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Simultaneous allocation of distributed energy resource using improved particle swarm optimization

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HIGHLIGHTS

- This paper addresses a multi-objective formulation for simultaneous allocation of DERs in RDNs to maximize annual savings.
- An improved particle swarm optimization is proposed to overcome inherent tendency of local trappings in PSO.
- A node sensitivity-based guided search algorithm (GSA) is suggested to enhance overall performance of optimizing tool.
- Proposed method is investigated on benchmark IEEE 33-bus and 69-bus test distribution systems.
- Proposed approach is useful for electric utilities to enhance profits and stagger future expansion plans.

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ABSTRACT

Smart grid initiatives require integrated solution for radial distribution networks (RDNs) to achieve their optimum performance. The optimal allocation of distributed energy resources (DERs), such as shunt capacitors and distributed generation, when integrated with distribution network reconfiguration (DNR), can achieve desired objectives of smart distribution systems. This paper addresses a multi-objective formulation for simultaneous allocation of DERs in RDNs to maximize annual savings by reducing the charges for annual energy losses, peak power losses and substation capacity release against the annual charges incurred to purchase DERs while maintaining better node voltage profiles and feeder current profiles. An improved particle swarm optimization (IPSO) method is proposed to overcome against the inherent tendency of local trappings in PSO. A node sensitivity-based guided search algorithm (GSA) is also suggested to enhance the overall performance of the optimizing tool. GSA virtually squeezes the problem search space without loss of diversity. Distribution networks are optimally reconfigured after optimally placing DERs. The proposed method is investigated on the benchmark IEEE 33-bus and 69-bus test distribution systems. The application results show that the proposed integrated approach is very useful for electric utilities to enhance their profits and stagger their future expansion plans.

1. Introduction

The electric power industries have witnessed many reforms in recent years. The present trend toward the deregulation in power sector is forcing distribution network operators (DNOs) to improve energy efficiencies for cost reduction whereas customers are becoming more sensitive to reliability and power quality. Distributed energy resources (DERs) such as shunt capacitors (SCs) and distributed generators (DGs) are some of the essential components for achieving higher energy efficiency in distribution system operation. The energy efficient grid requires integrated solutions to well-formulated problems that reflect facts on the ground where all such devices coexist to achieve smart grid goals of efficiency through loss minimization and high-quality power delivered to the ultimate user [1]. Optimal DER placement can improve network performance in terms of better node voltage profiles, reduced power flows, reduced feeder losses, improved power quality and reliability of electric supply, but inappropriate DER placement may increase system losses as well as network capital and operating costs [2]. Whatever be the particular driver for a DNO, e.g., to allow the connection of more DG capacity, to reduce energy losses, or to increase network reliability, the DG planning tools must take into account essential network constraints such as voltage and thermal limits [3].

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Nomenclature

c_1, c_2	acceleration coefficients
D	number of design variables
d	discount rate
E	total number of branches in the system
GQ_B	grid reactive power at base case (kVAr)
GP_B	grid active power at base case (kW)
GQ_{TSC}^n	grid reactive power with test capacitor at the nth node (kVAr)
GP_{TDG}^n	grid active power with test DG at the nth node (kW)
$gbest^k$	best particle position based on overall swarm experience at kth iteration
H_j	load duration at jth load level (h)
$I_n^{\max}$	maximum current of nth branch (p.u.)
I_{pf}	feeder current deviation penalty function
I_{nj}	current of nth branch at jth load level (p.u.)
ΔI_{nj}	current deviation of nth branch at jth load level (p.u.)
itr	current iteration
itr_{max}	maximum iteration count
itr_s	predefined iteration count
K_e	unit cost of energy (US $/kW h)
K_p	unit cost of peak power losses (US $/kW)
K_S	cost of annual charges for sub-station capacity release (US $/kVA)
K_{SC}	cost of annual charges on shunt capacitor installation (US $/kVAr)
K_{DG}	cost of annual charges on DG installation (US $/kW)
K_b	number of capacitor banks
K_d	number of discrete dispatches of DG
L	set of load levels
loc	total number of candidate locations for capacitor/DG placement
N_L	total number of load levels
N_{SC}/N_{DG}	candidate nodes for capacitor/DG placement
N	set of system nodes
n	branch number
nsc	maximum number of candidate capacitor banks at a node
ndg	maximum number of discrete dispatches of DG at a node (kW)
P	population size
P_D	nominal active power demand of the system (kW)
$P_{loss,bj}$	power loss for uncompensated system at jth load level (kW)
$P_{loss,aj}$	power loss for compensated system at jth load level (kW)
$P_{loss,b}^P$	peak power loss for uncompensated system (kW)
$P_{loss,a}^P$	peak power loss for compensated system (kW)
$P_{DG,min}/P_{DG,max}$	minimum/maximum active compensation limit at a node (kW)
P_d	unit size of DG (kW)
P_{nj}/Q_{nj}	real/reactive power for sending end of nth branch at jth load level (kW/kVAr)
ΔP	minimum discrete dispatch of DG (kW)
$pbest_p$	best position of pth particle achieved based on its own experience
$Q_{SC,min}/Q_{SC,max}$	minimum/maximum reactive power generation limit at a node (kVAr)
Q_{SC}/P_{DG}	reactive/active power generation at a candidate node (kVAr/kW)
Q_D	nominal reactive power demand of the system (kVAr)
Q_b	size of capacitor bank (kVAr)
ΔQ	tapping size of capacitor bank (kVAr)
R_n	resistance of the nth branch (Ω)
$r_1()$, $r_2()$	random number in the range [0,1]
S_b^P	sub-station capacity at base case (kVA)
S_a^P	sub-station capacity after DER allocation and reconfiguration (kVA)
S_{SC}^n	sensitivity of nth node for capacitor placement
S_{DG}^n	sensitivity of nth node for DG placement
s_p^k/s_p^{k+1}	position of pth particle at kth/$(k+1)$th iteration
Δt	time step (s)
V_{pf}	node voltage deviation penalty function
V_{max}/V_{min}	maximum/minimum permissible node voltage (p.u.)
V_{minS}	minimum specified node voltage (p.u.)
V_{nj}	voltage of nth node at jth load level (p.u.)
ΔV_{nj}	maximum node voltage deviation of nth node at jth load level (p.u.)
v_p^k/v_p^{k+1}	velocity of pth particle at kth/$(k+1)$th iteration
w	inertia weight
w_{max}/w_{min}	maximum/minimum value of inertia weight
Y	planning horizon
ζ	capital recovery factor
λ	penalty function
Φ_j	closed loop at jth load level

