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Optimal placement of capacitors in radial distribution system using shark smell optimization algorithm

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Abstract Optimal size and location of shunt capacitors in the distribution system plays a significant role in minimizing the energy loss and the cost of reactive power compensation. This paper presents a new efficient technique to find optimal size and location of shunt capacitors with the objective of minimizing cost due to energy loss and reactive power compensation of distribution system. A new Shark Smell Optimization (SSO) algorithm is proposed to solve the optimal capacitor placement problem satisfying the operating constraints. The SSO algorithm is a recently developed metaheuristic optimization algorithm conceptualized using the shark's hunting ability. It uses a momentum incorporated gradient search and a rotational movement based local search for optimization. To demonstrate the applicability of proposed method, it is tested on IEEE 34-bus and 118-bus radial distribution systems. The simulation results obtained are compared with previous methods reported in the literature and found to be encouraging.

1. Introduction

Distribution systems normally consist of a main feeder and lateral distributors. It acts as a link between high voltage transmission line and the low voltage consumers. The low voltage and high current characteristics of distribution system leads to high power losses compared to that of transmission system. About 13% of total power generated is consumed as power losses at the distribution system [1]. The power losses can be separated into two parts based on the active and reactive components of branch currents. The losses produced by reactive

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Nomenclature

v_n	voltage at nth bus	Q_T	total reactive power demand of system in kVAr
v_{min}	minimum voltage of the system in p.u.	Q_{cn}	reactive power injection at bus-n in kVAr
$r_{n,\ n+1}$	resistance of branch connecting buses 'n' and 'n + 1'	$Q_{cn,min}$	minimum reactive power compensation in kVAr
$x_{n,\ n+1}$	reactance of branch connecting buses 'n' and 'n + 1'	$Q_{cn,max}$	maximum reactive power compensation in kVAr
P_{TLoss}	total real power loss of the system	X	position of sharks (solution vector)
nb	number of branches	NP	population size
K_e	cost of energy losses in \$/kW h	ND	number of elements/dimensions of each solution
T	time duration (8760 h)	V	vector representing velocity of sharks
σ	depreciation factor	k_{max}	number of iterations for SSO
K_{ins}	installation cost of capacitor in \$ per node	$R1,\ R2$	uniform random numbers in the interval [0, 1]
NC	number of buses for capacitor placement	g	gradient scaling factor
K_c	purchase cost of capacitor in \$ per kVAr	α_k	inertial constant, $\in[0, 1]$
K_{ope}	operating cost of capacitor in \$ per year per node	β_k	velocity limiter ratio
$v_{n,\ min}$	minimum permitted voltage at nth bus in p.u.	$R3$	random number from uniform distribution in the interval $[-1, 1]$
$v_{n,\ max}$	maximum permitted voltage at nth bus in p.u.	M	rotational movement variable

components of branch currents can be reduced by the installation of shunt capacitors. Capacitive compensation reduces power loss, improves voltage profile of system, increases the power factor and releases kVA capacity of distribution equipments for additional load growth. The most critical factors that influence the technology and economical impacts of capacitor placement problem are the type, size and location of shunt capacitors in distribution systems. The objective of the optimal capacitor placement problem is to find the optimal locations, type and size of capacitors to be placed on the Radial Distribution System (RDS). Optimal capacitor placement is a complex combinatorial problem. Analytical methods [2,3] have been used in most of the early works of optimal placement of capacitors which require no powerful computing resources. Simulated Annealing (SA) is an iterative optimization algorithm which is based on the annealing of solids. SA has been used to minimize capacitor installation costs in [4]. Heuristic search strategies [5,6] were implemented to find solution to the capacitor placement problem using heuristic rules which searches through a set of possible solutions.

In the recent years optimal placement of capacitor problems has been solved using population based optimization algorithms such as Genetic Algorithm [7], Particle Swarm Optimization algorithm [8], Artificial Bee Colony (ABC) algorithm [9,10] and Cuckoo Search Algorithm (CSA) [11]. In [12], a direct search algorithm has been proposed to find optimal locations and optimal sizes of fixed and switched capacitors. An evolutionary algorithm called modified cultural algorithm has been implemented to the optimal capacitor allocation problem in [13]. In [14], a combination of Fuzzy-GA approach is presented to find the optimal sizes of fixed and switched capacitors. Plant growth simulation algorithm is based on the process of plant growth and has been applied to find the optimal size of capacitors to the identified candidate buses in [15].

