Hybrid Symbiotic Organisms Search for Optimal Fuzzified Joint Reconfiguration and Capacitor Placement in Electric Distribution Systems

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Abstract Network reconfiguration and capacitor allocation are two valuable tools to optimally manage distribution systems. In the present work, an efficient algorithm is proposed for the joint problem of reconfiguration and capacitor placement in distribution systems. The multi-objective problem is formulated to minimize objective functions of total network power losses, bus voltage violation, and branch loading deviations subject to different technical and operational constraints. To enhance exploration ability, the Symbiotic Organisms Search algorithm is strengthened with Particle Swarm Optimization capabilities to develop the Hybrid Symbiotic Organisms Search algorithm, which is applied to solve the proposed problem. Objective functions are fuzzified and aggregated by a geometric mean operator to have the same scales. The proposed joint optimization problem is solved with the introduced Hybrid Symbiotic Organisms Search algorithm in two different case studies of balanced and unbalanced test systems. According to obtained results that are compared with some well-known evolutionary algorithms, the superiority of the Hybrid Symbiotic Organisms Search algorithm is confirmed in terms of solution optimality and convergence speed.

Keywords Optimal reconfiguration · Capacitor placement · Hybrid Symbiotic Organisms Search (HSOS) · Multi-objective optimization · Distribution systems

Introduction

In electric distribution systems, capacitors have been applied to compensate load reactive power demands and to prevent the violation of voltages from their permissible limits. The efficiency of the compensation depends on the location and size of capacitors. Recent trends in electricity markets pushes existing power systems to better employ network resources (Rosen and Madlener 2013). Also, recent integration of renewable energy sources into power systems requires more operational challenges to keep the system more effective (Chang 2014). In addition, feeder reconfiguration is the process of altering the topology and configuration of distribution systems by changing the open or closed status of switches. Two types of switches are used in distribution systems to change network topology; they include normally closed switches (sectionalizing switches) and normally open switches (tie switches). Both tasks of capacitor placement and reconfiguration have a vital effect on performance indices of distribution systems such as power losses and voltage profile. Optimal network reconfiguration and capacitor placement, which is formulated as a type of optimal power flow (Murillo-Sánchez et al. 2013), have been separately implemented in research papers using different approaches, different objective functions, and diverse optimization solution methods.

Network reconfiguration is researched in literature using different objective functions and approaches; most of these algorithms are based on heuristic techniques and artificial intelligence methods. For instance, a method to enhance

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power quality and reliability of distribution systems by employing optimal network reconfiguration was presented by Shareef et al. (2014), which was applied independently to a system in a specified period to minimize the number of propagated voltage sags and other reliability indices. The Quantum-inspired Binary Firefly algorithm is used to find the optimal network reconfiguration. A methodology for the reconfiguration of radial electrical distribution systems based on the bio-inspired meta-heuristic Artificial Immune System (AIS) to minimize energy losses was presented by De Oliveira et al. (2014), in which radiality and connectivity constraints as well as different load levels for planning the system operation were considered. Sedighzadeh et al. (2013) have proposed an efficient Hybrid Big Bang-Big Crunch (HBB-BC) optimization algorithm to solve the multi-objective reconfiguration of balanced and unbalanced distribution systems in a fuzzy framework. The considered objectives were the minimization of total active power losses, minimization of bus voltage deviation, and load balancing in feeders. An adapted Ant Colony Optimization (ACO) for the reconfiguration of radial distribution systems and minimization of real power losses was used by Swarnkar et al. (2011), in which conventional ACO was adapted by the graph theory to continuously create feasible radial topologies during the whole evolutionary process which avoided tedious mesh check and hence, it reduced the computational burden. Amanulla et al. (2012) have used a Binary Particle Swarm Optimization (BPSO) for finding the optimal status of switches for distribution system reconfiguration. Maximizing reliability indices and minimizing real power losses were objectives of the optimization. Mendoza et al. (2009) have utilized a Pareto-based optimization technique called Micro-genetic Algorithm (MGA) for distribution system reconfiguration. This algorithm finds optimal status of switches for maximizing reliability indices and minimizing real power losses. Bernardon et al. (2010) have suggested an efficient fuzzy decision maker based on Bellman-Zadeh's method for optimal distribution network reconfiguration. The goal was to reduce power losses, enhance voltage profile of customers, and increase reliability levels. Tomoiagă et al. (2013) have proposed a Pareto-based optimal reconfiguration of power distribution systems using Genetic Algorithm (GA) based on Non-dominated Sorting GA (NSGA-II). Minimization of active power losses and the system average interruption frequency index were the goals of optimization. Ghasemi and Moshtagh (2014) have found the optimal reconfiguration of distribution networks by a novel codification and modified heuristic approach for reducing power losses cost and increasing cost-benefit from voltage improvement. Saffar et al. (2011) have suggested an optimal reconfiguration of distribution systems using a new fuzzy-ant colony search

based algorithm. The goals of optimization are the loss reduction and load balancing. Aman et al. (2014) have performed the optimal reconfiguration using Discrete Artificial Bee Colony (DABC) approach considering the Continuation Power Flow (CPF) theorem and radial distribution load flow analysis. The goal is the maximization of loadability. The graph theory is used to ensure the radiality and connectivity of the system. The graph theory is mainly valuable in graphical user interface-based application such as voltage stability and optimization programming tool (Aman et al. 2016a). Aman et al. (2016b) simultaneously investigated the Distributed Generation (DG) optimal allocation and optimum tie switch allocation using DABC algorithm. The aim is to maximize the loadability subject to allowed deviation in bus voltage and allowed branch loading. The radiality and connectivity constraints are also satisfied.

On the other hand, the problem of capacitor placement in electric distribution systems has been extensively investigated in articles mostly for loss reduction. For example, a fuzzy-based approach was proposed by Ramadan et al. (2014) to optimally allocate and size capacitors in distribution systems using different membership functions for voltage profile and power loss objective functions. Abul'Wafa (2013) considered a two-stage method for loss reduction and the optimal operational status of devices was determined using GA resulting in determining the optimal location and number of capacitors. Carpinelli et al. (2012) have investigated the single objective probabilistic optimal allocation to solve the capacitor placement problem. Devabalaji et al. (2015) have studied the optimal location and sizing of capacitors using the Bacterial Foraging (BF) optimization algorithm in radial distribution systems. Kannan et al. (2011) have used fuzzy Differential Evolution (DE) and fuzzy Multi Agent PSO (MAPSO) methods for optimal capacitor placement in radial distribution feeders in order to reduce real power losses, to improve the voltage profile, and to achieve economic saving. Aman et al. (2013) simultaneously determined the optimum DG and shunt capacitor placements using the PSO algorithm to minimize the active power losses and enhance voltage regulation.