Several successful attempts have been made in the recent past to solve the problem of optimal allocation of either SCs [4–10] or for DGs [11–16] separately. However, the simultaneous placement strategy of DERs is more practical and can independently set and control the real and reactive power flow in distribution network (DN) [12]. Some researchers [17–24] have attempted this simultaneous allocation strategy and have shown mutual impact of these devices on the performance of distribution network using analytical or/and heuristic technique. Zou et al. [17] proposed an analytical approach for the simultaneous placement of SCs and DGs for minimizing investment cost. They reduced the search space by identifying voltage support zones using analytical approach and solved the problem using particle swarm optimization (PSO). Abu-Mouti and El-Hawary [18] employed artificial bee colony (ABC) algorithm to determine the optimal size of DGs' power factor, and location to minimize power losses while considering various scenarios. It has been shown that there is a substantial enhancement in the results in terms of voltage profile improvement and loss reduction. A heuristic approach is suggested by Naik et al. [19] where a node sensitivity analysis is used to identify the optimal candidate locations, and then the optimal capacity of SCs/DGs are determined by suggesting heuristic curve fitting technique. Moradi et al. [22] proposed a combined imperialist competitive algorithm (ICA)–genetic algorithm (GA) method to solve this multi-objective optimization problem. In this method, first the ICA is used to find siting and sizing of distributed resources and then the operators of GA are used to further refine these solutions. In Ref. [24] different types of DGs are employed for real and reactive power injections to minimize power losses. The problem is solved using an analytical approach and PSO. The authors concluded that the heuristic approach is more suitable for larger systems. However, these attempts have considered only loss minimization and node voltage enhancement as the problem objectives and not considered peak power losses, feeder current profiles and substation capacity release for DER allocation.

Distribution network reconfiguration (DNR) is another operational strategy which has been frequently used to achieve multiple performance objectives such as power loss minimization, voltage profile enhancement and congestion management. Therefore, coordinated approach for DER allocation with DNR can more effectively achieve the objectives such as increased energy efficiency, decreased peak power losses and enhancing substation capacity release. Usually, the SCs are placed by power distribution utility whereas the owner of DGs is a private investor. The electric utility should provide coordinated solution for the siting and sizing of DERs to the DG investor so that both DGs and SCs can be allocated simultaneously. In fact, such coordinated initiative can provide maximum benefits for the network owner and/or the network users, and can evaluate the feasibility of DERs investment versus other traditional planning options [2].

The optimal placement of DERs involves the determination of their optimal number, sizing and siting in DN. It is a nonlinear complex combinatorial optimization problem. Swarm and evolutionary based optimization techniques, like GA, PSO, etc. have proven potential to obtain global or near global optima. However, care should be taken to avoid premature or slow convergence, particularly in large scale applications [3], where enormously large search space is offered to these techniques. Several attempts [4,7,9–11,16,17,19] have been reported to reduce the search space by employing node sensitivity based approaches for optimal allocation of DERs. In these approaches a node priority list (NPL) is prepared. From this list only a few top priority nodes are selected for DER allocation. However, these approaches are not foolproof and provide only a coarse guidance about the priority of candidate nodes. In fact the node sensitivities are calculated for the base case conditions where no such devices have been installed [6]. Furthermore, when selecting only top few nodes as the sensitive components, it did not give the true picture of the entire distribution network [8].

In this paper a coordinated approach is proposed for the simultaneous allocation of DERs and optimal network reconfiguration using an improved PSO (IPSO) method. The proposed approach maximizes the annual profit of electric utility by reducing the annual charges on energy losses, peak power losses and substation capacity release against the annual charges incurred to purchase DERs. A node sensitivity-based guided search algorithm (GSA) is suggested to enhance the overall performance of the proposed method. GSA virtually squeezes the problem search space without loss of diversity. The proposed IPSO method is investigated on two standard test distribution systems.

2. Problem formulation

The problem for the optimal allocation of DERs is formulated to maximize annual savings in such a way that maximizes the annual profit by reducing the charges for annual energy losses, peak power losses and substation capacity release against the annual charges incurred to purchase DERs while maintaining better node voltage and feeder current profiles under multi-level load pattern. A penalty function approach is suggested to check the maximum node voltage deviation and thermal limit of distribution feeders. The objective function is therefore formulated as below:

$$\begin{aligned} Max.\ F = \lambda\Bigg(& K_e\left(\sum_{j=1}^{N_L} P_{loss,bj}H_j - \sum_{j=1}^{N_L} P_{loss,aj}H_j\right) + \zeta K_p\left(P^P_{loss,b} - P^P_{loss,a}\right) \\ &+ \zeta K_S\left(S^P_b - S^P_a\right)\Bigg) - \zeta K_{SC}\sum_{n=1}^{loc} Q_{SC,n} - \zeta K_{DG}\sum_{n=1}^{loc} P_{DG,n}; \\ &\forall n \in N,\quad \forall j \in L \end{aligned} \tag{1}$$

where N and L denote the set of system nodes and the set of load levels, respectively. N_L and H_j refer to the number of load levels and their corresponding load durations, respectively which are considered in the multi-level piece-wise annual load profile. $P_{loss,bj}$ and $P_{loss,aj}$ are the power losses for uncompensated and compensated system at jth load level, $P^P_{loss,b}$ and $P^P_{loss,a}$ are the peak power loss for uncompensated and compensated system, S^P_b is the sub-station capacity for base case, S^P_a is the sub-station capacity after DER allocation and reconfiguration, Q_{SC} and P_{DG} are the reactive and active compensation at a candidate node. K_e, K_p, K_S, K_{SC}, K_{DG} represent the unit cost of energy, unit cost of peak power losses, annual charges for sub-station capacity release, annual charges on shunt capacitor installation and annual charges on DG installation, respectively. Therefore, the first and second terms represents the cost of annual energy loss reduction and the cost of peak power loss reduction, respectively. The third term, refers to the annual charges for the substation capacity release. The fourth and last terms denote the annual charges to install SCs and DGs, respectively. λ is the proposed penalty function to take care node voltage deviations and feeder current limits and is defined by the geometric mean of the node voltage penalty function V_{pf} and the feeder current penalty function I_{pf} as shown below:

$$\lambda = \sqrt{(V_{pf} \times I_{pf})} \tag{2}$$

where

$$V_{pf} = \frac{1}{1 + Max(\Delta V_{nj})};\quad \forall n \in N,\quad \forall j \in L \tag{3}$$

$$I_{pf} = \frac{1}{1 + Max(\Delta I_{nj})};\quad \forall n \in N,\quad \forall j \in L \tag{4}$$

