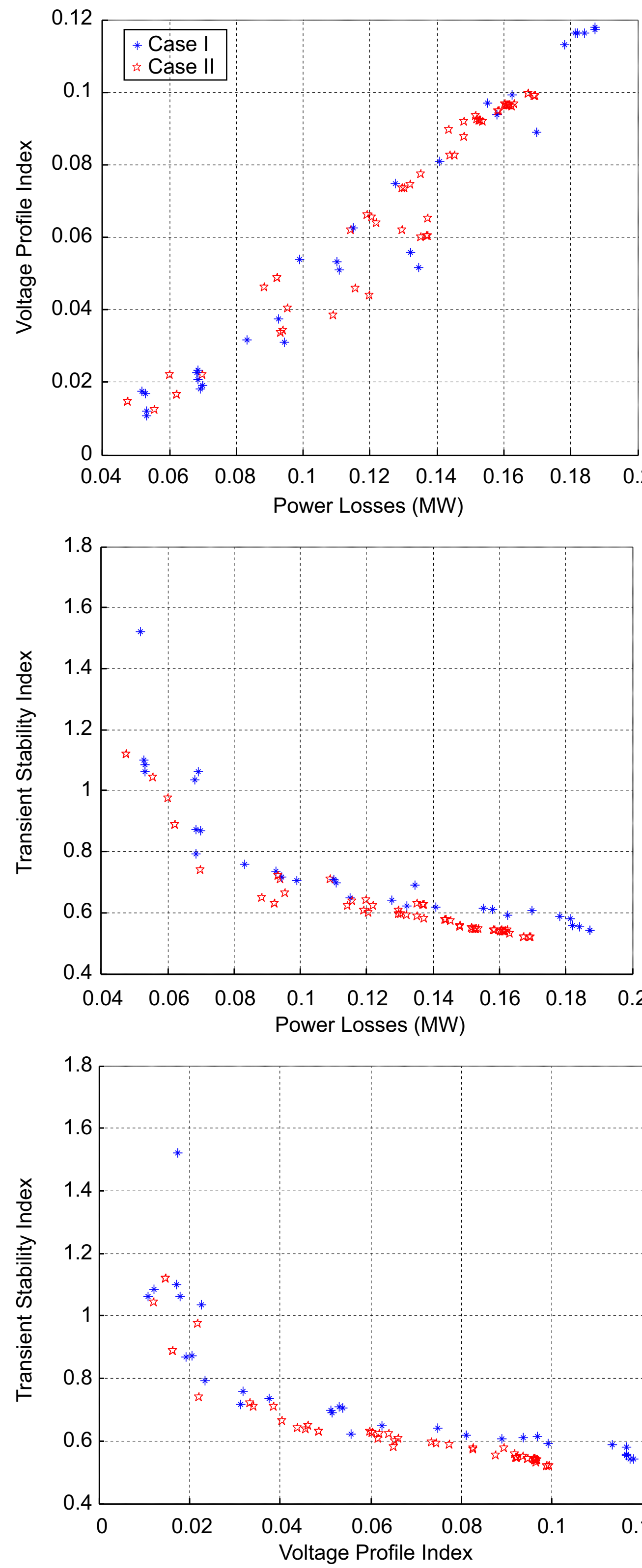

Fig. 5. Three pair dimensions of Pareto optimal set (*XY*, *XZ* and *YZ* views) from optimization of all three objective functions for both Cases I and II.

Table 5
The most preferred Pareto solution for the Cases I and II.

Case	OF_1 (MW)	OF_2 (p.u.)	OF_3 (p.u.)	Locations of micro-turbines	Sizes of micro-turbines, respectively (kW)
Case I	0.053273	0.010898	1.06337	14, 16, 33, 8, 31	312.8, 334.4, 323, 279, 200
Case II	0.055567	0.012256	1.042318	33, 12, 14, 26, 13	275.1, 252.3, 306.2, 237.6, 290

flow studies. Therefore, the exponents α and β in Eqs. (7) and (8) are equal to zero.

