Integrated approach of network reconfiguration with distributed generation and shunt capacitors placement for power loss minimization in radial distribution networks

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A B S T R A C T

This article presents the significance of efficient hybrid heuristic search algorithm (HS-PABC) based on Harmony search algorithm (HSA) and particle artificial bee colony algorithm (PABC) in the context of distribution network reconfiguration along with optimal allocation of distributed generators and shunt capacitors. The premature and slow convergence over multi model fitness landscape is the main limitation in standard HSA. In the proposed hybrid algorithm the harmony memory vector of HSA are intelligently enhanced through PABC algorithm during the optimization process to reach the optimal solution within the search space. In hybrid approach, the exploration ability of HSA and the exploitation ability of PABC algorithm are integrated to blend the potency of both algorithms. The box plot and Wilcoxon rank sum test are used to show the quality of the solution obtained by hybrid HS-PABC with respect to HSA. The computational results prove the integrated approach of the network reconfiguration problem along with optimal placement and sizing of DG units and shunt capacitors as an efficient approach towards the objective. The results obtained on 69 and 118 node network by proposed method and the standard HSA reveals the powerfulness of the proposed approach which guarantees to achieve global optimal solution with less iteration.

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1. Introduction

The locality of electrical energy generation is far away from the consumer loads connected with lengthy feeder lines leading to additional power loss in the transmission and distribution network. Power loss reduction is achieved by reconfiguring the existing network topology and by installing fixed/switched shunt capacitor banks and distributed generation units (DG) in close proximity to the consumer loads in transmission and distribution networks. The allocation of such sources has numerous advantages such as postponement for investing new transmission and distribution network construction, reduction in power loss, bus voltage profile enhancement. Prior to the implementation of loss reduction techniques in the distribution network; there is a necessary to investigate their consequence, such as power loss, bus voltage magnitude, harmonic distortion and system voltage stability. A suitable planning method must be implemented to get the benefits of integrating the DG units and shunt capacitors into the distribution networks.

The network reconfiguration of the RDN is the method of changing the topological structure of the network by opening and closing of sectionalizing and tie switches to achieve optimal topology with minimum power loss. During the reconfiguration process, the system radiality should be maintained with all loads connected to the network. In recent years, a noticeable research work has been carried out for loss reduction using network reconfiguration problem. Since there are numerous candidate switching combinations to find the optimal topology of the network, the reconfiguration problem is modeled as combinatorial, non-differentiable, constrained optimization problem. The discrete nature of sectionalizing and tie switches along with radiality constraints avert the application of classical optimization methodologies. So there has been a growing interest in various population based heuristic search algorithms such as Artificial Immune (AIS) Systems [1], Modified particle swarm optimization [2], Binary group search optimization [3], Adapted ant colony [4], Fireworks algorithm [5], Harmony search [6] algorithm. A fuzzy multi objective network reconfiguration methodology for radial distribution systems has been proposed in

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Nomenclature

- $Q_{DG_{i}}$: Reactive power injection of $i$th DG unit
- $p_{f_{max}}$: Maximum allowable power factor of $i$th unit
- $p_{f_{min}}$: Minimum allowable power factor of $i$th unit
- $p_{f_{DG}}$: Power factor of $i$th DG unit
- $n_{bus}$: Total number of nodes in the RDN
- $n_{b}$: Total branches in the RDN
- $I_{i,i+1}$: Current flow between $i$th branch and $i+1$th branch
- $I_{i+1_{max}}$: Allowable maximum permissible current at branch $i+1$
- $I_{max}^{b}$: Maximum allowable branch current
- $I_{comp}^{b}$: Branch current flow in $i$th branch with compensation
- $\mu_{i}^{v_{comp}}$: Real over load in the branch between nodes $i$ and $i+1$ with DG units, shunt capacitor
- $\mu_{i}^{v_{loss}}$: Total power loss in the RDN with DG units, shunt capacitor
- $V_{i}$: Bus voltage magnitude of $i$th bus
- $v_{min}$: Specified lower bound of bus voltage of the RDN
- $v_{max}$: Specified upper bound of bus voltage of RDN
- $P_{DG_{max}}$: Maximum size of DG unit in kilowatts
- $P_{DG_{min}}$: Minimum size of DG unit in kilowatts
- $Q_{c_{L}}$: Sum of total reactive demand of the RDN
- $P_{DG_{i}}$: Reactive power injection by the $j$th shunt capacitor
- $P_{DG_{i}}$: Size of $i$th DG unit in kilowatts

The tabu search approach has been proposed for network reconfiguration in [8–10]. Mathematical illustration of radiality constraints associated with the radial distribution network reconfiguration problem has been addressed in [11]. Optimal network reconfiguration along with the placement of distribution generation units for power loss minimization has been proposed in [12,13]. As compared with classical optimization techniques, meta-heuristic algorithms are capable to achieve a near optimal solution for DG units and shunt capacitors sizing and placement problem in distribution networks. Artificial Bee Colony (ABC) algorithm which mimics the foraging nature of honey bees swarm has been proposed in [14] to find the best possible size of static capacitors. Various models and methods applied for the optimal DG allocation, impact of dispatchable and non-dispatchable type DG units integration in the modern distribution system, current and future trends in this field has been addressed in [15,16]. Analytical approach based DG units sizing and its optimal operating power factor for different types of DG units for power loss reduction has been addressed in [17]. An analytical approach for simultaneous allocation and sizing of DG units and shunt capacitor to achieve power loss reduction is proposed in [18].

In [19] a heuristic algorithm, mimicking the improvisation process of musical instruments to get a pleasant harmonious melody so called harmony search algorithm (HSA) is proposed. The performance of the developed algorithm is demonstrated with a traveling salesman problem and minimum-cost pipe network design problem. In [20] an improved harmony search algorithm (IHSA) is proposed which intelligently generates new solution vector for the best solution and convergence of HSA. HSA is a stochastic search procedure which does not need any derivative information to solve the complex combinatorial optimization problem. In [21] the discrete search strategy of HSA is utilized for structural size optimization problem with discrete design variables. In [22,23] a hybrid heuristic search approach is proposed which makes use of ABC algorithm and its variants to enhance the solution vector in the HS algorithm and the simulation results are compared with the harmony search algorithm (HSA), improved harmony search algorithm (IHSA), global harmony search algorithm (GHSA) and self-adaptive global harmony search (SGHS) algorithm. The parameters of hybrid algorithm and its impact has been studied with uniform design experiments optimization problems. In [24,25] the optimal design of water distribution networks is addressed using HSA incorporated particle swarm algorithm (PSO) and the result outcomes are better than the genetic algorithm, simulated annealing and Tabu search technique. In [26] a self-adaptive global best harmony search algorithm (SGHS) is proposed which utilize a new harmony memory enhancement strategy by dynamic adaptation of HMCRR and PAR, distance bandwidth (BW) as learning mechanism to balance the exploration and exploitation ability. In [27] a hybrid heuristic algorithm is proposed which makes use of sequential quadratic programming technique (HSA-SQP) to accelerate the local search ability and to get better accuracy in HSA solutions. To exhibit the effective and sturdiness of the proposed hybrid HSA-SQP algorithm, various benchmark engineering optimization problems are taken into consideration. The intellignet honey bee foraging behavior of bee swarm is utilized in [28–30] to obtain the optimal solution in multi-dimensional numerical optimization problems. The simulation results outperform the results obtained with the other meta-heuristic algorithms such as a particle swarm optimization algorithm, differential evolution algorithm and genetic algorithms. In calculus based methods, the optimal solution is obtained by using derivatives which is suitable only for continuous-valued functions rather than discrete-valued functions. In [31,32] a new HS algorithm is proposed for solving engineering optimization problems with continuous as well as discrete design variables. In [33,34] the overview of the recent applications of HSA, which uses a ‘probabilistic-gradient’ to select the neighboring values of decision variables is addressed. It is an efficient meta-heuristic optimization tool for practitioners to solve complex optimization paradigms such as construction, telecommunications, engineering, health and energy, and robotics. The HSA provides probabilistic-gradient based search to get the local or global optimal solution instead of mathematical gradient as in conventional optimization techniques. In [35–38] A HSA based optimal solution is obtained for complex optimization problems like scheduling of multiple dam systems, broadcast scheduling in packet radio networks, estimation of the success of companies and vehicle routing. In [39] a hybrid grouping HSA is proposed for the multiple-type access node location problem to determine the optimum location. In [40] a hybrid approach is used to deploy 24-h medical emergency resources by combining the HSA with the grouping encoding concept to repair infeasible solutions. In [41] a multi-objective harmony search for urban road network reconfiguration problem to offer near-optimal solution to improve the vehicles mobility is proposed. In [42] a quasi-oppositional harmony search algorithm is proposed to investigate the optimal controller gains to enhance the performance of Automatic Generation Control (AGC) of the power system. A new hybrid PSO algorithm has been addressed in [43] to augment the exploration and exploitation capability by introducing the global dimension selection strategy using HSA and validated with the PSO variants, and other meta-heuristic algorithms. In [44] a new self-adaptive HS-PSO search algorithm is proposed with an effective initialization scheme by utilizing the PSO algorithm to improve the solution quality of the initial harmony memory in the HSA. A new self-adaptive adjusting method for control parameters PAR and BW is designed to accelerate the convergence rate and solution accuracy of the proposed algorithm. The poor exploitation ability of the ABC algorithm makes an issue of slow convergence in solving non-linear and constrained optimization nature of engineering design problems. To overcome these insufficiencies, a modified version of the ABC algorithm is suggested in [45–49] by incorporating adap-
tive inertia weights and acceleration coefficient parameters of PSO algorithms.