The Eq. (3) shows that V_{pf} is determined by evaluating maximum node voltage deviation among all system nodes while considering all load levels, where ΔV_{nj} denotes the voltage deviation of the nth node from the source voltage at jth load level. Similarly I_{pf} is determined using (4), where ΔI_{nj} denotes the deviation of the nth feeder current from its rated ampacity during the jth load level. The value of ΔV_{nj} and ΔI_{nj} are calculated by proposing (5) and (6), respectively. It is noteworthy that a soft voltage constraint is used in (5) by defining minimum specified node voltage V_{minS} which has to be kept less than the minimum permissible node voltage V_{min}, which is being specified by the power regulation authorities. V_{max} is the maximum permissible node voltage specified by the regulation authorities and $I_n^{\max}$ is the rated line ampacity of the nth line.

$$\Delta V_{nj} = \left\{\begin{array}{ll} 1 - |V_{nj}|; & V_{minS} < V_{nj} < V_{min} \\ 0; & V_{min} \leqslant V_{nj} \leqslant V_{max} \\ \text{a very large number}; & \text{else} \end{array}\right\};\quad \forall n \in N,\quad \forall j \in L \tag{5}$$

$$\Delta I_{nj} = \left\{\begin{array}{ll} 0; & I_{nj} \leqslant I_n^{\max} \\ \text{a very large number}; & \text{else} \end{array}\right\};\quad \forall n \in N,\quad \forall j \in L \tag{6}$$

The capital recovery factor ζ for DERs investments is obtained as below:

$$\zeta = (d(1+d)^Y)/((1+d)^Y - 1) \tag{7}$$

where d is the discount rate and Y refers the planning horizon for the DER allocation project.

The following operational constraints are employed:

$$g_j(h) = 0;\quad \forall j \in L \tag{8}$$

where $g_j(h)$ represents the set of power flow equations during jth load level.

The total active and reactive power injected by DG and SCs at each node must be within their permissible range as defined by:

$$Q_{SC,min} \leqslant Q_{SC,n} \leqslant Q_{SC,max};\quad \forall n \in N \tag{9}$$

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$$P_{DG,min} \leqslant P_{DG,n} \leqslant P_{DG,max}; \quad \forall n \in N \tag{10}$$

where $P_{DG,min}$ and $P_{DG,max}$ are the minimum and maximum active power generation limit at a node, respectively. Similarly, minimum and maximum reactive power generation limit at a node is defined by $Q_{SC,min}$ and $Q_{SC,max}$, respectively.

The system power generation limits for SCs and DGs are defined as:

$$\sum_{n=1}^{loc} Q_{SC,n} \leqslant Q_D; \quad \forall n \in N \tag{11}$$

$$\sum_{n=1}^{loc} P_{DG,n} \leqslant P_D; \quad \forall n \in N \tag{12}$$

Where it is assumed that the sum of active and reactive power injected by DGs and SCs at all candidate nodes locations should be less than nominal active P_D and reactive power demand Q_D of the system, respectively. Eqs. (13) and (14) prohibit the repetition of candidate sites for DERs.

$$N_{SC,a} \neq N_{SC,b}; \quad a, b \in N \tag{13}$$

$$N_{DG,a} \neq N_{DG,b}; \quad a, b \in N \tag{14}$$

where N_{SC} and N_{DG} refer candidate sites for SCs and DGs, respectively. Since DERs are commercially available in discrete sizes and thus are modeled as:

$$Q_{SC} \leqslant K_b Q_b; \; K_b = 0, 1, 2, \ldots, nsc \tag{15}$$

$$P_{DG} \leqslant K_d P_d; \; K_d = 0, 1, 2, \ldots, ndg \tag{16}$$

where Q_b and P_d represent the respective unit size of SCs and DGs. K_b and K_d represent number of capacitor banks and discrete dispatches of DG, respectively.

First optimizing (1), the solution obtained provides the optimal siting and sizing of DERs, while considering the annual load profile. Next, (1) is optimized, but for each load level separately, to determine the optimal power dispatches of installed DERs. However, the sites for DERs are kept freeze and their sizing is restricted to that provided by the obtained solution. The additional constraints required to determine the optimal dispatches of SCs and DGs are modeled as below:

$$Q_{SC,n} = K_t \Delta Q; \; K_t = 0, 1, 2, \ldots, Q_{SC,n}/\Delta Q \tag{17}$$

$$P_{DG,n} = K_{md} \Delta P; \; K_{md} = 0, 1, 2, \ldots, P_{DG,n}/\Delta P \tag{18}$$

where ΔP and ΔQ represent the available commercial discrete sizes of SCs and DGs, respectively.

The distribution network is reconfigured for each load level separately after optimally placing DERs. The reconfiguration problem is solved to minimize real power loss P_{loss} at jth load level while satisfying various network operational constraints. The mathematical formulation for the DNR problem is formulated as:

$$Min.\; P_{loss,j} = \sum_{n=1}^{E} R_n \frac{P_{nj}^2 + Q_{nj}^2}{|V_{nj}|^2}; \quad \forall n \in N, \quad \forall j \in L \tag{19}$$

where E represents total number of branches in the system, the active and reactive power flows in nth branch are expressed by the P_{nj} and Q_{nj}, respectively. R_n denotes resistance of the nth branch whereas V_{nj} denotes the nth node voltage at jth load level.

Eq. (19) is subject to the following constraints:

1. Radial topology constraint

The reconfigured network topology must be radial, i.e. with no closed path. Therefore, for the rth radial topology the radiality constraint is defined as:

$$\Phi_j(r) = 0; \quad \forall j \in L \tag{20}$$

where $\Phi_j(r)$ is the symbolic representation for closed loop.