In addition to above mentioned works that studied reconfiguration and capacitor placement separately, there are some other studies which have simultaneously dealt with both network reconfiguration and capacitor placement. For instance, Farahani et al. (2012) applied the simple branch exchange method for the reconfiguration problem and revealed that the sequence of loop selection affects the optimal configuration and network losses. They also proposed a joint optimization algorithm for combining the improved method of reconfiguration and capacitor placement. Discrete GA was used to optimize the location

and size of capacitors and the sequence of loop selection in reconfiguration. The problem of optimal voltage regulation and power loss minimization in distribution systems equipped with shunt capacitor banks was investigated by Augugliaro et al. (2004) and the optimal reconfiguration of tie-switches and capacitor banks on feeders of a meshed distribution system is addressed with objective functions of power losses and voltage deviations using an adopted evolutionary algorithm and fuzzy set theory for scaling the objective functions. The membership function used for scaling is a bell-shaped normal distribution function and objective functions are combined with their minimum (intersection) and product approach. Sultana and Roy (2016) used a computationally efficient methodology namely the Krill Herd (KH) algorithm for capacitor placement and reconfiguration problem. Montoya and Ramirez (2012) utilized the Minimum Spanning Tree (MST) algorithm to determine minimum losses in the reconfiguration problem and used GA for achieving the greatest savings through the optimal capacitor placement problem. Sedighzadeh et al. (2014) investigated the planning issues for the priority of reconfiguration and capacitor placement problems based on an Improved BPSO (IBPSO) algorithm employing a different structure for the optimization problem.

Considering the above-mentioned features, the contribution of this paper is to present a fuzzy-based formulation for the simultaneous optimal reconfiguration and capacitor placement problem in distribution systems. The Hybrid Symbiotic Organisms Search (HSOS) algorithm is employed here as a new evolutionary optimization tool for solving the proposed multi-objective problem. The objective functions include the minimization of total real power losses and bus voltage violation as well as load balancing in feeders. Objective functions are transformed into fuzzy memberships and finally, they are combined into a single objective function, which is optimized subject to a variety of power system operational constraints. Also, unbalanced power systems are considered in the reconfiguration and capacitor allocation problem, a matter which has been rarely addressed in literature.

Proposed Method for Reconfiguration and Capacitor Allocation

In this section, the proposed formulation for distribution system reconfiguration in the presence of capacitors is elaborated with its objective functions and constraints.

Objective Functions

Minimizing Power Losses

Power losses are one of vital quantities in distribution systems and it is critical to keep power losses low for a better usage of network resources. The system total power losses are determined as sum of losses in all branches and it is minimized as the first objective function as:

$$\text{Min } f_1 = P_{\text{loss}} = \sum_{k=1}^{N_{br}} R_k |I_k|^2 \quad (1)$$

where R_k and I_k represent the resistance and current of branch k , respectively; N_{br} is the total number of branches in the system.

Minimizing Bus Voltage Deviation Index

For the purpose of a better voltage profile, the Voltage Deviation Index (VDI) is defined and optimized as follows:

$$\text{Min } f_2 = VDI_i = \max(|1 - V_{\min,i}|, |1 - V_{\max,i}|) \quad (2)$$

where $V_{\min,i}$ and $V_{\max,i}$ are minimum and maximum values of bus voltage in configuration i , respectively. In fact, VDI_i gives the largest deviation in voltage for configuration i .

Minimizing Load Balancing Index

For the purpose of load balancing, a parameter is defined as the ratio of branch loading. It is called the Line Usage Index (LUI) of branches and calculated as follows (Saffar et al. 2011):

$$LUI_k = \frac{I_k}{I_k^{\max}} \quad (3)$$

where I_k represents the current of branch k ; $I_k^{\max}$ is the permitted rating of branch k . These LUI values are normalized and shown with parameter of Y as:

$$Y = \left[\frac{I_1}{I_1^{\max}} \frac{I_2}{I_2^{\max}} \frac{I_3}{I_3^{\max}} \dots \frac{I_{N_{br}}}{I_{N_{br}}^{\max}} \right] \quad (4)$$

So, the Load Balancing Index (LBI) objective function is expressed as follows:

$$\text{Min } f_3 = LBI = \text{Var}(Y) \quad (5)$$

where Var represents the variance operation. By minimizing variance of branch loading in the LBI objective function, loads are dispatched over branches more uniformly resulting in a small variance.

Fuzzy-based Combination of Objective Functions

In order to find a solution in which all objective functions are optimized, a multi-objective programming method should be used. In order to avoid scaling problem and to transform objective functions into the same range, the fuzzification method is used (Esmaili and Goldoust 2015). All objective functions are fuzzified and transformed into the same range of $[0, 1]$ using the trapezoidal fuzzy membership function which is expressed as (Sedighizadeh et al. 2017):

$$\rho_i = \begin{cases} 1 & f_i \leq f_i^{\min} \\ \frac{f_i^{\max} - f_i}{f_i^{\max} - f_i^{\min}} & f_i^{\min} < f_i < f_i^{\max} \\ 0 & f_i \geq f_i^{\max} \end{cases} \quad (6)$$

where $f_i^{\min}$ and $f_i^{\max}$ represent the ideal and nadir values for objective function i , respectively; f_i is objective function value; and ρ_i is its fuzzy membership value. Ideal and nadir values (Akorede et al. 2011) represent the best and worst accessible values of each objective function, respectively, in the solution space of the problem. As depicted in Fig. 1, a smaller value of the objective function leads to a larger membership function, which is more preferred when the objective function is for minimization. In the proposed method, three memberships of ρ_{Loss} , ρ_{VDI} , and ρ_{LBI} are calculated for the objective functions of loss, VDI, and LBI, respectively.

There are several methods to combine these memberships and establish an overall fuzzy fitness function. We here use a recent operator called “max geometric mean” (Gupta et al. 2010) to integrate objective functions. Using this technique, the degree of overall fuzzy satisfaction is computed as follows:

$$\mu_f = (\rho_{Loss} \cdot \rho_{VDI} \cdot \rho_{LBI})^{1/3} \quad (7)$$

where μ_f represents the overall fitness function of the multi-objective solution. This overall fitness function is the objective function that is maximized in our multi-objective problem.

Fig. 1 Trapezoidal fuzzy membership function for objective functions

Constraints

The proposed multi-objective problem for simultaneous reconfiguration and capacitor allocation is optimized subject to following constraints.

Power Flow Equations

Active and reactive power balance at each node of the network should be observed using following constraints (Esmaili and Rajabi 2013):

$$PG_i - PD_i = \sum_{j=1}^{N_{bus}} |V_i| |V_j| |Y_{ij}| \cos(\delta_i - \delta_j - \varphi_{ij}) \quad (8)$$

$$i = 1, \dots, N_{bus}$$

$$QG_i - QD_i = \sum_{j=1}^{N_{bus}} |V_i| |V_j| |Y_{ij}| \sin(\delta_i - \delta_j - \varphi_{ij}) \quad (9)$$

$$i = 1, \dots, N_{bus}$$

where PG_i and QG_i are active and reactive generations at bus i ; PD_i and QD_i are active and reactive demands at bus i ; V_i and δ_i represent the magnitude and angle of voltage phasor at bus i ; $|Y_{ij}|$ and φ_{ij} are the magnitude and angle of ij entry from the bus admittance matrix, and N_{bus} is the number of buses.

Network Radiality and Connectivity

Network radiality can be achieved by the Kirchhoff algebraic method based on the bus incidence matrix (Abdelaziz et al. 2010). This connection matrix is obtained by the graph theory (Park and Basole 2016) and has one row for each branch and one column for each node. Each member of this matrix is determined by the following rules:

- $a_{i,j} = 0$ if branch i is not connected to node j .
- $a_{i,j} = 1$ if branch i is directed away from node j .
- $a_{i,j} = -1$ if branch i is directed toward node j .

The first column corresponding to the reference node is removed and the resultant branch-to-node matrix is denoted by A . The system radiality is specified by the determinant of A : if the determinant of A is equal to 1 or -1 , then the system configuration is radial; but, if the determinant of A is equal to zero, either the system configuration is not radial or some loads are not energized.