The combined approach of network reconfiguration problem along with the placement of distributed generators and shunt capacitors is complex combinatorial problems which involves discrete (status of sectionizing and tie switches) and continuous control variables (size of DG units and shunt capacitors). To find the optimal topology all the feasible radial topologies of the network are to be evaluated. Tracing such optimal topology is computationally expensive and NP-hard in nature. Solving such type of hard optimization problems using meta-heuristic techniques will lead to premature convergence and local optima. Improper balance between intensification and diversification to find the optimal solution is the major issue in meta-heuristic techniques. This necessitates the hybridization of meta-heuristics which makes use of complementary characteristic of different optimization strategies to get the improved solution.

In this article, hybridization of HSA with PSO embedded artificial bee colony algorithm (HS–PABC) has been proposed and utilized to provide the optimal network reconfiguration problem along with the placement of DG units and shunt capacitors to realize minimization of real power loss at distinct load levels. In hybrid, HS–PABC approach, the global searching ability (exploration) of HSA and the local searching (exploitation) ability of PABC are integrated to harmoniously enhance the HS algorithm performance. In this way, the strength of local searching ability of standard HSA is improved to find out the best solution quickly and ride over the local optima. In this work, different test scenarios are considered with an aim to enumerate the benefits of RDN through graph theory based network reconfiguration along with the allocation of shunt capacitors and DG units. Simulation results point out that the proposed hybrid HS–PABC algorithm is proficient than standard HSA algorithm.

This article is structured as: In Section 2 the formulation of the problem and graph theory based network reconfiguration is discussed. Outline of standard HSA algorithm and the proposed hybrid HS–PABC algorithm is summarized in Section 3. In Section 4, simulation results and discussion are presented. In Section 5 conclusions of the work are presented.

2. Problem formulation

A multi objective optimization model has been proposed which includes technical factors such as real power loss reduction, line loading reduction and voltage profile improvement. The multi objective proposition is considered simultaneously using weighting factors for obtaining maximum benefits as in Eq. (1). All the performance indices are given equal weightage.

Min. fitness = W_1(\text{RPLRI}) + W_2(\text{MBCLI}) + W_3(\text{VDI})

(1)

where \(\sum_{i=1}^{3} W_i = 1.0\) \(\forall W_i \in [0,1]\).

A set of performance improvement indices is described mathematically as stated below to enumerate the technical benefits.

2.1. Real power loss reduction index (RPLRI)

The objective of real power loss reduction index is to quantify the power loss reduction in the distribution network. The real power loss reduction index (RPLRI) is defined as the ratio between the real power loss of the network with and without DG units and shunt capacitor compensation as in Eq. (2).

\[ \text{RPLRI} = \frac{\text{ploss}_{\text{wcomp}}}{\text{ploss}_{\text{wcomp}}} \]

(2)

2.2. Maximum branch current capacity limit index (MBCLI)

This index is used to reflect the improvement in reserve capacity limit of the feeder lines. It is the ratio of current flow through the feeder lines after compensation and the maximum current carrying limit of that feeder branch as in Eq. (3).

\[ \text{MBCLI} = \max\left(\frac{|IB^\text{wcomp}_i|}{|IB^\text{max}_i|}\right) \]

(3)

2.3. Voltage deviation index (VDI)

The optimal network reconfiguration along with DG units and shunt capacitor placement provides the reduction in bus voltage deviation. The bus voltage deviation index (VDI) can be defined as in Eq. (4).

\[ \text{VDI} = \max\left(\frac{|V_j - V_i|}{V_i}\right) |V_j = 1, 2, \ldots, \text{nbus} \] where \(V_i\) is taken as 1.0 p.u.

(4)

2.4. Constraints associated with the objective function

The nominal bus voltage limit, thermal limit of the feeder lines, maximum real and reactive power injection by the DG units and shunt capacitors, radial structure of the distribution network are considered as constraints in Eqs. (5)-(10).

\[ |V_{\text{spec min}}| \leq |V_i| \leq |V_{\text{spec max}}| \]

(5)

\[ 0.9 \leq |V_i| \leq 1.1 \quad i = 1, 2, \ldots, \text{nbus} \]

(6)

\[ |I_{i,i+1} \| \leq |I_{i,i+1}\text{max}|, \quad i = 1, 2, \ldots, \text{nbus} \]

(7)

The DG units are modeled as controllable synchronous machine based biomass plants with active and reactive power injection capabilities at an operating power factor of 0.85 lagging [17]. The real power output (kW) range of DG units sizing is selected as 10–50% of the total active power demand of the RDN.

\[ p^\text{DG}_{\text{min}} \leq p^\text{DG} \leq p^\text{DG}_{\text{max}} \]

(8)

where \(p^\text{DG}_{\text{min}} = 0.1 \sum_{i=2}^{n} p^\text{DG}_i \) and \(p^\text{DG}_{\text{max}} = 0.5 \sum_{i=2}^{n} p^\text{DG}_i \).

\[ Q^\text{DG} = p^\text{DG} \tan(\cos^{-1}(p.f)) \]

(9)

\[ p^\text{DG}_{\text{min}} \leq p^\text{DG} \leq p^\text{DG}_{\text{max}} \]

(10)

Radiality constraints:

\[ \text{N}_{\text{b}} = \text{N}_{\text{bus}} - 1 \]

where \(\text{N}_{\text{b}}\) is the number of branches, \(\text{N}_{\text{bus}}\) is the number of nodes in the RDN.

2.5. Spanning tree approach for network reconfiguration

A directed graph representation of the radial distribution network is utilized to form the adjacency matrix (AM) with '1's and
‘0’s representing the presence and absence of direct edge between nodes. The node isolation is identified by determining the columns of the adjacency matrix with only zeros except the root node and in each degree of each node is limited to one by determining the columns with only one nonzero element. The formation of the loop during reconfiguration process is identified using MATLAB function graphisdag(AM).