2. Node voltage constraint

A hard voltage constraint is employed during the DNR as it is one of the important network operational strategies. All node voltages V_{nj} of the system must be maintained within the minimum and maximum permissible limits i.e. V_{min} and V_{max}, respectively, during the optimization process.

$$V_{min} \leqslant V_{nj} \leqslant V_{max}; \quad \forall n \in N, \quad \forall j \in L \tag{21}$$

and the power flow constraint is defined by (8).

The radiality constraint imposes the biggest hurdle while solving the problem of network reconfiguration. In the present work, the codification proposed in [25] is used to solve the problem. This is a rule-based codification to check and correct infeasible radial topologies. According to this codification, following three rules are framed which are based on graph theory to identify and correct infeasible individuals whenever appeared in the computational process.

Rule 1: Each candidate switch must belong to its corresponding loop vector.
Rule 2: Only one candidate switch can be selected from one common branch vector.
Rule 3: All the common branch vectors of a prohibited group vector cannot participate simultaneously to form an individual.
The definitions of loop vector, common branch vector and prohibited group vector may be referred from [25].

3. Proposed IPSO

PSO is a robust stochastic swarm computational technique which is based on the movement and intelligence of swarms [26]. The conventional PSO is initialized with a population of random solutions and searches for optima by updating particles' positions. The velocity of particles is influenced by three components namely, initial, cognitive and social components. Each particle updates its previous velocity and position vectors according to the following model [27].

$$v_p^{k+1} = w v_p^k + c_1 \times r_1() \times \frac{pbest_p - s_p^k}{\Delta t} + c_2 \times r_2() \times \frac{gbest^k - s_p^k}{\Delta t} \tag{22}$$

$$s_p^{k+1} = s_p^k + v_p^{k+1} \times \Delta t \tag{23}$$

where v_p^k is the velocity of pth particle at kth iteration, $r_1()$ and $r_2()$ are random numbers in the range $[0, 1]$, s_p^k is the position of pth particle at kth iteration, c_1, c_2 are the acceleration coefficients, $pbest_p$ is the best position of pth particle achieved based on its own experience, $gbest$ is the best particle position based on overall swarm experience, Δt is the time step, usually set to 1 s. The inertia weight w is allowed to decrease linearly with iterations through its maximum and minimum bounds w_{max} and w_{min}, respectively and is modeled as:

$$w = w_{max} + (w_{min} - w_{max}) \times itr/itr_{max} \tag{24}$$

where itr and itr_{max} denote the current iteration and the maximum iteration count, respectively.

The velocity and position updates of particles tend to surf the search space on the behalf of cognitive and social paradigm of the swarm. PSO has shown proven potential to solve complex engineering optimization problems, but it typically shows premature convergence due to local trapping phenomenon [5].

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Enormous search space is offered when the problem of simultaneous placement of DERs is solved using any population based technique. The accuracy and convergence of these techniques are significantly affected by the manner in which the individuals surf the search space. While initializing, or otherwise, it will be better if all the tentative solutions are scattered in the problem search space in such a way so that most of them lie near the promising region. But, this is a difficult task. Nevertheless, an adequate diversity is essential to explore new solution points in the problem search space to avoid local trappings. Moreover, the intrinsic nature of PSO can only generate continuous decision variables. Thus the accuracy and efficiency of PSO reduces while it is applied to optimization problems having discrete decision variables. Therefore, following measures are suggested in the proposed IPSO to avoid local trapping.

3.1. Guided search algorithm

Several researchers have applied perturbation based node sensitivity approach to get the NPL for optimal allocation of DER and then selecting top few nodes from it to redefine the problem search space [4,7,9–11,16,17,19]. These approaches however reduce the problem search space drastically, but are highly unreliable as the optimal node may be left outside from the reduced search space. Thus, the algorithm eventually converges to sub-optimal solution. Therefore, GSA is suggested where first the NPL is obtained by proposing a new node sensitivity-based approach, and then the candidate sites for DERs allocation are selected using a probabilistic approach, as described below.

The flow of active and reactive power in the DN can be independently controlled by the active and reactive power injections of DGs and SCs, respectively. Even when very small test capacity of these components is placed in DN, they resister their presence in terms of change in power flow pattern among distribution feeders. Thus the power transaction with grid is also affected, the node causes more variation in grid power transaction may be more suitable to place these components. Therefore, following separate node sensitivity indices are defined in order to identify the sensitivity of candidate nodes for the allocation of SCs and DGs in the DN.

$$S^n_{SC} = 100(GQ_B - GQ^n_{TSC})/GQ_B; \quad \forall n \in N \tag{25}$$

$$S^n_{DG} = 100(GP_B - GP^n_{TDG})/GP_B; \quad \forall n \in N \tag{26}$$

Here, GP_B and GQ_B are the grid active and reactive power exchange at base case. Whereas, GP^n_{TDG} and GQ^n_{TSC} are the grid active and reactive power exchange with test DG and capacitor at the nth node.

The perturbation with very small capacity of test SC is carried in the given DN and thereby the NPL is generated, the node with highest S^n_{SC} finds its place at the top of the NPL. Similarly, a separate NPL is created for DG allocation. The candidate nodes are then selected from the respective NPL using probabilistic based Roulette Wheel Selection (RWS). In this way, all system nodes are allowed to participate in the computational process according to their probability of priority. This causes directed search, as better nodes have higher probability of selection. On the other hand, poor nodes still remain in the problem search space and therefore contribute adequate diversity in population. Therefore, the algorithm quickly picks up the best combination of candidate nodes for SCs and DGs without much wandering and thus may lead to better solution in lesser time. This causes virtual squeezing of the problem search space without loss of diversity.

3.2. Local escape algorithm

PSO has the philosophy of "to follow the leader" [28]. Therefore, whenever the best particle stagnates, it eventually converges to local optima. If the best particle is improved by employing some mechanism, probable local trappings can be avoided. Interestingly, the inability of PSO to produce discrete decision variables has been employed in the proposed IPSO as its affirmative strength to avoid local trappings. For this purpose, a local escape algorithm (LEA) is proposed which is explained as under.