Branch Current Limits

In order to protect cables and feeders against excessive currents, their rating should be taken into account:

$$|I_k| \leq I_k^{\max} \quad k = 1, \dots, N_{br} \quad (10)$$

Bus Voltage Permissible Range

After reconfiguration and capacitor allocation, bus voltages should remain within their permissible range specified by the system operator:

$$V_{\min} \leq |V_i| \leq V_{\max} \quad i = 1, \dots, N_{\text{bus}} \quad (11)$$

where $V_{\min}$ and $V_{\max}$ are minimum and maximum allowable voltages, respectively.

Hybrid Symbiotic Organisms Search Algorithm as a Solution Tool

In this section, after briefly reviewing the basic Symbiotic Organisms Search (SOS) method, the modified version as HSOS is introduced to solve the proposed formulation.

The Basic Symbiotic Organisms Search

First, Cheng and Prayogo introduced the SOS algorithm as a new optimization method in 2014 (Cheng and Prayogo 2014) by employing symbiotic interaction strategies adopted by organisms to survive and propagate in ecosystems. This population-based method has a simple implementation, low computational time, and high convergence speed. Cheng and Prayogo (2014) revealed the outstanding performance of the SOS method in solving various complex numerical problems by solving several mathematical problems.

Similar to other meta-heuristic algorithms, the SOS algorithm is based on natural phenomena and imitates the symbiotic interactions within a paired organism relationship utilized for finding the fittest organism. In this algorithm, a population of candidate solutions is selected in the search space in looking for the optimal solution. The initial population is called ecosystem. A group of organisms is produced randomly in the search space for filling the initial ecosystem. Indeed, each organism is a potential candidate solution to the problem and it provides a certain fitness value which clarifies the degree of its quality. Similar to most meta-heuristic algorithms, this algorithm applies a sequence of operations to initial solutions over iterations in order to produce new solutions for the next iteration. In SOS, a new solution generation is reproduced based on a three-phase biological interaction between two organisms in the ecosystem: the mutualism phase (benefit both sides), commensalism phase (benefit one side and do not impact the other), and parasitism phase (benefit one side and actively harm the other). All of these phases may happen when organisms interact with each other randomly during

iterations. This process is repeated until termination criteria are satisfied.

The Mutualism Phase

Let's denote the i th organism of the ecosystem as X_i . Another organism X_j is chosen randomly from the ecosystem to interact with X_i . Both organisms can cooperate in a mutualistic relationship to enhance mutual survival advantage in the ecosystem. According to the mutualistic symbiosis between organisms, new candidate solutions of X_i and X_j are calculated as follows:

$$X_i^{(k+1)} = X_i^{(k)} + \text{rand}(0, 1) \left(X^{\text{best}} - \left(\frac{X_i^{(k)} + X_j^{(k)}}{2} \right) \times BF_1 \right) \quad (12)$$

$$X_j^{(k+1)} = X_j^{(k)} + \text{rand}(0, 1) \left(X^{\text{best}} - \left(\frac{X_i^{(k)} + X_j^{(k)}}{2} \right) \times BF_2 \right) \quad (13)$$

where k denotes iteration number; BF_1 and BF_2 are benefit factors of organism X_i and X_j , respectively; X^{best} is the global solution up to iteration k ; $\text{rand}(0, 1)$ is a random number generated at each iteration.

The BF coefficient shows the rate of receiving benefits for each organism from other organisms in mutualism relationships. When BF_1 is larger than BF_2 , organism i receives more beneficial advantage from organism j . Here, benefit factors are identified randomly as either 1 or 2. In (12) and (13), the second term shows the mutualistic attempt to achieve their goal in increasing their survival advantage. The new candidate solutions replace the existing ones if their new fitness is better than their pre-interaction fitness.

The Commensalism Phase

In this phase, similar to the mutualism phase, organism X_j is chosen randomly from the ecosystem to interact with X_i . Afterwards, organism X_i tries to promote from the interaction. However, this interaction is neither beneficial nor harmful for organism X_j . This relationship is modeled by the following equation:

$$X_i^{(k+1)} = X_i^{(k)} + \text{rand}(-1, 1) (X^{\text{best}} - X_j^{(k)}) \quad (14)$$

The second term in (14) represents the beneficial advantage provided by X_j to help X_i enhance its survival advantage in the ecosystem to the highest degree in the current organism (represented by X^{best}). Organism X_i is replaced by its new value only if its new fitness is better than its pre-interaction fitness.

The Parasitism Phase

In this phase, organism X_i creates an artificial parasite called the parasite vector (P_V). P_V is generated in the search space through duplicating organism X_i , and then, it adjusts randomly chosen dimensions by a random number. The randomly selected organism X_j from the ecosystem acts as a host to the P_V that attempts to replace X_j in the ecosystem. The fitness related to both organisms is then calculated. If P_V has a better fitness value, it will remove organism X_j and occupy its position in the ecosystem. If X_j has a better fitness value, X_j will have immunity from the parasite and P_V cannot stay in that ecosystem. All of the three phases mentioned above are repeated until a stopping criterion is satisfied.

Overview of PSO and Improved PSO

PSO is a population-based stochastic optimization algorithm and has recently acquired wide applications in optimizing design problems because of its simplicity and ability to optimize complex constrained objective functions in multi-modal search spaces. In PSO, each potential solution is referred to a particle and each set of particles composes a population. Each particle maintains the position associated with the best fitness ever experienced by it in a personal memory called $pbest$. Besides, the position associated with the best value obtained so far among particles is called $gbest$. In each iteration, $pbest$ and $gbest$ values are updated and each particle modifies its velocity to stochastically go on. This concept can be formulated as (Moarref et al. 2016):

$$V_j^{(k+1)} = w \cdot V_j^{(k)} + c_1 r_1 (pbest_j^{(k)} - x_j^{(k)}) + c_2 r_2 (gbest^{(k)} - x_j^{(k)}) \quad j = 1, \dots, N \quad (15)$$

$$x_j^{(k+1)} = x_j^{(k)} + V_j^{(k+1)} \quad j = 1, \dots, N \quad (16)$$

where k is the iteration number; $V_j^{(k)}$ is the velocity of particle j at iteration k ; $x_j^{(k)}$ is particle j position at iteration k ; w is inertia weight factor; c_1 and c_2 are cognitive and social acceleration factors, respectively; r_1 and r_2 are uniformly distributed random numbers in the range of $[0, 1]$; $pbest_j^{(k)}$ and $gbest^{(k)}$ represent the best position of the j th particle and the best global position up to iteration k , respectively; N is the number of particles.

Appropriate selection of c_1, c_2 , and w plays an important role in the efficiency of PSO. In some cases, convergence is premature, especially for small inertia weight factor. As the early found global best in the searching procedure may be a local minimum, an Improved PSO (IPSO) is used to avoid such a case. Chao et al. (2015) proposed this variant of

PSO as IPSO. Initially, a growth indicator β is defined for each particle; it increases if the current fitness value of particle is better than that of the previous iteration. When the personal bests of all particles are updated in each generation, the personal bests with better fitness values than the global best are considered as the candidate to replace the global best. That is, the global best will be replaced by the personal best with the highest growth indicator of β .