In this proposed work, the graph data structure is used to construct the RDN as spanning tree. The vertices representing the nodes of RDN connected with edges (branches) are used to form the directed graph. The load flow algorithm developed is based on the formation of BIBC and BCBV matrices [50]. The BIBC matrix represents the bus current injection with branch current where as BCBV matrix relates the branch current with bus voltage which represents the line impedance of the RDN. In each switching operation, the adjacency matrix and BCBV matrix are changed in accordance with the change in the system structure. The depth-first search (DFS) discovery order is utilized for traversing the graph from each node. Based on the discovery order from each node, the corresponding BIBC matrix is generated by assigning ‘1’ to discover paths.

The hypothetical 6 node RDN with sectionalizing and tie switch is shown in Fig. 1(a). The adjacency matrix representation is shown in Eq. (18). Let E be a set of direct edges \{(1,2),(2,3),(3,4),(4,5),(5,6)\}. Each element in the adjacency matrix \(AM_{ij} = 1\) if \((i, j) \in E\) and \(AM_{ij} = 0\) if \((i, j) \notin E\). The adjacency matrix before closing the tie switch is formulated as in Eq. (11).

\[
AM = \begin{bmatrix}
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]  

(11)

Fig. 1(b) represents the directed graph generated using adjacency matrix represented in (11). The RDN structure modification is obtained by closing the tie switch between the node 5 & 6 and opening the sectionalizing switch between the node 4 & 5 and the corresponding modified adjacency matrix obtained is shown in Eq. (12). Fig. 1(c) represents the directed graph generated using adjacency matrix represented in Eq. (12) for the modified structure of the RDN.

\[
AM = \begin{bmatrix}
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]  

(12)

The steps involved in solving the optimal network reconfiguration problem of RDN are lined as follows:

**Step 1:** Generate the adjacency matrix (AM) of the given RDN with ‘1’ and ‘0’ representing the presence and absence of direct edge between the nodes.

**Step 2:** Generate the directed graph using function, bio-graph (bg) from the adjacency matrix (AM).

**Step 3:** Traverse the directed graph in depth first search (DFS) order using function traverse(bg, S) where S = 1, 2, …, n to obtain discovery vector. The power flow matrix [i.e., BIBC] is formed by filling ‘1’ in position \((i, j)\) where ith row corresponds to each value of S and jth column corresponds to each element in discovery vector with respect to S.

**Step 4:** Obtain the branch current \([BC]\) by multiplying BIBC matrix obtained from step 3 with bus current injection \([I]\)

\[
[BC] = [BIBC \ast I]
\]  

(13)

**Step 5:** The distribution load flow matrix (DLF) is obtained by multiplying BCBV and BIBC matrices which relates the bus current injection and bus voltages and it is expressed as,

\[
\Delta V = [BCBV] \ast [BIBC] \ast [I] = [DLF] \ast [I]
\]  

(14)

The bus current injection in \(i + 1\)th node at \(k\)th iteration can be obtained as follows,

\[
i_{k+1}^i = \sqrt{\frac{P_{k+1}^i + Q_{k+1}^i}{V_i^k}}
\]  

(15)

The change in bus voltage at \(i + 1\)th node at \(k + 1\)th iteration can be obtained as follows,

\[
V_{k+1}^{i+1} = DLF \ast i_{k+1}^i
\]  

(16)

\[
V_{k+1}^{i+1} = \sqrt{\Delta V_{k+1}^{i+1}} + V^k_{i+1}
\]  

(17)

In this similar fashion, the bus voltages are updated during iterative steps. The iterative steps are terminated once the required tolerance limit is reached.

3. Evolutionary algorithms

3.1. Overview of harmony search algorithm

Harmony search algorithm (HSA) was proposed by Geem et al. [19]. The HSA algorithm requires fewer mathematical calculations and it does not require any derivative information due to its stochastic searching nature. Various advantages of HS algorithm are (a) it does not require differential gradients, thus it can be suitable for discontinuous as well as continuous functions; (b) it can have the capability to handle discrete as well as continuous decision variables [32]; (c) it does not require initial value setting for the decision variables.

HMCR, PAR and BW are considered as tuning parameters in HSA. The computational procedures of HSA are a) random initialization of decision variables in the harmony memory vector (HMV) b) Improvisation of HMV values by updating the solutions by memory consideration c) pitch adjustment and random re-initialization process. Repeat the improvisation process in the HMV until the termination criteria.

Updating of harmony memory vector is described below.

if (rand \((0,1)\) < HMCR)

\[X^{new} = Xi \in \{X_1^i, X_2^i, ..., X_{NS}^i\}\]

else

\[X^{new} = Xi\]

end

HM is pitch adjusted or modified slightly with a probability of PAR as,
If \((\text{rand} \leq 0.1) < \text{PAR}\)

\[ X^{new}_i = X_i \pm \lambda \]  // for discrete decision variables

where \(\lambda\) is the amount between two neighboring values in discrete decision variable set

\[ X^{new}_i = X_i \pm \text{rand}(-1,1) \times \text{BW} \]  // for continuous decision variables

else

\[ X^{new}_i = X_i \]

(19) where “BW” represents a random distance bandwidth. In this way the HMV is improved iteratively.

3.2. PSO embedded artificial bee colony algorithm (PABC algorithm)

Particle swarm optimization (PSO) is one of the recent stochastic algorithm based on the idea of swarm intelligence of social models such as bird flocking, fish schooling [50]. In PSO, simultaneous co-existence of multiple candidate solutions flies within the problem search space. Each particle adjusts its flying position based on its own experience as well as the best flying position of the neighboring particles to reach the optimal solution point. In this way each particle retains its best position \((P_{\text{best}}—\text{local search through its own experience})\) and its neighboring particle's best position \((G_{\text{best}}—\text{global search through neighboring particles experience})\) during the search process to find the optimal solution within the search space of the problem.

The PSO algorithm has three steps: The algorithm process starts the initialization of randomly distributed populations within the search solution space. Then at each iteration, the velocities and positions of each particle is updated using velocity and position equations expressed as below,

\[ V^t_{i+1} = \omega \cdot V^t_i + C_1 \cdot \text{rand}(1) \cdot (P_{\text{best}1} - X^t_i) + C_2 \cdot \text{rand}(2) \cdot (G_{\text{best}1} - X^t_i) \]  (20)

\[ X^t_{i+1} = X^t_i + V^t_{i+1} \]  \(i = 1, 2, ..., N, \ d = 1, 2, ..., D\)  (21)

where “\(N\)” is the total number of particles; \(D\) is the dimension of the search space. \(V^t_i\) symbolize the velocity of the \(i\)th particle at the \(t\)th iteration; \(X^t_i\) is the \(i\)th particle position at the \(t\)th iteration. The term “\(\omega\)” indicate the inertia weight which provides a balance between exploration and exploitation. The \(C_1\) and \(C_2\) are positive social weight parameters, which has control over the preeminence and neighboring particle's position on the current one. \(P_{\text{best}}\) imitates the previous best position of the particle and “\(G_{\text{best}}\)” known as global best position which provides the best “\(P_{\text{best}}\)” amongst all the \(P_{\text{best}}\) position; \(\text{rand}(1)\) and \(\text{rand}(2)\) are the random real value in the range of \([0,1]\).

Karaboga and Basturk [28] proposed artificial bee colony algorithm (ABC) from the foraging nature of honey bee swarm to solve the constrained optimization problems. The ABC algorithm consists of the following groups; employed bee, onlooker bee and scout.
be. The role of employed bees is to search for the food source and share the information to the onlooker bees; based on the better food source information shared from the employed bees, the onlooker further searches the better food source neighboring the selected food source. If any food source is found abandoned, the new food source is randomly searched by the scout bees.