Suppose the current best particle suggested by PSO has D continuous decision variables and it is kept in the memory. Whenever this particle stagnates, say after a predefined number of iterations itr_s, it is recalled and then two particles are generated from it; one by ceiling and the other by flooring of all decision variables. Now with all possible combinations of these decision variables, 2^D particles are produced, each of them with only discrete decision variables. If any particle is found infeasible, it is corrected under the guidance of constraint handling algorithm. The fitness of these particles is evaluated and is compared with that of the best particle. If it is found better, it replaces the particle with least fitness. Occasionally, the best particle suggested by PSO may be with all discrete variables. In such situations, all 2^D particles so produced will be replica of the best particle itself, and that makes the proposed LEA useless. To overcome this difficulty, one replica of the best particle is created. The best particle and its replica are mutated before generating 2^D particles. However, candidate locations of these mutated particles are selected using GSA.

3.3. Particle's structure

The proposed structure of the particles for IPSO is shown in Fig. 1 which is composed of candidate sites and sizing for the respective candidate DERs. While determining optimal installed capacities of DERs, the candidate sites are allocated using GSA whereas their sizing is selected randomly within their respective predefined bounds. Afterwards, when determining optimal power dispatches of DERs for each load level, the algorithm again runs with the same structure of particles. However, DERs locations now freeze to those values that have been already obtained and the limit of sizing is restricted to the installed capacities of DERs.

The termination criterion is taken as, "When either the maximum iteration count is exhausted or all solutions acquire the same fitness, the computational process stops."

4. Simulation results

The proposed method is investigated on the benchmark IEEE 33-bus [29] and 69-bus [4] test distribution systems. The initial system data of these systems are given in Table 1 and the detailed data may be referred from the respective references. The penetration limit of SCs and DGs is considered as nominal active and reactive power loading for both test systems. The other design parameters considered for these distribution systems are presented in Table 2.

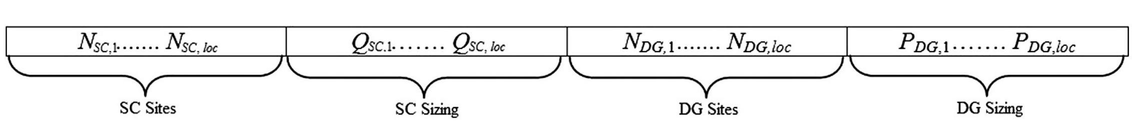

Fig. 1. Particle's structure for IPSO.

Table 1
Brief data of test distribution systems.

Particular	33-bus system	69-bus system
Line voltage (kV)	12.66	12.66
P_D (kW)	3715	3802.19
Q_D (kVAr)	2300	2694.6
Sectionalizing switches	1–32	1–68
Initial configuration	33–37	69–73
P_{loss} at light/nominal/peak load (kW)	47.07/202.50/575.39	51.61/225/652.53
V_{min} at light/nominal/peak load (p.u.)	0.9583/0.9131/0.8528	0.9567/0.9092/0.8445
N	1–33	1–69
I_n^{max} (n)	400(1, 2), 250(3–5, 18–20, 22–29), 150(6–17, 21, 30–37)	400(1–9), 300(46–50, 53–65), 200(10–45, 51, 52, 66–73)

Table 2
Design parameters for test distribution systems.

Parameter	Value	Parameter	Value
Q_b (kVAr)	300	Peak load (%)	160
P_d (kW)	1	H_j (light/nominal/peak)	2000/5260/1500
$\Delta Q/\Delta P$ (kVAr/kW)	100/1	K_e (US \$/kW h)	0.10
$Q_{SC,min}/Q_{SC,max}$ (MVAr)	0/1.2	K_P (US \$/kW)	42.6
$P_{DG,min}/P_{DG,max}$ (MW)	0/2	K_S (US \$/kVA)	19.8
V_{min} (p.u.)	0.95	K_{SC} (US \$/kVAr)	3.0
V_{max} (p.u.)	1.05	K_{DG} (US \$/kW)	300
V_{minS} (p.u.)	0.90	Loc	3
Light load (%)	50	N_L	3
Nominal load (%)	100	d (%)	8
		Y (years)	20

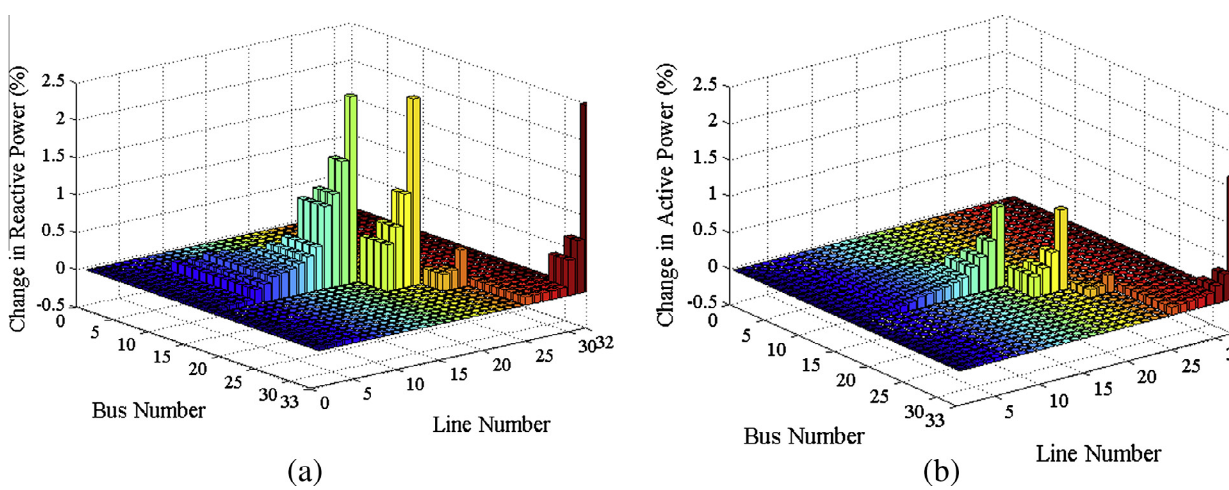

Fig. 2. Percentage change in the power flow pattern for perturbations of test (a) SC and (b) DG.