The Proposed HSOS Algorithm

The HSOS algorithm, which is used in the current paper, incorporates PSO capabilities into SOS for a higher efficiency. In the HSOS, after calculating new organisms according to the three phases of SOS, they are updated as using PSO. When PSO starts, we have $k+1$ values available; they are already calculated according to subsection “The basic symbiotic organisms search”. At this stage, they are updated as:

$$V_{jSOS}^{(k+1)} = w \cdot V_j^{(k)} + c_1 r_1 (pbest_j^{(k+1)} - x_j^{(k+1)}) + c_2 r_2 (gbest^{(k+1)} - x_j^{(k+1)}) \quad (17)$$

$$x_{jHSOS}^{(k+1)} = x_{jSOS}^{(k+1)} + V_{jSOS}^{(k+1)} \quad j = 1, \dots, M \quad (18)$$

where M is number of organisms in the ecosystem. Equation (17) gives the new velocity of SOS organisms and (18) obtains HSOS organisms using SOS velocity and organisms.

To obtain a discrete solution in optimization problems with integer variables, the function of $round(x)$ is used to round elements of x to the nearest integer as:

$$x_{jHSOS}^{(k+1)} = round(x_{jHSOS}^{(k+1)}) \quad j = 1, \dots, M \quad (19)$$

Integration of the HSOS Algorithm into the Proposed Problem

In the proposed formulation, the number of switches to be opened to maintain a feasible radial configuration and the capacitors units that should be placed in the candidate buses are considered as control variables. So, control variables are integer numbers; the length of control variables is the sum of the number of tie switches and the number of buses that are candidates for capacitor placement as:

$$N_{cv} = N_L + N_{busc} \quad (20)$$

where N_{cv} is the number of control variables; N_L is the number of tie switches; and N_{busc} is the number of network buses that are candidates for capacitor placement (equal to

the number of network buses minus the slack bus). The number of tie switches is obtained as follows (Sedighzadeh et al. 2013):

$$N_L = N_{br} - N_{bus} + 1 \quad (21)$$

where N_L is the number of tie switches; N_{br} is the total number of network branches; N_{bus} is the number of network buses.

In order to shed light on the problem, we focus on the 33-bus test system that will be studied in section “Simulation results”. In the first step, loop and capacitor vectors should be identified. In the proposed algorithm, each loop vector consists of switches that form a loop in the network. In other words, the number of loop vectors is equal to the number of fundamental loops or tie switches. In the 33-bus test system, the number of fundamental loops or loop vectors is five. Each loop vector is specified with its section numbers as (see the one-line diagram in Fig. 2):

$$\text{Loop vector 1} = [S2, S3, S4, S5, S6, S7, S18, S19, S20, S33] \quad (22)$$

$$\text{Loop vector 2} = [S8, S9, S10, S11, S21, S33, S35] \quad (23)$$

$$\text{Loop vector 3} = [S9, S10, S11, S12, S13, S14, S34] \quad (24)$$

$$\text{Loop vector 4} = [S3, S4, S5, S22, S23, S24, S25, S26, S27, S28, S37] \quad (25)$$

$$\text{Loop vector 5} = [S6, S7, S8, S15, S16, S17, S25, S26, S27, S28, S29, S30, S31, S32, S36] \quad (26)$$

To define the capacitor vector for a bus, six discrete sizes of capacitors as 300, 600, 900, 1200, 1500, and 1800 kVAr are used, according to Sedighzadeh et al. (2014) and Chang (2008), to be placed at selected buses. Then, the

capacitor vector for each bus that is a candidate for capacitor placement becomes:

$$\text{Capacitor vector} = [0, 300, 600, 900, 1200, 1500, 1800] \quad (27)$$

The number of tie switches and buses for capacitor placement is 5 and 32, respectively (the slack bus is excluded from capacitor placement). Then, the length of decision vector is 37. For example, if an organism in the HSOS algorithm leads to the decision vector of $x = [4, 8, 34, 25, 16, 0, 300, 0, 600, 900, 0, \dots, 0, 1200, 300]$, it means that switch 4 from loop 1, switch 8 from loop 2, switch 34 from loop 3, switch 25 from loop 4, and switch 16 from loop 5 should be open (see the one-line diagram in Fig. 2). In addition, this decision vector means that capacitors should be installed as 300 kVAr at bus 2, 600 kVAr at bus 4, 900 kVAr at bus 5, 1200 kVAr at bus 31, and 300 kVAr at bus 32.

The HSOS algorithm is applied to the problem of the multi-objective network reconfiguration and capacitor placement as follows. The flowchart of this algorithm is also depicted in Fig. 3.

1. Supply input data including initial network configuration, line impedances, total number of fundamental loops and capacitor vectors for each bus, number of switches in each loop, number of organisms (ecosystem size), termination criteria, and internal parameters of the algorithm (BF_1, BF_2, c_1, c_2, w).
2. Generate the initial ecosystem. For initialization of each individual, one switch from each fundamental loop or loop vector is randomly chosen to open and one capacitor from the capacitor vector is randomly placed; set the counter $i = 1$.
3. Check the radiality of the network and all loads being in service for each individual. If the network is not radial or at least one load has been isolated, the value of fitness function is considered zero for that individual.

Fig. 2 One-line diagram of the Baran and Wu 33-bus distribution test system

Fig. 3 Flowchart of the proposed HSOS algorithm

4. Execute a load flow. The value of the fitness function (μ_f) is calculated using the results of distribution load flow for each radial structure according to (7).
5. Determine the best organism (X_{best}).
6. Select randomly one organism X_j .
7. Modify organism X_i ($X_j \neq X_i$) based on their mutual relationship according to (12) and (13). BF_1 and BF_2 are chosen randomly as 1 or 2.
8. Calculate the overall fuzzy satisfaction for new X_i and X_j . If the modified organisms have a better

fitness than the previous one, replace the previous one with the modified organisms. Otherwise, reject them.

9. Randomly select one organism X_j , where $X_j \neq X_i$.
10. Modify organism X_i using organism X_j according to (14).
11. Calculate the overall fuzzy satisfaction for new X_i . If the modified organisms have a better fitness than the previous one, replace the previous one with the modified organisms. Otherwise, reject them.
12. Randomly select one organism X_j , where $X_j \neq X_i$.
13. Create a parasite (P_V) from organism X_i .
14. Calculate the overall fuzzy satisfaction for the new X_i . If P_V has a fitness better than organism X_j , replace organism X_j with P_V. Otherwise, keep organism X_j and remove P_V.
15. If i is equal to the length of ecosystem size, go to the next step; otherwise, $i = i + 1$ and go to step 3.
16. Calculate the best solution of each organism ($pbest_j$) and the best global solution ($gbest$).
17. Calculate new candidates according to (17) and (18).
18. Check the termination criterion. If the overall fuzzy satisfaction is almost fixed and converged to a value or the number of iterations reached the predefined maximum number, stop the algorithm. Otherwise, go to step 3.

Simulation Results

In order to evaluate the performance of the proposed algorithm, two case studies consisting of a balanced 33-bus network and an unbalanced 25-bus distribution system are investigated and their numerical results are compared with those of other algorithms such as PSO and IPSO. The algorithm is implemented in MATLAB on a PC with 2.67 GHz CPU and 2 GB RAM. Table 1 presents parameters of the HSOS algorithm that are experimentally selected for simulations. These parameters are already described in previous sections.