Let us suppose the solution space of the optimization problem is D-dimensional. The algorithm is initiated with randomly generated population and it can be represented as \(X_j = (X_{j1}, X_{j2}, \ldots, X_{jD})\) where \(j \in (1, 2, \ldots, SN)\). SN is the size of the food source. Then the employed bee’s could modify the solution in its memory by randomly selecting a neighboring food source position using the following Eq. (22),

\[
V^{t+1}_j = (X_j^t + \text{rand}(0, 1)(X_j^t - X_k^t))
\]

where \(K \in (1, 2, \ldots, SN)\) is chosen randomly with \(j \neq K\); \(\text{rand}(1)\) is a random number within the range of \([-1, 1]\).

In onlooker bee phase, the onlooker bees start searching the solution around the best food source provided by the employed bees using Eq. (22) based on the probability value \(P_j\) as in Eq. (23).

\[
P_j = \frac{\text{fitness}_j}{\sum_{j=1}^{SN} \text{fitness}_j}
\]

Fitness is the fitness value of jth the solution. The fitness of each solution is computed by Eq. (24) as,

\[
\text{Fitness}_j = \left[1/(1 + \text{min. fitness})\right]
\]

During this improvisation process, if any food source found abandoned after a predetermined number of cycles (called as limit) it is replaced with new random food source by the scout bee using the following Eq. (25).

\[
X_j^{t+1} = (X_{\text{max}} + \text{rand}(0, 1)(X_{\text{max}} - X_{\text{min}}))
\]

where \(X_{\text{max}}, X_{\text{min}}\) are the maximum and minimum bound of the food source position.

If the new candidate food source position has better quality (fitness function) than the previous one, then such candidate food source is retained by replacing the older one. Repeat the above steps until the optimal solution is obtained.

The standard ABC algorithm encounters the problem in exploitation and exploitation ability when handling high dimensional optimization problems. The solution search space is explored and exploited by the employed and onlooker bees using Eq. (22) is superior in terms of tracing diverged solution (well exploration ability) but fails to exploit within the search space. Greedy selection method on the bee’s trajectories will lead the ABC algorithm to trap into local optima. In this work, to cope with this problem, the intensification and diversification capability of ABC algorithm is balanced by integrating the PSO into the ABC algorithm. The improved ABC algorithm (PABC) updates the bee’s position by making use of Eq. (26). The inertia weight and acceleration constants are incorporated into the employed bee phase of the ABC algorithm to improve the searching capability of the bees. These capabilities alleviate the premature convergence and avoidance of the local optima in standard ABC algorithm.

3.3. Proposed hybrid HS-PABC algorithm

It is a common practice to combine different search procedure to overcome the deficiencies of the individual heuristic optimization algorithms in order to provide a robust optimization technique. Standard HSA is incompetent in local search ability [27] and it encounters the problem of slow convergence, traps in local optimal solution over multi model fitness landscape. The local searching capability of the HSA has been enhanced by crossbreeding the HSA with other optimization algorithms [22].

It is evident that in the HS algorithm the harmony memory (HM) plays a vital part which decides the algorithm performance. In this work, to augment the solution accuracy of the standard HSA, the particle ABC algorithm is integrated and a new HS-PABC has been proposed. In hybrid HS-PABC algorithm, the HMV in the HSA is taken as the initial food source by the PABC algorithm to produce a diverse range of potentially optimal solutions while at the same instant it intensifies its search in the vicinity of optimal solution. New improvised HMV values are used as initial values by the PABC algorithm to search for optimal solution. If the locally optimized vector produced by the PABC algorithm has better fitness value than those in the HMV, they will be retained in the HM. The harmony vector (HMV) in the HSA is improved by utilizing the potency of both heuristic algorithms to get the best solution. Besides this hybrid algorithm requires the tuning of the control parameters such as Harmony Memory Size (HMS), Pitch Adjustment Rate (PAR), Harmony Memory Consideration Rate (HMCR) and Maximum Cycle Number (MCN). The flowchart of the proposed hybrid HS-PABC algorithm is presented in Fig. 2.

The computational procedure of the proposed hybrid HS-PABC algorithm is detailed as follows,

**Step 1:** Initialize the parameters of HS-PABC algorithm; HMS, PAR, HMCR, MCN.

**Step 2:** Initialize the Harmony Memory Vector (HMV) with random population.

**Step 3:** Cycle = Cycle + 1

**Step 4:** Employed bee phase initiation: Random populations generated in the HMV is improvised by using Eq. (26) to update the bee’s position.

\[
X_{jk}^{\text{new}} = [wX_{jk} + C_1 \varphi_{jk}(X^{\text{best}}_k - X_{jk}) + C_2 \varphi_{jk}(X_{nk} - X_{jk})]
\]

where \(X_{jk}^{\text{new}}\) is the new feasible solution on its preceding solution \(X_{jk}\). The term “w” indicate the inertia weight utilized to modify the current position of bees with respect to its prior one. To explore global search at initial stage of the search, the inertia weight is declined linearly from 0.9 to 0.4 as suggested in [51] to explore global search initially. The \(C_1\) and \(C_2\) are positive social weight parameter values chosen as 2.05 [51]. \(X^{\text{best}}_k\) reflects the finest food source amongst the population. \(X_{nk}\) is the random neighbor value of the population and \(\varphi_{jk}\) is the random value in the range of \([0, 1]\). After the estimate of each candidate food source position, the greedy selection procedure is applied among the solution obtained through step 2 and 4. The onlooker bees utilize the nectar information shared from the employed bees and select the food source based on the probability value accompanied with that food source \(P_j\) from Eq. (27).

\[
P_j = \frac{\text{fitness}_j}{\sum_{j=1}^{SN} \text{fitness}_j}
\]

The fitness value of jth solution is taken as fitness. The fitness of each solution is computed by Eq. (28) as,

\[
\text{Fitness}_j = \left[1/(1 + \text{min. fitness})\right]
\]

“min. fitness” is obtained through the BFS based power flow solution for each fitness using Eq. (1).

**Step 5:** Onlooker bee phase initiation: Based on the employed bee phase best fitness probability, the new food source position \(X_{jk}^{\text{new}}\) in the vicinity of food source \(X_{jk}^{\text{old}}\) is determined by using Eq. (29).

\[
X_{jk}^{\text{new}} = (X_{jk}^{\text{old}} + u(X_{jk}^{\text{old}} - X_{n,k}))
\]
Fig. 2. Flowchart of proposed hybrid HS-PABC algorithm.

where $n \in \{1,2,\ldots,CS\}$ and $k \in \{1,2,\ldots,D\}$ are random indices; $D$ is the total number of parameters in the optimization problem which decides the dimension of the problem; $n \neq j$; $'\cdot'$ signifies a random number produced which lies between $[-1,1]$. If the calculated value of the candidate food position $X_{jk}^{\text{new}}$ using Eq. (25) may violate the predefined boundary, resetting scheme is employed, which put the violating boundary values to the adjoining boundary limit value, i.e.,

$$X_{jk}^{\text{new}} = X_{j\min}, \quad \text{if } X_{jk}^{\text{new}} \leq X_{j\min}$$

$$X_{jk}^{\text{new}} = X_{j\max}, \quad \text{if } X_{jk}^{\text{new}} \geq X_{j\max}$$
After the estimation of each candidate food source position, the greedy selection method is adopted.

**Step 6:** Scout bee phase initiation: If any abandoned solution is present, it is swapped with a new arbitrary solution generated by the scout bee phase using Eq. (30).

\[
X_{j,k}^{new} = \min(X_{j}^{k}) + \text{rand}(0, 1)[\max(X_{j}^{k}) - \min(X_{j}^{k})]
\]  

**Step 7:** Retain the best solution obtained so far in HMV

**Step 8:** Improve the populations (decision variables) in the HMV by HMCR, PAR and Random selection steps in the HS algorithm.