An illustration to determine NPLs using proposed GSA for the 33-bus system is briefly presented here. Fig. 2(a) shows the percentage change in reactive power flow among distribution feeders when the perturbations of test SC are employed. The figure shows that some prominent areas of DN have more sensitivity for reactive power injection. Similarly, it can be observed from the Fig. 2(b) that some prominent areas of DN have more sensitivity for active power injection. However, it is more important that by what amount the grid power transactions are being affected by the perturbations of small capacity of DERs. Fig. 3 shows the proposed node sensitivity indices for all system nodes. The nodes can be arranged in the descending order of proposed sensitivity index to generate NPLs for SCs and DGs. The NPLs obtained for 33-bus test distribution system are shown in Table 3. An important conclusion can be drawn by comparing Fig. 3(a) and (b) that the priority of nodes are different for SCs and DGs, thus a node which is more suitable for SC may not be so for DG allocation. Similarly, NPLs are determined for 69-bus system as shown in Table 3.

The control parameters selected for IPSO are obtained after usual trade-off and are presented in Table 4. The proposed IPSO has been developed using MATLAB® 7.10 and simulations have been carried on a personal computer of Intel i5, 3.2 GHz, and 4 GB RAM.

4.1. 33-bus system

The simulation results obtained for this system using proposed method are presented in Table 5. The table shows the optimal sites and sizing of DERs. It is interesting to note that the optimal sites obtained are different for SCs and DGs. The table also shows optimal dispatches of DERs at each load level and the corresponding optimal network configurations obtained after placing these

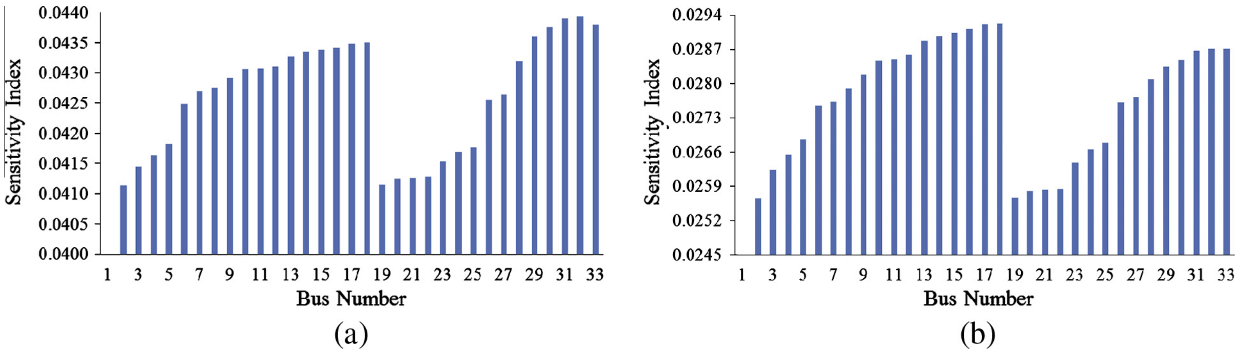

Fig. 3. Node sensitivity index for (a) SC and (b) DG.

Table 3
NPL for SCs and DGs.

Test system	NPL (SC)	NPL (DG)
33-bus system	33, 32, 31, 30, 29, 18, 17, 16, 15, 14, 13, 28, 12, 11, 10, 9, 8, 7, 27, 26, 6, 5, 25, 24, 4, 23, 3, 22, 21, 20, 19, 2, 1, ...	18, 17, 16, 15, 14, 13, 33, 32, 31, 12, 11, 30, 10, 29, 9, 28, 8, 27, 7, 26, 6, 5, 25, 24, 4, 23, 3, 22, 21, 20, 19, 2, 1, ...
69-bus system	65, 64, 63, 62, 61, 60, 59, 58, 57, 56, 27, 26, 25, 24, 23, 22, 21, 20, 19, 18, 17, 16, 15, 14, 55, 13, 69, 68, 12, 54, 67, 66, 11, 10, 53, 9, 52, 51, 8, 7, 50, 49, 6, 48, 46, 45, 44, 43, 42, 41, 5, 35, 40, 39, 34, 38, 33, 37, 32, 47, 31, 30, 4, 29, 36, 28, 3, 2, 1, ...	65, 64, 63, 62, 61, 60, 59, 58, 57, 27, 26, 25, 24, 23, 22, 21, 20, 19, 18, 17, 16, 15, 14, 56, 13, 55, 69, 68, 12, 67, 66, 11, 54, 10, 53, 9, 52, 51, 8, 7, 6, 50, 49, 46, 45, 44, 43, 35, 42, 34, 41, 5, 48, 33, 32, 40, 39, 38, 31, 30, 37, 47, 4, 29, 36, 28, 3, 2, 1, ...

Table 4
Control parameters for PSO and IPSO.

Parameter	P	itr_{max}	c_1	c_2	w_{min}	w_{max}
Value	50	100	2.0	2.0	0.1	0.9

capacities of DERs in the distribution network. It can be seen that the optimal network topology is affected by the presence of DERs. The performance of the network after applying the integrated solution is presented in Table 6. The table shows a significant power loss reduction at each load level. The minimum node voltage at all load levels are found to be well above permissible limits. The table also shows that an annual energy loss, sub-station capacity release and peak power loss reduction of about 85%, 38% and 81%, respectively are achieved using proposed method.

The improvement in node voltage profiles using proposed method is shown in Fig. 4. The significant improvements are observed at all load levels, and all node voltages lie within permissible limits. This shows the effectiveness of the penalty function proposed to check maximum node voltage deviations. Thus, the desired objectives for DERs allocation have been achieved using proposed method.

4.2. 69-bus system

The optimal sites and sizing of SCs and DGs obtained for this system are presented in Table 7. The table shows that the installed capacities for SCs and DGs are 1800 kVAr and 1898 kW, respectively. The table also shows optimal dispatches of these DERs at each load level. After placing these DERs, the optimal configuration

Table 6
Network performance using proposed method.