Case Study 1: the 33-bus Balanced Test System

The Baran and Wu's (Srinivasa Rao et al. 2011) distribution test system was used as the first case study with 3 feeders, which is shown in Fig. 2. The system has 32 sectionalizing switches (normally closed), 5 tie switches (normally open), and 37 branches. The total real and reactive power loads in the base case (before reconfiguration and capacitor placement) are 3715 kW and 2300 kVar, respectively. Objective functions including total power losses, VDI, and LBI in the base case configuration

Table 1 Parameters of the HSOS algorithm for the studied test systems

Test system	Ecosystem size	w	c_1	c_2	Max iterations
Balanced 33-bus	30	1	0.6	0.6	50
Unbalanced 25-bus	30	1	0.6	0.6	100

of the network are obtained as 202.67 kW, 0.0869, and 0.1575, respectively. It is noted that these results may slightly differ from literature works due to different convergence tolerance, type of power flow utilized, and branch impedances.

In the first step, the three objective functions are separately optimized and their results are shown in Table 2. Regarding statistical characteristic of the HSOS algorithm, the results were reported after 50 times of running the proposed and other algorithms and afterwards, the best solution, worst solution, average, and standard deviation for each algorithm are reported in Table 2. It can be seen that different methods and objectives have resulted in various configurations of switches and as a result, power losses, the VDI, and LBI become different.

According to Table 2, in the case of power losses minimization, the proposed HSOS method eventuated in five open switches of 7, 11, 14, 32, and 37 and installed capacitors of 300 kVAr installed in nine buses of 2, 4, 11, 13, 18, 24, 28, 29, and 30. This configuration leads to the power losses of 92.57 kW, which is the best achievable value among the reported values of Table 2 when power losses are minimized. According to this table, the proposed method had the CPU time of 5.875 s which was the shortest time among reported values of the table (when f_1 is minimized). In case of $f_2 = \text{VDI}$ minimization, the configuration with the proposed HSOS method was the open switches of 7, 9, 34, 36, and 37 along with total rating of capacitors as 5400 kVAr installed at buses reported in Table 2. In this case, regarding the goal of minimization of VDI, the proposed method has chosen more capacitors to increase bus voltages and minimize VDI. Table 2 shows also that the HSOS method has the best performance for the case of LBI minimization. According to this table, the best solution for this case study was the LBI of 0.0282 and CPU time of 5.675 s, which are the best solutions among the values shown in Table 2 with that objective function. As a result, the comparison presented in this table validates the performance of the proposed HSOS method compared with other methods.

Results obtained by optimizing the multi-objective fitness function in the 33-bus test system are shown in Table 3. The value obtained in the multi-objective case by the proposed HSOS algorithm for objective functions is 100.05 kW for power losses, 0.0383 for VDI, and 0.0466 for LBI; these values are the most optimal values

of all algorithms as seen in the table. In addition, the resulted open switches and installed capacitors differs from the previously pointed single objective solutions in Table 2 implying that the multi-objective optimization of joint reconfiguration and capacitor allocation offers a solution in which all objective functions are simultaneously optimized.

As seen in Table 3, the proposed multi-objective method resulted in a better voltage deviation. In order to observe the resulted voltage status of the network more precisely, voltage profile before and after reconfiguration and capacitor allocation using the HSOS is depicted in Fig. 4. In fact, the proposed method has improved the weakest bus voltage as motivated by the VDI objective function. It is worth noting that the weakest bus voltage of a power system can be its Achilles heel as the starting point of voltage collapse; consequently, the whole power system voltage condition is improved by strengthening the weakest voltage. This process happened in the proposed method where the minimum voltage of 0.9127 pu (at bus 18) at the base case is improved to 0.9541 pu after applying the method. In this figure, the voltage of bus 0 (slack) of the test system connected to the upstream grid is kept at 1 pu, as illustrated in Fig. 4. Also, buses 1 and 18 have similar voltages because bus 1 was close to the slack bus (shown in Fig. 2) and bus 18 enjoyed the similar voltage of bus 1 as a result of the small impedance of branch 1-18.

In Fig. 5, branch current profiles before and after optimal joint reconfiguration and capacitor placement in the 33-bus test system are depicted. As seen, branch loadings are more uniform and has a smaller standard deviation after optimization. This happens because of the LBI objective functions in (5) that tries to more uniformly distribute currents among branches. Since this network has 5 tie switches, the number of open switches (out of 37 switches in Fig. 2) should be 5. As seen in Fig. 5, there are 5 open switches in the base case on branches 33-37 with zero current (on the circled curve). However, the open switches after optimal reconfiguration and capacitor placement (on the squared-curve) are located on five branches of 7, 10, 14, 32, and 37.

In Fig. 6, the convergence of the proposed multi-objective method is illustrated against IPSO and PSO algorithms. As seen in this figure, the HSOS algorithm has converged after 33 iterations, a fact that emphasizes the fast convergence of this algorithm. Furthermore, the HSOS algorithm has quickly moved toward the optimal solution as seen by the rapid increase in its fitness value. This behavior implies its suitable ability in exploring new regions in the search space. This capability was due to the fact that the proposed algorithm had hybrid feature strengthened by adding PSO capabilities as discussed in (17) and (18) in subsection “The proposed HSOS

Table 2 Results of optimizing individual objective functions by different method in the 33-bus test system

Optimized objective function	Method	Best solution	Worst solution	Average	Standard deviation	Open switches in the best solution	Size of capacitors (kVAr) and their location	Total capacitors (kVAr)	CPU time (s)
Min f_1 = Power losses (kW)	ACO (Sedighzadeh et al. 2014)	95.79	–	–	–	7, 9, 14, 32, 37	450 (28), 600 (20, 29)	1650	–
	IBPSO (Sedighzadeh et al. 2014)	93.06	–	–	–	7, 9, 14, 32, 37	300 (11, 24, 32), 600 (6, 29)	2100	–
	MST + GA (Montoya and Ramirez 2012)	101.49	–	–	–	–	–	–	–
	Simulated Annealing (SA) (Su and Lee 2001)	124.29	–	–	–	7, 14, 9, 32, 37	1050 (6), 450 (28), 300 (29), 300 (30), 150 (9)	2250	–
	Harmony Search Algorithm (HSA) (Srinivasa Rao 2010)	119.72	–	–	–	33, 14, 8, 32, 28	900 (6), 300 (28), 600 (29), 300 (30), 300 (9)	2400	–
	Modified flower pollination algorithm (MFPA) (Namachivayam et al. 2016)	101.77	–	–	–	7, 14, 9, 36, 37	200 (28), 200 (29), 550 (30)	950	–
	PSO	95.38	98.24	96.27	1.27	7, 10, 14, 37, 36	300 (9, 10, 31), 600 (6, 29)	2100	6.247
	IPSO	93.83	96.35	94.59	1.56	11, 28, 33, 34, 36	300 (5, 13, 32), 1200 (28)	2100	7.065
	HSOS	92.57	94.37	93.01	1.11	7, 11, 14, 32, 37	300 (2, 4, 11, 13, 18, 24, 28, 29, 30)	2700	5.875
	HSOS	92.57	94.37	93.01	1.11	7, 11, 14, 32, 37	300 (2, 4, 11, 13, 18, 24, 28, 29, 30)	2700	5.875
Min f_2 = VDI	PSO	0.0305	0.0415	0.0355	0.0145	7, 11, 28, 34, 36	300 (9, 14, 19, 25), 600 (28), 900 (31)	2700	6.984
	IPSO	0.0234	0.0354	0.0286	0.0137	7, 9, 34, 36, 37	300 (1, 9, 14, 15, 20, 22, 32), 1500 (28), 600 (29)	4200	7.168
	HSOS	0.0138	0.0265	0.0189	0.0124	7, 9, 34, 36, 37	300 (1, 9, 14, 15, 20, 22, 32), 1200 (23), 1500 (28), 600 (29)	5400	5.546
Min f_3 = LBI	PSO	0.0890	0.1123	0.1035	0.0121	7, 32, 34, 35, 37	300 (7), 600 (29, 31), 900 (32)	2400	6.342
	IPSO	0.0303	0.0465	0.0354	0.0117	11, 33, 34, 36, 37	300 (25, 26, 27), 900 (16, 32)	2700	7.167
	HSOS	0.0282	0.0374	0.0325	0.0103	11, 33, 34, 36, 37	300 (25, 26), 900 (16, 32)	2400	5.675

algorithm". As it is evident from the zoomed part in this figure, the proposed HSOS method has resulted in a solution with a higher fitness than IPSO and PSO even with a less number of iterations. This confirms the efficiency of HSOS in optimal reconfiguration and capacitor placement in the 32-bus test system.