**Step 9:** Evaluate new HMV and check new HMV is better than existing HMV. If so, update HMV

**Step 10:** Cycle = Cycle + 1

**Step 11:** Check if the stopping criterion is met, i.e., total number of MCN is reached.

**Step 12:** If not, go to step 4 and reiterate from step 4 until Cycle = MCN

### 3.4. The pseudo code of proposed hybrid HS-PABC algorithm

**Step 1:** Initialize the parameters: Machine cycle (MCN), Harmony memory size (HMS), Harmony memory consideration rate (HMCR) and Pitch Adjustment Rate (PAR)

**Step 2:** Initialize HMS.

For i = 1 to HMS do

For j = 1 to D do

\[ X_{i,j} = \text{lb}_{j} + \text{rand}(1) \times (\text{ub}_{j} - \text{lb}_{j}) \]

**Step 2.1:** Calculate fitness value.

\[ f(X_{i}) = \text{Evaluate}(X_{i}) \]

**Step 3:** Start Cycle = 1

**Step 4:** HMS is improved by Particle ABC. Initialize the trial limit.

**Step 4.1:** Employed bees search:

For i=1 to HMS do

\[ X_{i,j}^{new} = \text{[omega]} \times X_{i,j} + \text{[random]} \times (X_{i,j}^{best} - X_{i,j}) + \text{[random]} \times (X_{i,j} - X_{i,j}) \] (j is chosen randomly)

If \( f(X_{i,j}^{new}) < f(X_{i}) \)

\[ \text{trial}[i] = 0; X_{i,j} = X_{i,j}^{new}; \]

else \( \text{trial}[i]++; \)

**Step 4.2:** For i=1 to HMS do

\( \{ p[i] = \text{computeprob}(i) \} \)

**Step 4.3:** Onlooker bees search:

For i=1 to HMS do

\[ X_{i,j}^{new} = X_{i,j} + \text{[random]} \times (X_{i,j}^{best} - X_{i,j}) \] (j is chosen randomly)

If \( f(X_{i,j}^{new}) < f(X_{i}) \)

\[ \text{trial}[i] = 0; X_{i,j} = X_{i,j}^{new}; \]

else \( \text{trial}[i]++; \)

**Step 4.4:** Scout bee search:

For i=1 to HMS do

\( \{ \text{if (trial [i] > limit)} X_{i,j} = \text{lb}_{j} + \text{rand} \times (\text{ub}_{j} - \text{lb}_{j}) \} \)

**Step 5:** Improve a New Harmony \( X_{i}^{new} \) as below

For j=1 to D do

\( \{ \text{d = rand}(1) \}

\( \text{IF (d < HMCR)} \)

\( \{ X_{i,j}^{new} = X_{i,j} + \text{[random]} \times (X_{i,j}^{best} - X_{i,j}) \}

\( \text{IF (y < PAR)} \)

\( \{ X_{i,j}^{new} = X_{i,j} + \text{[random]} \times (X_{i,j}^{best} - X_{i,j}) \}

\( \text{else} \)

\[ X_{i,j}^{new} = X_{i,j}^{old} + \text{[random]} \times (X_{i,j}^{best} - X_{i,j}) \]

**Step 6:** If \( f(X_{i}^{new}) > f(X_{i}) \), update the HM as \( X_{i} = X_{i}^{new} \)

**Step 7:** Retain the best solution in the HMV.

**Step 8:** Next Cycle = Cycle + 1

**Step 9:** If Cycle number < MCN, goto step 4; else stop the iterative procedure

### 4. Numerical results and discussions

This article proposes an efficient hybrid heuristic search algorithm for the enhancement of distribution network performance by implementing the four test scenarios with an objective of optimizing the multi-objective performance improvement indices such as power loss reduction, bus voltage deviation and branch current of the RDN. The backward/forward sweep based power flow method (BFS) is utilized to find the load flow solution [50]. The proposed hybrid optimization algorithm is applied on 69 and 118 node radial test networks on a Matlab7.7.0 platform. For both the test networks, substation voltage is taken as 1.0 p.u. The four test scenarios at seven discrete load levels are,

**Scenario 1**: Optimal allocation (location and sizing) of shunt capacitors

**Scenario 2**: Optimal allocation and sizing of DG units

**Scenario 3**: Simultaneous allocation (location and sizing) of DG units and shunt capacitors

Scenario 4: Simultaneous optimal network reconfiguration along with DG units and shunt capacitor compensation

The daily load schedule for the RDN is modeled for 24-h time interval of the day and it is assumed to be repetitive for 365 days to get the annual load schedule. The average daily load interval schedule is depicted in Table 1. There are seven discrete load levels varying from 40% to 100% as shown in Fig. 3. The DG unit's injection is considered as a negative PQ load with real and reactive power injection capability with 0.85 lagging as an operating power factor. The status of sectionalizing and tie switches, location and size of DG unit and shunt capacitors are taken as the decision variables. The maximum penetration limit of DG unit is limited to 50% of the total system real power demand.

4.1. Simulation results of 69 node RDN

To test the effectiveness of the proposed hybrid HS-PABC algorithm a medium scale 69 node radial distribution network is considered with the real power load demand of 3802.1 kW and reactive power load demand of 2694.5 kVAR. This test system has 73 line segments with five tie switches. The tie switches are numbered from 69 to 73 and the sectionalizing switches are numbered from 1 to 68. The active and reactive power loss at nominal load level is 224.97 kW and 102.15 kVAR respectively. The system operates with the nominal bus voltage magnitude of 12.66 kV with 100 MVA base. Minimum bus voltage magnitude of 0.9092 p.u. is observed at 65th node. The test network data are obtained from [17].

The simulation results obtained with proposed hybrid algorithm and standard HSA for scenarios I–IV is summarized in Tables 2 and 3. The real power loss reduction obtained with HSA and hybrid HS-PABC algorithm is summarized in Table 4. From Table 4, it is observed that at 40% load level the base case loss of 32.50 kW is reduced to 21.65 kW, 10.54 kW, 11.09 kW and 7.07 kW with respect to the scenarios I–IV using hybrid approach. At medium load level (70%), the power loss reduction is from 104.52 kW to 69.91 kW, 32.99 kW, 35.37 kW and 21.72 kW at nominal load level (100%) the power loss reduction is from 224.96 kW to 145.68 kW, 69.08 kW, 73.11 kW and 48.62 kW. The bus voltage profile with the scenarios I–IV at 100% load level is depicted in Fig. 4. It can be seen that, the proposed hybrid algorithm provides a significant improvement of minimum bus voltage profile with scenario-IV as compared with other scenarios. Fig. 5 depicts the optimal reconfiguration topology and directed graph representation of 69 node RDN along with DG units and shunt capacitor placement (Scenario-IV) at 100% load level. It is observed that scenario-IV provides better loss reduction with improved bus voltage profile at all load level as compared with other scenarios. Since the power flow path is optimized in scenario IV by retaining the DG and shunt capacitor location obtained in scenario-III (@ node 19 for capacitor location and @ node 60 for DG unit location) better power loss reduction is achieved. Table 5 shows the minimum bus voltage profile obtained.
with standard HSA and hybrid HS-PABC algorithm. The results presented in Tables 4 and 5 reflect the efficiency of the proposed hybrid algorithm over standard HSA with respect to loss reduction and voltage profile improvement in all load levels.

The active power loss in each branch of the RDN with the scenarios I–IV at 100% load level is depicted in Fig. 6. The reduction in total real power loss of the RDN with scenario-IV at 40%, 70% and 100% load level using hybrid HS-PABC algorithm is depicted in Fig. 7. It is revealed that scenario-IV offers more loss reduction with enhanced bus voltage profile as compared with other scenarios.

4.2. Simulation results of 118 node RDN

To show the suitability of the proposed hybrid approach on large scale RDN it is applied on 118 node balanced three phase radial distribution network. The system operates under 11 kV voltage level at 100 MVA base with active load demand of 22709.7 kW and reactive load demand of 17041.1 kVAR respectively. The active and reactive power loss before compensation is 1298.1 kW and 978.74 kVAR respectively. The line and load data are obtained from [8]. This test network consists of 118 nodes with 117 sectionalizing switches (normally closed) and fifteen tie switches (normally open). The tie switches are numbered from 118 to 132.