Particular	Load level		
	Light	Nominal	Peak
P_{loss} (kW)	5.48	25.73	110.05
ΔP_{loss} (%)	88.36	87.29	80.87
V_{min} (p.u.)	0.9940	0.9860	0.9633
Energy loss (kW h)	10957.59	135332.96	165078.01
Annual energy loss reduction (%)	84.60		
Sub-station capacity release (%)	37.95		

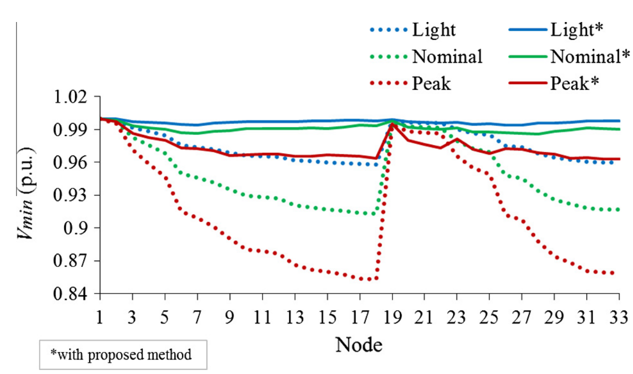

Fig. 4. Comparison of node voltage profiles at all load levels.

of the distribution network is obtained which is also shown in the table. Once again it has been observed that the optimal network configuration changes for each load level. The performance of the

Table 5
Optimal solution and optimal dispatches of DERs, and optimal network configuration.

DER	Optimal sites (optimal sizing)	Load level	Optimal dispatches of DERs	Network configuration
SC (kVAr)/DG (kW)	14(600), 25(300), 30(1200)/10(219), 17(462), 31(935)	Light	14(200), 25(200), 30(500)/10(219), 17(228), 31(497)	7, 27, 32, 34, 35
		Nominal	14(400), 25(300), 30(1000)/10(219), 17(462), 31(935)	7, 9, 28, 35, 36
		Peak	14(600), 25(300), 30(1200)/10(219), 17(462), 31(935)	7, 8, 10, 29, 37

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Table 7
Optimal solution and optimal dispatches of DERs, and optimal network configuration.

DER	Optimal sites (optimal sizing)	Load level	Optimal allocation of DERs	Network configuration
SC (kVAr)/DG (kW)	18(300), 61(900), 64(600)/22(195), 61(1220), 64(483)	Light	18(200), 61(500), 64(100)/22(195), 61(735), 64(142)	10, 11, 13, 55, 72
		Nominal	18(300), 61(900), 64(300)/22(195), 61(1220), 64(483)	10, 12, 14, 22, 72
		Peak	18(300), 61(900), 64(600)/22(195), 61(1220), 64(483)	12, 56, 64, 69, 70

Table 8
Network performance using proposed method.

Particular	Load level		
	Light	Nominal	Peak
P_{loss} (kW)	1.49	8.11	53.77
ΔP_{loss} (%)	97.11	96.39	91.76
V_{min} (p.u.)	0.9960	0.9894	0.9656
Energy loss (kW h)	2984.96	42667.30	80661.51
Annual energy loss reduction (%)	94.42		
Sub-station capacity release (%)	38.80		

Table 9
Grid power transactions.

Test system	Load level	*GP* (MW)	*GQ* (MVAr)	Reduction *GP* (%)	Reduction *GQ* (%)
33-bus system	Light	0.9190	0.2539	51.75	78.51
	Nominal	2.1247	0.6185	45.75	74.59
	Peak	4.4379	1.6588	31.93	59.19
69-bus system	Light	0.8298	0.5490	57.49	59.94
	Nominal	1.9108	1.2052	52.51	56.88
	Peak	4.2368	2.5775	37.08	44.01

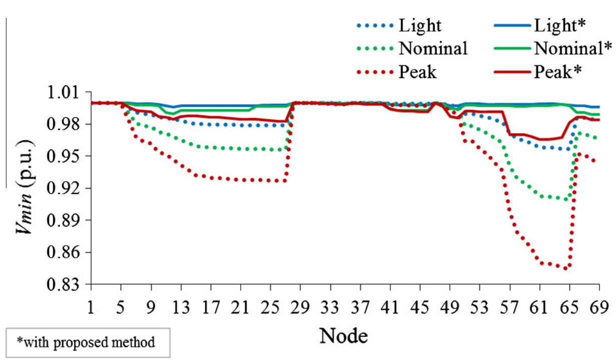

Fig. 5. Comparison of node voltage profiles at all load levels.

Table 10
Cost-benefit appraisal.

Particular (US$)	33-bus system	69-bus system
Annual investment on DERs	50,020	58,545
Annual cost of energy loss reduction	171,103	213,878
Annual cost of peak power loss reduction	2019	2598
Annual cost of sub-station capacity release	5939	6448
Total annual savings	129,041	164,379
Benefit/cost ratio	2.58	2.81

network after applying this integrated solution is presented in Table 8. The table shows a significant improvement in the performance of the network in terms of power loss reduction and node voltage profile enhancement. The annual energy loss reduction obtained for this system is about 94%, which is quite substantial. The table also shows that the sub-station capacity release and peak power loss reduction of about 39% and 92%, respectively are achieved using proposed method.

The improvement in node voltage profiles using proposed method is shown in Fig. 5. The significant improvement in node voltage profiles at all load levels is shown in figure. It can also be observed from the figure that all node voltages are within permissible voltage limits. This shows consistency of the proposed penalty function. Thus integrated solution to distribution network are very useful for DNOs.

5. Discussion

5.1. Technical aspects

The simulation results obtained for both case studies are impressive. A remarkable reduction in annual energy losses, especially during peak load hours could reflect as fruitful impact on the annual profits of DNOs, feeder congestion management, useful life of system components, carbon credits earned, reliability of electric supply, etc. This however occurs by installing DERs which is about one third capacity of the peak demand of the system and regulating their power generations with varying load conditions. Moreover, only few DERs are nicely controlling the distribution network which is important from their installation, maintenance and operation point of view. The results presented are based on the best solution obtained for DER allocation using proposed method. However, many other close solutions are also provided by the proposed method which may be utilized under certain situations, say when the optimal DG location is not feasible due to non-availability of land, densely populated area, political reasons, etc.

The grid power transactions of the distribution network using proposed method are shown in Table 9. In the table, *GP* and *GQ* represent the import of active and reactive powers from the grid, respectively, i.e. the power flows through the feeder 1 of the distribution network. The table also shows percentage reduction of active and reactive power import from the grid at all load levels. It can be observed from the table that a significant reduction in grid power import has been achieved using proposed method. The reduced grid power transactions during peak load level reflect in substation kVA capacity release which helps utilities to stagger their future expansion plans against upcoming peak demand on the sub-station.