Case Study 2: the 25-bus Unbalanced Test System

The second case study examined here is the 25-bus 4.16 kV unbalanced distribution system consisting of 24 sectionalizing switches (normally close) and 3 tie

switches (normally open). This test system is chosen to evaluate the performance of the proposed method on unbalanced networks. This system is depicted in Fig. 7 and its details of line and load data can be found in Vulasala et al. (2009). Since this test system is unbalanced, an unbalanced load flow is used in the load flow module of the proposed method in the flowchart of Fig. 3.

In the base case (before reconfiguration and capacitor placement), power losses are obtained as 150.13 kW and minimum bus voltage in phases *a*, *b*, and *c* is 0.9284, 0.9283, and 0.9365 pu, respectively. The optimal solutions

Table 3 Results of optimizing the multi-objective fitness function in the 33-bus test system

Method	Power losses (kW)	VDI	LBI	Opens witches	Size of capacitors (kVAr) and their location	Total capacitors (kVAr)	CPU Time (sec)
Base case	202.67	0.0869	0.1575	33, 34, 35, 36, 37	–	–	–
PSO	102.06	0.0575	0.0473	7, 11, 34, 37, 36	300 (16, 25, 30, 32), 600 (1, 5)	2400	6.752
IPSO	101.11	0.0466	0.0469	7, 10, 14, 37, 36	300 (11, 17, 25), 600 (28, 32), 900 (2)	3000	7.225
HSOS	100.05	0.0383	0.0466	7, 11, 34, 37, 36	300 (16, 25, 30, 32), 600 (1, 2, 5)	3000	5.476

Fig. 4 Voltage profiles before and after optimal reconfiguration and capacitor placement in the 33-bus system

Fig. 5 Branch current profiles before and after optimal joint reconfiguration and capacitor placement in the 33-bus system

as a result of individually optimizing objective functions of total power losses, bus voltage, and load balancing are presented in Table 4. In optimizing objective function $f_2 = \text{VDI}$, the worst phase voltage is reported in the table. As seen in this table, the proposed HSOS

Fig. 6 Convergence trend of HSOS along with other algorithms when examined in the 33-bus test system

Fig. 7 One-line diagram of the 25-bus unbalanced distribution system

algorithm has shown a better performance than other algorithms listed in the table when each objective function is optimized individually.

Table 4 Results of optimizing individual objective functions in the 25-bus unbalanced test system

Optimized objective function	Method	Best solution	Worst solution	Average	Standard deviation	Open switches in best solution	Size of capacitors (kVAr) and their location	Total capacitors (kVAr)	CPU time (s)
Min f_1 = Power losses (kW)	PSO	146.54	149.06	147.62	1.56	20, 17, 15	300 (5), 600 (3)	900	8.345
	IPSO	124.36	125.34	124.87	0.56	5, 11, 3	300 (10, 8), 600 (7)	1200	10.065
	HSOS	91.54	92.07	91.75	0.34	22, 17, 15	300 (3, 10), 600 (7)	1200	9.723
Min f_2 = VDI (phase c)	PSO	0.0293	0.0313	0.0301	0.001	22, 17, 15	300 (5, 7), 600 (3)	1200	7.456
	IPSO (phase c)	0.0197	0.0224	0.0214	0.001	22, 17, 15	300 (5, 7), 600 (3)	1200	9.567
	HSOS (phase b)	0.0133	0.0179	0.0159	0.002	20, 17, 15	300 (5, 8), 900 (14)	1500	9.453
Min f_3 = LBI	PSO	0.0472	0.0534	0.0501	0.0038	20, 17, 15	300 (5, 7, 10, 11)	1200	9.324
	IPSO	0.0431	0.0523	0.0476	0.0054	22, 17, 15	600 (3, 5)	1200	10.261
	HSOS	0.0323	0.0421	0.0375	0.0036	5, 11, 13	300 (10, 6), 600 (19)	1200	9.234

Table 5 Results of multi-objective optimization in the 25-bus unbalanced test system

Method	Power losses(kW)	Minimum voltage phase <i>a</i> (p.u.)	Minimum voltage phase <i>b</i> (p.u.)	Minimum voltage phase <i>c</i> (p.u.)	LBI	Open switches	Capacitors and their buses	Total capacitor (kVAr)	CPU Time (s)
Base case	150.13	0.92841	0.92837	0.93657	0.10095	25, 26, 27	–	–	–
PSO	110.45	0.96012	0.95328	0.96219	0.04776	20, 17, 15	300 (5), 600 (9)	900	10.345
IPSO	109.43	0.96155	0.95321	0.96189	0.04698	5, 11, 13	600 (5,7)	1200	11.265
HSOS	97.23	0.96238	0.95426	0.96356	0.04662	25, 17, 5	900 (9)	900	11.456

Results of multi-objective optimization for the 25-bus test system are shown in Table 5. As seen, the HSOS algorithm eventuated in better values for objective functions: power losses are obtained as 97.23 kW which is much better than others. Although the HSOS algorithm has resulted VDI values a bit larger than others, its compromised solution satisfies all objective functions in a better way.

In order to have a closer look at voltages of the 25-bus test system, they are plotted in Fig. 8 for all phases. As seen, bus 12 has the least voltage in all phases after applying the proposed method: phase voltages of this bus as specified in the figure by data tips are 0.9647, 0.9634, and 0.9727 pu for phase *a*, *b*, and *c*, respectively. Therefore, the proposed method elevated base case voltage profile of phases above the minimum threshold of 0.95 pu.

The convergence behavior of HSOS, IPSO, and PSO algorithms are depicted in Fig. 9. As seen, the HSOS has

converged to the fitness function of 0.792 in iteration 67. However, IPSO and PSO algorithms have converged to a smaller fitness value even with higher number of iterations. This result confirms the efficiency of the HSOS algorithm in getting a more optimal solution (a better exploration) in a faster time. In Fig. 9, although the IPSO algorithm converges to a local optima in iterations 22 to 42, it moves toward its ultimate fitness by continuing iterations; however, the HSOS offers a faster trend and a better fitness in getting its optimal solution.