Simulation results obtained using HS and hybrid HS-PABC algorithm at different load level of the network along with the candidate nodes for the placement of DG units and shunt capacitors are presented in Tables 6–11. The real power loss reduction obtained with HSA and hybrid HS-PABC algorithms with four test scenarios are summarized in Table 12. From Table 12, it is observed that loss reduction realized using proposed hybrid algorithm at light load level (40%) is from 187.17 kW (base case) to 126.13 kW, 59.59 kW, 66.75 kW and 54.91 kW with respect to the scenarios I–IV. At medium load level (70%), the power loss reduction is from 602.18 kW to 399.78 kW, 185.32 kW, 209.21 kW and 163.91 kW with respect to the scenarios I–IV. At nominal load level (100%) the power loss reduction is from 1298.09 kW to 847.75 kW, 384.65 kW, 435.62 kW and 340.12 kW with respect to the scenarios I–IV. It is observed that scenario-IV provides better loss reduction with improved bus voltage profile at all load level as compared with other scenarios. Fig. 8 depicts the optimal reconfiguration topology and directed graph representation of 118 node RDN along with DG units and shunt capacitor placement (Scenario-IV) at 100% load level.

Table 13 shows the minimum bus voltage profile with different scenarios obtained with standard HSA and hybrid HS-PABC algorithms. It can be inferred from the results presented in
Tables 12 and 13, that the proposed hybrid algorithm provides better loss reduction with improved bus voltage profile as compared with the standard HSA (with scenarios I–IV) at all load levels. The bus voltage profile with the scenarios I–IV at 100% load level is depicted in Fig. 9. It can be seen that, the proposed hybrid algorithm provides a significant improvement of minimum bus voltage profile in scenario-IV as compared with other scenarios. The active power loss in each branch of the RDN with the scenarios I–IV at 100% load level is depicted in Fig. 10. The reduction in total real power loss of the RDN with scenario-IV at 40%, 70% and 100% load levels using hybrid HS-PABC algorithm is depicted in Fig. 11. It can be inferred that the combined approach of optimal network reconfiguration problem along with DG units and shunt capacitors compensation (Scenario-IV) yields more loss reduction with improved bus voltage profile as compared with other scenarios.

4.3. Parameter settings

An empirical study is performed to determine the impact of control parameters towards the solution quality of the hybrid HS-PABC algorithm. To demonstrate the effects of single parameter change on the fitness function for 69-node RDN, 12 different cases...
Fig. 6. Variation of power loss at each line of 69 node RDN with different scenarios with hybrid HS-PABC algorithm at 100% load level.

Fig. 7. Power loss reduction in 69 node RDN with different scenarios with hybrid HS-PABC algorithm at 100% load level.

Fig. 8. Directed graph representation of optimal reconfiguration topology of 118 node RDN (Scenario-IV at 100% load level).
are tested as shown in Table 14. Each case is tested over 50 runs in three stages. In stage 1–3, HMCR, HMS, PAR and MCN are varied respectively, and other parameters are kept constant. If the HMCR value selection is too low, the algorithm behaves like a pure random search which leads to slow convergence. If the HMCR value is higher, all the harmonies in the HM are utilized, the other harmonies are not well explored and this may lead to local optimal solution. As shown in Table 14, large and small HMCR values lead to a decrease in the solution quality. The pitch adjustment (PAR) is used to produce new solution around the existing best solution. Selection of low PAR will limit the exploration and it can lead to slow convergence. Higher PAR selection will lead the solution to scatter around some potential optima similar to random search. The selection of larger and smaller values of HMS will decrease the efficiency of the algorithm as seen in Table 14. From the empirical study, the parameters chosen for 69 node network are HMS = 20, HMCR = 0.9, PAR = 0.3, MCN = 15. Similarly for 118 node RDN the control parameter values are selected as HMS = 50, MCN = 50, HMCR = 0.9, PAR = 0.3.

Table 3
Simulation results of 69 node RDN at different load levels obtained with HSA.

<table>
<thead>
<tr>
<th>%Load level</th>
<th>Fixed/Switched Capacitor</th>
<th>Scenario-I</th>
<th>Scenario-II</th>
<th>Scenario-III</th>
<th>Scenario-IV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Capacitor (kVAR) @ node (67)</td>
<td>Capacitor (kVAR) @ node (23)</td>
<td>Capacitor (kVAR) @ node (61)</td>
<td>DG1 (kW) @ node (63)</td>
</tr>
<tr>
<td>40</td>
<td>Fixed</td>
<td>200</td>
<td>100</td>
<td>450</td>
<td>11.13</td>
</tr>
<tr>
<td>50</td>
<td>Switched</td>
<td>50</td>
<td>50</td>
<td>200</td>
<td>121.29</td>
</tr>
<tr>
<td>60</td>
<td>Switched</td>
<td>50</td>
<td>–</td>
<td>100</td>
<td>138.57</td>
</tr>
<tr>
<td>70</td>
<td>Switched</td>
<td>100</td>
<td>–</td>
<td>150</td>
<td>71.94</td>
</tr>
<tr>
<td>80</td>
<td>Switched</td>
<td>50</td>
<td>350</td>
<td></td>
<td>128.07</td>
</tr>
<tr>
<td>90</td>
<td>Switched</td>
<td></td>
<td></td>
<td></td>
<td>133.97</td>
</tr>
<tr>
<td>100</td>
<td>Switched</td>
<td>–</td>
<td></td>
<td>100</td>
<td>104.06</td>
</tr>
</tbody>
</table>

Table 4
Reduction in real power loss with different scenarios using HSA and hybrid HS – PABC.

<table>
<thead>
<tr>
<th>%Load level</th>
<th>Real Power loss (kW)</th>
<th>Scenario-I</th>
<th>Scenario-II</th>
<th>Scenario-III</th>
<th>Scenario-IV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Before Compensation</td>
<td>Capacitors @ node: (67),(23),(61)</td>
<td>DG units @ node (63),(61),(64)</td>
<td>DG unit @ node (60)</td>
<td>Capacitor @ node (19)</td>
</tr>
<tr>
<td>40</td>
<td>32.50</td>
<td>21.65</td>
<td>21.65</td>
<td>10.65</td>
<td>10.54</td>
</tr>
<tr>
<td>50</td>
<td>51.59</td>
<td>34.41</td>
<td>34.26</td>
<td>16.64</td>
<td>16.61</td>
</tr>
<tr>
<td>60</td>
<td>75.51</td>
<td>49.88</td>
<td>49.88</td>
<td>24.81</td>
<td>24.13</td>
</tr>
<tr>
<td>70</td>
<td>104.52</td>
<td>68.91</td>
<td>68.91</td>
<td>32.99</td>
<td>32.99</td>
</tr>
<tr>
<td>80</td>
<td>138.88</td>
<td>93.96</td>
<td>93.89</td>
<td>44.22</td>
<td>43.66</td>
</tr>
<tr>
<td>90</td>
<td>178.92</td>
<td>117.44</td>
<td>117.58</td>
<td>56.23</td>
<td>55.41</td>
</tr>
<tr>
<td>100</td>
<td>224.96</td>
<td>146.11</td>
<td>145.68</td>
<td>77.25</td>
<td>69.08</td>
</tr>
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</table>

Table 5
Minimum bus voltage magnitude with different scenarios using HSA and hybrid HS-PABC.