The node voltage enhancement obtained using proposed method may cause increased power intake by all static loads (voltage dependent loads) connected to the distribution network. So feeder power losses will be somewhat more to that presented in this study where all loads are assumed to be constant power type. Similarly, the results obtained may also deviate due to system unbalance operation and line current harmonics on account of the presence of non-linear loads. These issues have been kept outside the scope of this work but should be seen at length in future study.

5.2. Financial aspects

For simplified analysis, the time value of money is ignored thus net present value is not calculated for DER allocation project. As a

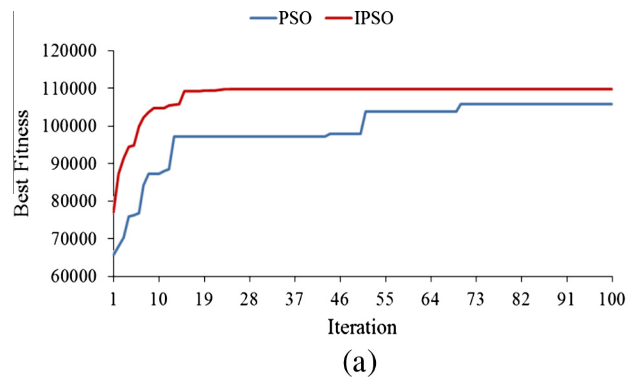

Fig. 6. Comparison of convergence characteristics of PSO and IPSO for (a) 33-bus system and (b) 69-bus system.

Table 11
Comparison of solution quality.

Particular	33-bus system		69-bus system	
	PSO	IPSO	PSO	IPSO
Best	109710.93	112081.58	135343.18	144360.69
Mean	102977.06	107185.97	127479.21	139281.95
Worst	92404.77	102582.8	116724.79	129414.8
SD	2799.58	1625.84	4144.13	3293.49
COV	2.72	1.51	3.25	2.36
CPU time (s)	139.31	120.36	467.04	429.21

prima facie, the benefit to cost ratio is considered for the given discount rate and planning horizon to check the feasibility of DER allocation project. The benefit to cost ratio is an indicator that attempts to summarize the overall value for money of a project or proposal. The ratio takes into account the aggregate amount of monetary gain realized by performing a project versus the amount it costs to execute the project. Higher the ratio, better will be the investment. In case, the ratio is more than unity, the project may be said to have a good investment. The cost-benefit appraisal for the DER allocation project is presented in Table 10. Various cost and investment terms presented in the table are calculated using various cost coefficients as mentioned in Table 2 and Eq. (1). Table 10 reveals that a good benefit to cost ratio has been achieved for both test systems. It can also observed from the table that the cost of energy loss savings are significant and plays major role to decide the benefit to cost ratio of the DER allocation project.

5.3. Optimization algorithm aspects

The convergence characteristic of IPSO is compared with PSO in Fig. 6. The figure shows that IPSO has better convergence than the standard PSO. In IPSO, suggested GSA provides dedicated search as it not only initializes algorithm with better fit particles but also maintains sufficient diversity to explore new solution points in the problem search space. Therefore, the swarm approaches to the promising region very early and then exploit it meticulously. Further, the local random walk provided to the best particle in LEA enhances exploitation of the promising region to avoid possible local optima. Thus, a proper balance is maintained in the exploitation and exploration of the search space.

In order to show the superiority of the proposed IPSO over PSO, the solution quality obtained for both test systems after 100 runs is presented in Table 11. It can be observed from the table that the best, mean and worst fitnesses of the sampled solutions are better for IPSO. Moreover, the statistical quality indices such as, standard deviation (SD), coefficient of variation (COV) are also found better with IPSO. Further, IPSO is taking less CPU time than PSO. Thus IPSO consistently performs better than the standard PSO.

Finally, the spread of sampled solutions (arranged in the descending order of fitness) obtained for these two test systems using PSO and IPSO are shown in Fig. 7. The figure clearly indicates the superiority of IPSO over PSO as all solutions obtained using IPSO are better than those obtained using PSO. This indicates that the proposed IPSO method is very efficient to handle large-scale optimization problems.

6. Conclusions

The optimal allocation of SCs and DGs is now becoming an important aspect in the planning and operation of modern distribution systems. While formulating the optimal allocation problem of these devices, their co-existence should be considered along with practical operational strategy of network reconfiguration. This paper addresses a coordinated strategy for the simultaneous allocation of DERs and NR in distribution systems by proposing

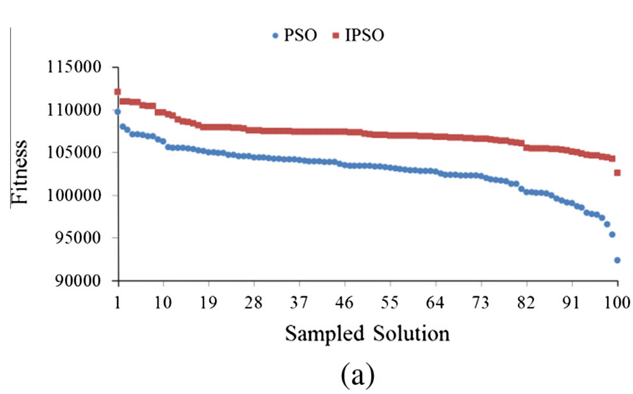

Fig. 7. Spread of sampled solutions using variants of PSO for (a) 33-bus system and (b) 69-bus system.

IPSO method. The proposed integrated approach provides a significant improvement in the desired objectives related to energy loss reduction and substation capacity release at minimal DER penetration. It has been observed that energy losses during peak and off-peak hours can be effectively controlled by only few optimally placed DERs. Therefore, the proposed integrated approach can be very useful for electric utilities to enhance their margins of profits and also to stagger their future expansion plans. A high value of benefit to cost ratio for DER allocation project implies the suitability of proposed method for DNOs. The performance of the proposed IPSO is improved by suggesting LEA and GSA. LEA utilizes inherent inability of PSO to deal with continuous decision variables and thus avoids several local trappings, whereas GSA virtually squeezes the problem search space though it maintains adequate diversity. The application results obtained on two standard test distribution systems show that the proposed IPSO performs better than its standard model. The proposed method can be extended with other types of non-dispatchable DGs operating at non-unity power factor, and also by considering uncertainty associated with their power generations along with the stochastic variation in load demand.

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