Conclusions

In this paper, the HSOS optimization algorithm is introduced as a result of strengthening the original SOS algorithm with capabilities of the PSO algorithm and then, it is

Fig. 8 Phase voltage profiles before and after optimal reconfiguration and capacitor placement in the 25-bus system

Fig. 9 Convergence behavior of HSOS and other algorithms in the 25-bus unbalanced test system

applied to solve the problem of multi-objective reconfiguration and capacitor placement in electric distribution systems. The considered objectives include the minimization of total network real power losses, minimization of bus voltage violations, and load balancing in feeders. Each objective function is transformed into the fuzzy domain by a membership function to constitute the ultimate fuzzy fitness function. In addition to the HSOS, PSO and IPSO algorithms are also implemented in the paper to evaluate

the performance of the HSOS algorithm. The main contributions of this paper include to strengthen the SOS algorithms by PSO capabilities, to scale the objective functions through a fuzzy operator, to apply the proposed HSOS and fuzzy operator for solving the problem of optimal reconfiguration and capacitor allocation, to implement and discuss it on the 25-bus unbalanced test system. The proposed method was tested on two case studies of 33-bus balanced and 25-bus unbalanced test systems in both single and multi-objective optimizations. In the first case study, the HSOS showed a better performance than other algorithms of PSO, IPSO, ACO, IBPSO, and MST + GA. Also, the proposed HSOS method converged in 33 iterations, which was faster than 37 and 44 iterations of IPSO and PSO algorithms, respectively. Also, the HSOS algorithm in the second case study converged to the fitness of 0.792 in 67 iterations, which was more efficient than both IPSO with 72 iterations and fitness of 0.758 and PSO with 91 iterations and fitness of 0.768. The reason why the HSOS method is capable of exploring its solution with less iterations could be attributed to its improved exploration that is strengthened with PSO capabilities. In the electricity markets, distribution companies try to reduce the investment and utilization costs and to enhance the system efficiency in delivering power to customers. The results of this paper can help them to plan and operate their networks more efficiently. Considering a fixed load level, i.e. the medium loading, is the main limitation of the current paper. It is clear that the load level is continually changing due to varying consumer power. Therefore, the optimal switch and capacitor arrangement is altered due to change in load level at each instant. Therefore, adding the stochastic behavior of load to the proposed method, which is underway in our future research, can enhance its efficiency.

References

- Abdelaziz AY, Mohamed FM, Mekhamer SF, Badr MAL (2010) Distribution system reconfiguration using a modified Tabu Search algorithm. *Electr Power Syst Res* 80:943–953. doi:10.1016/j.epsr.2010.01.001
- Abul'Wafa AR (2013) Optimal capacitor allocation in radial distribution systems for loss reduction: a two stage method. *Electr Power Syst Res* 95:168–174. doi:10.1016/j.epsr.2012.09.004
- Akorede MF, Hizam H, Aris I, Ab Kadir MZA (2011) Effective method for optimal allocation of distributed generation units in meshed electric power systems IET Generation. *Trans Distrib* 5:276. doi:10.1049/iet-gtd.2010.0199
- Aman MM, Jasmon GB, Solangi KH, Bakar AHA, Mokhlis H (2013) Optimum simultaneous DG and capacitor placement on the basis of minimization of power losses. *Int J Comput Electri Eng* 5:516–522