<table>
<thead>
<tr>
<th>Load level</th>
<th>Minimum bus Voltage (p.u) @ (Node)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Before compensation</td>
</tr>
<tr>
<td></td>
<td>HSA 0.96</td>
</tr>
<tr>
<td>40</td>
<td>0.9660</td>
</tr>
<tr>
<td>50</td>
<td>0.9560</td>
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<tr>
<td>60</td>
<td>0.9474</td>
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<td>70</td>
<td>0.9382</td>
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<tr>
<td>80</td>
<td>0.9287</td>
</tr>
<tr>
<td>90</td>
<td>0.9191</td>
</tr>
<tr>
<td>100</td>
<td>0.9091</td>
</tr>
</tbody>
</table>

Table 6
Optimal results obtained with hybrid HS-PABC algorithm—Scenario-I & II.

<table>
<thead>
<tr>
<th>Load level</th>
<th>Fixed/Switched Capacitor</th>
<th>Scenario-I</th>
<th>Scenario-II</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Qc1 (86)</td>
<td>Qc2 (82)</td>
<td>Qc3 (111)</td>
</tr>
<tr>
<td>40</td>
<td>Fixed</td>
<td>350</td>
<td>300</td>
</tr>
<tr>
<td>50</td>
<td>Switched</td>
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<td>80</td>
<td>Switched</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>90</td>
<td>Switched</td>
<td>50</td>
<td>100</td>
</tr>
<tr>
<td>100</td>
<td>Switched</td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>
Table 7
Optimal results obtained with hybrid HS-PABC algorithm—Scenario-III.

<table>
<thead>
<tr>
<th>%Load level</th>
<th>Fixed/Switched Capacitor</th>
<th>Scenario-III</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Qc1 Node (32)</td>
<td>Qc2 Node (50)</td>
</tr>
<tr>
<td>40</td>
<td>Fixed</td>
<td>800</td>
</tr>
<tr>
<td>50</td>
<td>Switched</td>
<td>200</td>
</tr>
<tr>
<td>60</td>
<td>Switched</td>
<td>200</td>
</tr>
<tr>
<td>70</td>
<td>Switched</td>
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</tr>
<tr>
<td>80</td>
<td>Switched</td>
<td>250</td>
</tr>
<tr>
<td>90</td>
<td>Switched</td>
<td>250</td>
</tr>
<tr>
<td>100</td>
<td>Switched</td>
<td>200</td>
</tr>
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</table>

Table 8
Optimal results obtained with hybrid HS-PABC algorithm—Scenario-IV.

<table>
<thead>
<tr>
<th>%Load level</th>
<th>Type of capacitor</th>
<th>Scenario-IV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fixed/Switched Capacitor size in kVAR</td>
<td>Optimal DG units sizing in kW</td>
</tr>
<tr>
<td></td>
<td>@ Node (32)</td>
<td>@ Node (50)</td>
</tr>
</tbody>
</table>
Table 9
Optimal results obtained with HSA—Scenario-I & II.

<table>
<thead>
<tr>
<th>Load level</th>
<th>Fixed/Switched Capacitor</th>
<th>Scenario-I</th>
<th>Scenario-II</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Qc1 @ (86)</td>
<td>Qc2 @ (82)</td>
<td>Qc3 @ (111)</td>
</tr>
<tr>
<td>40</td>
<td>Fixed</td>
<td>300</td>
<td>300</td>
</tr>
<tr>
<td>50</td>
<td>Switched</td>
<td>100</td>
<td>50</td>
</tr>
<tr>
<td>60</td>
<td>Switched</td>
<td>150</td>
<td>150</td>
</tr>
<tr>
<td>70</td>
<td>Switched</td>
<td>–</td>
<td>100</td>
</tr>
<tr>
<td>80</td>
<td>Switched</td>
<td>–</td>
<td>150</td>
</tr>
<tr>
<td>90</td>
<td>Switched</td>
<td>–</td>
<td>150</td>
</tr>
<tr>
<td>100</td>
<td>Switched</td>
<td>–</td>
<td>700</td>
</tr>
</tbody>
</table>

Table 10
Optimal results obtained with HSA—Scenario-III.

<table>
<thead>
<tr>
<th>%Load level</th>
<th>Fixed/Switched Capacitor</th>
<th>Scenario-III</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Qc1 @Node (50)</td>
<td>Qc2 @Node (15)</td>
</tr>
<tr>
<td>40</td>
<td>Fixed</td>
<td>700</td>
</tr>
<tr>
<td>50</td>
<td>Switched</td>
<td>250</td>
</tr>
<tr>
<td>60</td>
<td>Switched</td>
<td>200</td>
</tr>
<tr>
<td>70</td>
<td>Switched</td>
<td>200</td>
</tr>
<tr>
<td>80</td>
<td>Switched</td>
<td>250</td>
</tr>
<tr>
<td>90</td>
<td>Switched</td>
<td>250</td>
</tr>
<tr>
<td>100</td>
<td>Switched</td>
<td>350</td>
</tr>
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</table>

Table 11
Optimal results obtained with HSA—Scenario-IV.

<table>
<thead>
<tr>
<th>%Load level</th>
<th>Type of capacitor</th>
<th>Scenario-IV</th>
<th>Fixed/Switched Capacitor size in kVAR</th>
<th>Optimal DG units sizing in kW</th>
<th>Optimal topology (Open Switches)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>@ Node (32)</td>
<td>@ Node (50)</td>
<td>@ Node (15)</td>
</tr>
<tr>
<td>40</td>
<td>Fixed</td>
<td>50</td>
<td>1000</td>
<td>100</td>
<td>550</td>
</tr>
<tr>
<td>60</td>
<td>Switched</td>
<td>150</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>70</td>
<td>Switched</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
</tbody>
</table>

Table 12
Reduction in real power loss with scenarios: I–IV using HSA and hybrid HS-PABC.

<table>
<thead>
<tr>
<th>%Load level</th>
<th>Real Power loss (kW)</th>
<th>Scenario-I Capacitors at node: (86),(82),(111), (49),(32),(107),(71),(96)</th>
<th>Scenario-II DG units at node (109),(52),(70)</th>
<th>Scenario-III Capacitors at node (32),(50),(15),(93),(103)</th>
<th>Scenario-IV Reconfiguration along with DG at node (71),(110) Capacitors at node (32),(50),(15),(93),(103)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>HSA</td>
<td>HSA</td>
<td>HSA</td>
<td>HSA</td>
</tr>
<tr>
<td>40</td>
<td>187.17</td>
<td>128.07</td>
<td>60.25</td>
<td>69.33</td>
<td>61.57</td>
</tr>
<tr>
<td>50</td>
<td>297.14</td>
<td>200.12</td>
<td>96.15</td>
<td>110.95</td>
<td>99.53</td>
</tr>
<tr>
<td>60</td>
<td>434.97</td>
<td>290.52</td>
<td>144.48</td>
<td>154.03</td>
<td>135.16</td>
</tr>
<tr>
<td>70</td>
<td>602.18</td>
<td>400.06</td>
<td>197.31</td>
<td>210.83</td>
<td>179.83</td>
</tr>
<tr>
<td>80</td>
<td>800.46</td>
<td>529.08</td>
<td>246.15</td>
<td>277.10</td>
<td>226.10</td>
</tr>
<tr>
<td>90</td>
<td>1031.72</td>
<td>678.89</td>
<td>310.25</td>
<td>358.85</td>
<td>320.82</td>
</tr>
<tr>
<td>100</td>
<td>1298.09</td>
<td>853.35</td>
<td>385.89</td>
<td>438.10</td>
<td>380.21</td>
</tr>
</tbody>
</table>
### Table 13
Minimum bus voltage magnitude with scenarios: I–IV using HSA and hybrid HS-PABC.