In Case II, we consider the loads of the network as a mixture of industrial, residential, and commercial loads. For this purpose, each feeder is considered as one type of the mentioned load categories. Different load types for all network buses are specified in Fig. 2. Also, Table 4 presents the load types of feeders as well as related power components. Values of power components are the same as assumed values in [7–9].

Before to present the results, following points should be noted regarding the objective functions.

Calculated CCTs for the fault locations between DG and substation are lower than the faults between DG and the end buses of feeders. Indeed, the later faults have better situations in the viewpoint of transient stability. Also, by decreasing the output power of DGs, the CCT values and transient stability are generally improved. Therefore, by minimizing the OF_3, the DG locations tend to be close to the substation and the DG output powers tend to be close to their lower limit.

On the other hand, for improving power losses and voltage profile, two other objective functions (OF_1 and OF_2) generally have tendency to locate DGs near the end buses of feeders as well as increase DG output powers. This makes an appropriate conflict between the proposed third objective function and two other ones.

Figs. 3 and 4 illustrate the Pareto front obtained from simultaneous optimization of OF_1 and OF_3 (improving losses and transient stability index) using the proposed method for the Cases I and II, respectively. As seen, the Pareto solutions have a well distribution with high diversity over the trade-off curve due to the above discussions.

The Pareto optimal set attained by optimizing all three 3-objective functions are demonstrated in Fig. 5 for both the cases. In this figure, to better explain and compare the results, three pair dimensions of Pareto optimal set (*XY*, *XZ* and *YZ* views) are shown instead of three-dimensional. From these figures, the following observations can be inferred:

– The obtained Pareto optimal solutions have a similar manner for losses and voltage profile index (in *XY* view) which is in contrast to the transient stability index (in *XZ* and *YZ* views).
– As seen, in the case of voltage dependent load modeling, the results are changed. It can be seen that, in general, the values of transient stability index in Case II are lower than the Case I. Indeed, it is concluded that, the load models can significantly affect the optimal location and sizing of DGs in distribution systems, especially in the case of transient stability assessment.

It is worthy to note that each Pareto optimal solution is an alternative choice for system operator to be adopted as final solution in the various conditions. Therefore, after finding the Pareto optimal solutions, the decision-maker according to Eq. (11), selects the most-preferred solution among them. The system operator can select the weighting factors w_n based on the importance of objective functions. The solution which has the maximum membership function μ^k is the most-preferred solution and is selected as the best Pareto-optimal solution (the final solution) for the multi-objective optimization problem.

Table 5 presents the results of selecting the most-preferred solution over Pareto optimal set for $w_1=w_2=w_3=0.33$ in both Cases I and II. As it is seen from this table, considering the voltage-dependant loads will affects the final decision on the location and sizing of DGs. Therefore, the proposed framework in this paper can obtain more "real" results for the distribution systems.

5. Conclusions

In this paper a secure multi-objective optimization framework has been presented for DG placement and sizing in the distribution systems. The competing objective functions consist of minimizing the losses and voltage deviations as well as improving transient stability of DGs. For this purpose, multiple micro-turbines are used as DGs. The transient stability function is calculated using CCT index in the case of applying different contingencies related to the various fault locations. Also, to solve the optimization problem, a new hybrid technique is proposed based on the combination of PSO and SFL algorithms to benefit from the advantages of both of them. In the multi-objective approach, the efficient solutions are generated and then the most preferred Pareto optimal solution are selected among them applying a fuzzy decision making tool. In order to obtain a more precise result, all simulations are carried out in DIgSILENT® software with dynamic modeling and considering different voltage-dependent load models. The proposed framework permits the distribution system operators to consider the dynamic security issues in addition to other important aspects, and to compromise the conflicting objectives of the DG placement and sizing procedure. There are some future research works in this area to incorporate more security based objective functions (e.g. small signal stability margin) and to consider other types of DGs.

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