- Aman MM, Jasmon GB, Bakar AHA, Mokhlis H (2014) Optimum network reconfiguration based on maximization of system loadability using continuation power flow theorem. *Int J Electr Power Energy Syst* 54:123–133. doi:[10.1016/j.ijepes.2013.06.026](https://doi.org/10.1016/j.ijepes.2013.06.026)
- Aman MM, Jasmon GB, Abu Bakar AH, Mokhlis H, Naidu K (2016a) Graph theory-based radial load flow analysis to solve the dynamic network reconfiguration problem. *Int Trans Electr Energy Syst* 26:783–808. doi:[10.1002/etep.2108](https://doi.org/10.1002/etep.2108)
- Aman MM, Mokhlis H, Jasmon GB, Bakar AHA (2016b) Optimum tie switches allocation and DG placement based on maximisation of system loadability using discrete artificial bee colony algorithm IET generation. *Trans Distrib* 10:2277–2284. doi:[10.1049/iet-gtd.2015.0303](https://doi.org/10.1049/iet-gtd.2015.0303)
- Amanulla B, Chakrabarti S, Singh SN (2012) Reconfiguration of power distribution systems considering reliability and power loss. *IEEE Trans Power Deliv* 27:918–926. doi:[10.1109/tpwrd.2011.2179950](https://doi.org/10.1109/tpwrd.2011.2179950)
- Augugliaro A, Dusonchet L, Favuzza S, Sanseverino ER (2004) Voltage regulation and power losses minimization in automated distribution networks by an evolutionary multiobjective approach. *IEEE Trans Power Syst* 19:1516–1527. doi:[10.1109/tpwrs.2004.825916](https://doi.org/10.1109/tpwrs.2004.825916)
- Bernardon DP, Garcia VJ, Ferreira ASQ, Canha LN (2010) Multi-criteria distribution network reconfiguration considering sub-transmission analysis. *IEEE Trans Power Deliv* 25:2684–2691. doi:[10.1109/tpwrd.2010.2041013](https://doi.org/10.1109/tpwrd.2010.2041013)
- Carpinelli G, Noce C, Proto D, Russo A, Varilone P (2012) Single-objective probabilistic optimal allocation of capacitors in unbalanced distribution systems. *Electr Power Syst Res* 87:47–57. doi:[10.1016/j.epr.2012.01.008](https://doi.org/10.1016/j.epr.2012.01.008)
- Chang C-F (2008) Reconfiguration and capacitor placement for loss reduction of distribution systems by ant colony search algorithm. *IEEE Trans Power Syst* 23:1747–1755. doi:[10.1109/tpwrs.2008.2002169](https://doi.org/10.1109/tpwrs.2008.2002169)
- Chang K-H (2014) A decision support system for planning and coordination of hybrid renewable energy systems. *Decis Support Syst* 64:4–13. doi:[10.1016/j.dss.2014.04.001](https://doi.org/10.1016/j.dss.2014.04.001)
- Chao K-H, Lin Y-S, Lai U-D (2015) Improved particle swarm optimization for maximum power point tracking in photovoltaic module arrays. *Appl Energy* 158:609–618. doi:[10.1016/j.apenergy.2015.08.047](https://doi.org/10.1016/j.apenergy.2015.08.047)
- Cheng M-Y, Prayogo D (2014) Symbiotic organisms search: a new metaheuristic optimization algorithm. *Comput Struct* 139:98–112. doi:[10.1016/j.compstruc.2014.03.007](https://doi.org/10.1016/j.compstruc.2014.03.007)
- de Oliveira LW, de Oliveira EJ, Gomes FV, Silva IC, Marcato ALM, Resende PVC (2014) Artificial Immune Systems applied to the reconfiguration of electrical power distribution networks for energy loss minimization. *Int J Electr Power Energy Syst* 56:64–74. doi:[10.1016/j.ijepes.2013.11.008](https://doi.org/10.1016/j.ijepes.2013.11.008)
- Devabalaji KR, Ravi K, Kothari DP (2015) Optimal location and sizing of capacitor placement in radial distribution system using bacterial foraging optimization algorithm. *Int J Electr Power Energy Syst* 71:383–390. doi:[10.1016/j.ijepes.2015.03.008](https://doi.org/10.1016/j.ijepes.2015.03.008)
- Esmaili M, Goldoust A (2015) Multi-objective optimal charging of plug-in electric vehicles in unbalanced distribution networks. *Int J Electr Power Energy Syst* 73:644–652
- Esmaili M, Rajabi M (2013) Optimal charging of plug-in electric vehicles observing power grid constraints IET generation. *Trans Distrib* 8:583–590
- Farahani V, Vahidi B, Abyaneh HA (2012) Reconfiguration and capacitor placement simultaneously for energy loss reduction based on an improved reconfiguration method. *IEEE Trans Power Syst* 27:587–595. doi:[10.1109/tpwrs.2011.2167688](https://doi.org/10.1109/tpwrs.2011.2167688)
- Ghasemi S, Moshtagh J (2014) A novel codification and modified heuristic approaches for optimal reconfiguration of distribution networks considering losses cost and cost benefit from voltage profile improvement. *Appl Soft Comput* 25:360–368. doi:[10.1016/j.asoc.2014.08.068](https://doi.org/10.1016/j.asoc.2014.08.068)
- Gupta N, Swarnkar A, Niazi KR, Bansal RC (2010) Multi-objective reconfiguration of distribution systems using adaptive genetic algorithm in fuzzy framework IET generation. *Trans & Distrib* 4:1288–1298. doi:[10.1049/iet-gtd.2010.0056](https://doi.org/10.1049/iet-gtd.2010.0056)
- Kannan SM, Renuga P, Kalyani S, Muthukumaran E (2011) Optimal capacitor placement and sizing using Fuzzy-DE and Fuzzy-MAPSO methods. *Appl Soft Comput* 11:4997–5005. doi:[10.1016/j.asoc.2011.05.058](https://doi.org/10.1016/j.asoc.2011.05.058)
- Mendoza JE, López EA, López ME, Coello Coello CA (2009) Microgenetic multiobjective reconfiguration algorithm considering power losses and reliability indices for medium voltage distribution network IET Generation. *Trans Distrib* 3:825–840. doi:[10.1049/iet-gtd.2009.0009](https://doi.org/10.1049/iet-gtd.2009.0009)
- Moarref AE, Sedighzadeh M, Esmaili M (2016) Multi-objective voltage and frequency regulation in autonomous microgrids using Pareto-based Big Bang-Big Crunch algorithm. *Control Eng Pract* 55:56–68. doi:[10.1016/j.conengprac.2016.06.011](https://doi.org/10.1016/j.conengprac.2016.06.011)
- Montoya DP, Ramirez JM (2012) Reconfiguration and optimal capacitor placement for losses reduction. In: *Transmission and distribution: Latin America Conference and Exposition (T&D-LA)*, Sixth IEEE/PES 3–5 Sept. 2012, pp 1–6. doi:[10.1109/TDC-LA.2012.6319059](https://doi.org/10.1109/TDC-LA.2012.6319059)
- Murillo-Sánchez CE, Zimmerman RD, Anderson CL, Thomas RJ (2013) A stochastic, contingency-based security-constrained optimal power flow for the procurement of energy and distributed reserve. *Decis Support Syst* 56:1–10. doi:[10.1016/j.dss.2013.04.006](https://doi.org/10.1016/j.dss.2013.04.006)
- Namachivayam G, Sankaralingam C, Perumal SK, Devanathan ST (2016) Reconfiguration and capacitor placement of radial distribution systems by modified flower pollination algorithm. *Electric Power Compon Syst* 44:1492–1502. doi:[10.1080/15325008.2016.1172281](https://doi.org/10.1080/15325008.2016.1172281)
- Park H, Basole RC (2016) Bicentric diagrams: design and applications of a graph-based relational set visualization technique. *Decis Support Syst*. doi:[10.1016/j.dss.2016.02.001](https://doi.org/10.1016/j.dss.2016.02.001)
- Ramadan HA, Wahab MAA, El-Sayed A-HM, Hamada MM (2014) A fuzzy-based approach for optimal allocation and sizing of capacitor banks. *Electr Power Syst Res* 106:232–240. doi:[10.1016/j.epr.2013.08.019](https://doi.org/10.1016/j.epr.2013.08.019)
- Rosen C, Madlener R (2013) An auction design for local reserve energy markets. *Decis Support Syst* 56:168–179. doi:[10.1016/j.dss.2013.05.022](https://doi.org/10.1016/j.dss.2013.05.022)
- Saffar A, Hooshmand R, Khodabakhshian A (2011) A new fuzzy optimal reconfiguration of distribution systems for loss reduction and load balancing using ant colony search-based algorithm. *Appl Soft Comput* 11:4021–4028. doi:[10.1016/j.asoc.2011.03.003](https://doi.org/10.1016/j.asoc.2011.03.003)
- Sedighzadeh M, Ahmadi S, Sarvi M (2013) An efficient hybrid big bang-big crunch algorithm for multi-objective reconfiguration of balanced and unbalanced distribution systems in fuzzy framework. *Electr Power Compon Syst* 41:75–99. doi:[10.1080/15325008.2012.732658](https://doi.org/10.1080/15325008.2012.732658)
- Sedighzadeh M, Dakhem M, Sarvi M, Kordkheili HH (2014) Optimal reconfiguration and capacitor placement for power loss reduction of distribution system using improved binary particle swarm optimization. *Int J Energy Environ Eng* 5:1–11. doi:[10.1007/s40095-014-0073-9](https://doi.org/10.1007/s40095-014-0073-9)
- Sedighzadeh M, Esmaili M, Eisapour-Moarref A (2017) Voltage and frequency regulation in autonomous microgrids using Hybrid Big Bang-Big Crunch algorithm. *Appl Soft Comput* 52:176–189. doi:[10.1016/j.asoc.2016.12.031](https://doi.org/10.1016/j.asoc.2016.12.031)
- Shareef H, Ibrahim AA, Salman N, Mohamed A, Ling Ai W (2014) Power quality and reliability enhancement in distribution systems via optimum network reconfiguration by using quantum

- firefly algorithm. *Int J Electr Power Energy Syst* 58:160–169. doi:[10.1016/j.ijepes.2014.01.013](https://doi.org/10.1016/j.ijepes.2014.01.013)
- Srinivasa Rao R (2010) An hybrid approach for loss reduction in distribution systems using harmony search algorithm. *Int J Electr Comput Energ Electron Commun Eng* 4:557–563
- Srinivasa Rao R, Narasimham SVL, Ramalinga Raju M, Srinivasa Rao A (2011) Optimal network reconfiguration of large-scale distribution system using harmony search algorithm. *IEEE Trans Power Syst* 26:1080–1088. doi:[10.1109/idams.2010.2076839](https://doi.org/10.1109/idams.2010.2076839)
- Su C-T, Lee C-S (2001) Feeder reconfiguration and capacitor setting for loss reduction of distribution systems. *Electr Power Syst Res* 58:97–102. doi:[10.1016/s0378-7796\(01\)00124-9](https://doi.org/10.1016/s0378-7796(01)00124-9)
- Sultana S, Roy PK (2016) Oppositional krill herd algorithm for optimal location of capacitor with reconfiguration in radial distribution system. *Int J Electr Power Energy Syst* 74:78–90. doi:[10.1016/j.ijepes.2015.07.008](https://doi.org/10.1016/j.ijepes.2015.07.008)
- Swarnkar A, Gupta N, Niazi KR (2011) Adapted ant colony optimization for efficient reconfiguration of balanced and unbalanced distribution systems for loss minimization. *Swarm Evolut Comput* 1:129–137. doi:[10.1016/j.swevo.2011.05.004](https://doi.org/10.1016/j.swevo.2011.05.004)
- Tomoiağă B, Chindriș M, Sumper A, Sudria-Andreu A, Villafafila-Robles R (2013) Pareto optimal reconfiguration of power distribution systems using a genetic algorithm based on NSGA-II. *Energies* 6:1439–1455
- Vulasala G, Sirigiri S, Thiruveedula R (2009) Feeder reconfiguration for loss reduction in unbalanced distribution system using genetic algorithm. *Int J Comput Electr Autom Control Inform Eng* 3:1050–1058