<table>
<thead>
<tr>
<th>%Load level</th>
<th>Minimum bus Voltage (p.u) Φ(Node)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Before compensation Φ (78)</td>
</tr>
<tr>
<td></td>
<td>Scenario-I</td>
</tr>
<tr>
<td></td>
<td>HSA Φ (78) HS-PABC Φ (78)</td>
</tr>
<tr>
<td></td>
<td>Scenario-II</td>
</tr>
<tr>
<td></td>
<td>HSA Φ (47) HS-PABC Φ (47)</td>
</tr>
<tr>
<td></td>
<td>Scenario-III</td>
</tr>
<tr>
<td></td>
<td>HSA Φ (55) HS-PABC</td>
</tr>
<tr>
<td></td>
<td>Scenario-IV</td>
</tr>
<tr>
<td></td>
<td>HSA Φ (51) HS-PABC Φ (51)</td>
</tr>
<tr>
<td>40</td>
<td>0.9513 0.9658 0.9662</td>
</tr>
<tr>
<td>50</td>
<td>0.9385 0.9581 0.9582</td>
</tr>
<tr>
<td>60</td>
<td>0.9253 0.9487 0.9486</td>
</tr>
<tr>
<td>70</td>
<td>0.9117 0.9396 0.9307</td>
</tr>
<tr>
<td>80</td>
<td>0.8978 0.9312 0.9315</td>
</tr>
<tr>
<td>90</td>
<td>0.8835 0.9226 0.9228</td>
</tr>
<tr>
<td>100</td>
<td>0.8687 0.9122 0.9127</td>
</tr>
</tbody>
</table>

### Table 14
Impact of hybrid HS-PABC algorithm parameter variations on the fitness function (Scenario-IV) at 100% load level.

<table>
<thead>
<tr>
<th>Stage</th>
<th>Parameter settings</th>
<th>Fitness</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5</td>
<td>0.3</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>0.3</td>
</tr>
<tr>
<td>3</td>
<td>5</td>
<td>0.3</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>0.3</td>
</tr>
<tr>
<td>20</td>
<td>0.3</td>
<td>0.3</td>
</tr>
<tr>
<td>30</td>
<td>0.3</td>
<td>0.3</td>
</tr>
</tbody>
</table>

### Table 15
Statistical study to test the robustness of the HS and hybrid HS – PABC algorithm with 50 independent runs at 100% load level – 69 node RDN.

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Max. fitness</th>
<th>Min. fitness</th>
<th>Mean fitness</th>
<th>Median</th>
<th>Std deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>HSA</td>
<td>HS-PABC</td>
<td>HSA</td>
<td>HS-PABC</td>
<td>HSA</td>
<td>HS-PABC</td>
</tr>
<tr>
<td>I</td>
<td>0.525175272</td>
<td>0.515918944</td>
<td>0.515953</td>
<td>0.5158</td>
<td>0.517805366</td>
</tr>
<tr>
<td>II</td>
<td>0.37432</td>
<td>0.37057</td>
<td>0.3703</td>
<td>0.3698</td>
<td>0.371701</td>
</tr>
<tr>
<td>III</td>
<td>0.381935</td>
<td>0.368598</td>
<td>0.3473269</td>
<td>0.347311</td>
<td>0.368063</td>
</tr>
<tr>
<td>IV</td>
<td>0.385383465</td>
<td>0.384051451</td>
<td>0.3457147</td>
<td>0.344045</td>
<td>0.368376043</td>
</tr>
</tbody>
</table>

### Table 16
Statistical study to test the robustness of the HS and hybrid HS – PABC algorithm with 50 independent runs at 100% load level – 118 node RDN.

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Max. fitness</th>
<th>Min. fitness</th>
<th>Mean fitness</th>
<th>Median</th>
<th>Std deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>HSA</td>
<td>HS-PABC</td>
<td>HSA</td>
<td>HS-PABC</td>
<td>HSA</td>
<td>HS-PABC</td>
</tr>
<tr>
<td>I</td>
<td>0.38792539</td>
<td>0.379718752</td>
<td>0.3811177</td>
<td>0.37960</td>
<td>0.38356404</td>
</tr>
<tr>
<td>II</td>
<td>0.186545315</td>
<td>0.180655777</td>
<td>0.180605</td>
<td>0.180605</td>
<td>0.183937826</td>
</tr>
<tr>
<td>III</td>
<td>0.202517727</td>
<td>0.188078689</td>
<td>0.188329</td>
<td>0.18807569</td>
<td>0.197148549</td>
</tr>
<tr>
<td>IV</td>
<td>0.198168818</td>
<td>0.16600427</td>
<td>0.1630003</td>
<td>0.14670</td>
<td>0.18038661</td>
</tr>
</tbody>
</table>

### 4.4. Robustness and convergence rate of hybrid HS-PABC and HS algorithm

The formulated optimization problem (Scenarios-I–IV with 100% load level) is solved 50 times repeatedly with random popula-

Fig. 12. (a–d) Convergence plot of fitness function with HS and Hybrid HS-PABC algorithms (Scenario- I–IV)—100% load level-69 node RDN.

Fig. 14. (a–d) Convergence plot of fitness function with HSA and Hybrid HS-PABC algorithm (Scenario- I–IV)—100% load level-118 node RDN.

Fig. 13. (a–d) Box plot for the results of HS-PABC and HSA algorithms—Scenarios I–IV for 69 node RDN.
4.4.1. Statistical analysis

The box plot and Wilcoxon rank sum test is used to show the quality of the solution obtained by hybrid HS-PABC with respect to HSA.

4.4.1.1. Box-plot. Repeatedly 50 runs are performed to visualize the distribution of the samples in HS-PABC and HS algorithms with four scenarios in box plot format as shown in Figs. 13 and 15 (a-d). It is observed that the distribution of data based on minimum, first quartile, median, third quartile, and maximum are close to each other in proposed hybrid HS-PABC algorithm when compared with HSA. The results in box plots reveal the robustness and superiority of the proposed hybrid HS-PABC over standard HS algorithm.

4.4.1.2. Wilcoxon rank sum test. Wilcoxon rank sum test is a non-parametric test utilized to show the statistical comparison between the proposed hybrid HS-PABC and HS algorithm. This test assumes selection of different random samples with continuous probability distribution. The following hypotheses are tested:

- **H₀**: The probability distributions of fitness values obtained by HS-PABC and HSA are identical.
- **H₁**: Distribution of the fitness values differ between HS-PABC and HSA.

Wilcoxon rank sum test results are termed p-values (observed significance level). When p-values less than or equal to level of significance (α = 5%), we reject the null hypothesis. The approximation method is used to calculate the p-values and the results are presented in Table 17 to illustrate the efficiency of proposed hybrid HS-PABC algorithm over standard HS algorithm. For both the RDNs with scenario-IV, all the p-values are less than 0.05 (refer Table 17) which signifies the choice of selecting alternative hypothesis. It can be concluded that these test implies a significant statistical difference between the HS-PABC and standard HS algorithm. Therefore we can come to the conclusion that the proposed HS-PABC can maintain superior performance than the standard HSA.

5. Conclusion

This article presents a hybrid HS-PABC algorithm based approach for network reconfiguration problem along with optimal location and sizing of DG units and shunt capacitors for optimal planning of distribution networks. Different test scenarios are simulated on 69 and 118 node distribution network at varying load conditions. The hybrid HS-PABC algorithm offers a promising and preferable performance in terms of power loss reduction, improved bus voltage profile than standard HSA at all discrete load levels. From the simulation results, it is inferred that integrated approach of network reconfiguration problem with the simultaneous installation of DG units and shunt capacitors is an efficient approach towards more loss reduction with the enhanced bus voltage profile as compared with individual loss reduction approaches. A statistical analysis is performed using 50 independent trials for each approach on the test system. To measure and prove the quality of the solutions obtained by proposed approach, box plot and Wilcoxon rank sum test are performed. The HS-PABC is a co-evolutionary algorithm that runs in parallel to accomplish the optimal solution in high-dimensional optimization problems. The simulation results confirm the capability of proposed HS-PABC algorithm to reach the optimal solution with faster convergence rate than standard HS algorithm. Finally, this work provides interesting basis for combining promising aspects of different evolutionary algorithm techniques into a new hybrid meta-heuristic algorithm that shows significant performance.

References