Shark smell optimization algorithm is a new metaheuristic algorithm based on ability of shark to find prey. The effectiveness of SSO algorithm has been proven by comparing it with many other heuristic optimization methods after implementing it to the bench mark functions [16]. The main contribution of this paper is application of SSO algorithm to optimal capacitor placement problem. In this paper, the shark smell optimization algorithm has been proposed for finding optimal locations and sizes of shunt capacitors. The objective function has been considered as minimization of cost function. Size of capacitor banks is taken as discrete values.

2. Problem formulation

2.1. Power flow equations

Distribution load flow plays an important role in finding solution for capacitor placement problem. Generally distribution networks are radial and the R/X ratio is very high. Hence, the conventional Gauss Seidel, Newton–Raphson and Fast Decoupled load flow methods are inefficient in solving such networks. The distribution load flow algorithm proposed in [17] has been used in this paper.

Distribution system power flow is calculated by a set of recursive equations derived from single line diagram shown in Fig. 1.

Equivalent current injection at the nth bus is calculated as

$$I_n = \left(\frac{S_n}{v_n}\right)^* = \left(\frac{P_n + jQ_n}{v_n}\right)^* \tag{1}$$

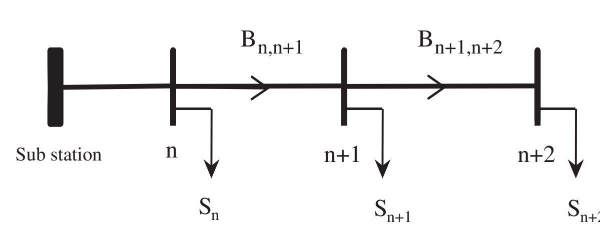

Figure 1 Single line diagram of a sample system.

Branch current 'B' in the line section between buses 'n' and '$n+1$' is calculated Kirchhoff's current law as

$$B_{n,n+1} = I_{n+1} + I_{n+2} \tag{2}$$

Eq. (2) can be written in generalized form as

$$[B] = [BIBC] * [I] \tag{3}$$

The relationship between branch currents and bus voltages can be expressed as

$$v_{n+1} = v_n - B_{n,n+1}(r_{n,n+1} + jx_{n,n+1}) \tag{4}$$

Power loss in the line section between buses 'n' and '$n+1$' is given by Eq. (5).

$$P_{loss}n, n+1 = \left(\frac{P_{n,n+1}^2 + Q_{n,n+1}^2}{|v_{n+1}|^2}\right) r_{n,n+1} \tag{5}$$

$$P_{TLoss} = \sum_{n=1}^{nb} P_{loss}n, n+1 \tag{6}$$

2.2. Objective function

The objective of capacitor placement problem in the distribution system is to minimize the cost due to system energy loss and reactive power compensation subject to the constraints. The cost of reactive power compensation includes purchase, installation and operation costs of capacitors. As the location and size of capacitors are to be treated discrete, the mathematical model can be expressed as a constrained nonlinear integer optimization problem:

$$\begin{aligned} \text{Minimize } f = {} & \text{Cost of energy loss} \\ & + \text{Cost of reactive power compensation} \end{aligned}$$

$$Min.f = K_e \times P_{TLoss} \times T + \sigma\left[(K_{ins} \times NC) + K_c \sum_{n=1}^{NC} Q_{cn}\right] + (K_{ope} \times NC) \tag{7}$$

Subject to the constraints:

(i) The voltage magnitude at each bus must be maintained within its limits and is expressed as follows:
$V_{n,min} \leqslant |v_n| \leqslant v_{n,max}$

(ii) The total reactive power injected is not to exceed the total reactive power demand in radial distribution system:

$$\sum_{n=1}^{NC} Q_{cn} < Q_T \tag{8}$$

(iii) The reactive power injection at each candidate bus is given by its minimum and maximum compensation limit.

$$Q_{cn,min} \leqslant Q_{cn} \leqslant Q_{cn,max} \tag{9}$$

In order to measure the value of voltage stability in the system, voltage stability index (VSI) [18] is determined. VSI at node ($n+1$) for the line section between buses 'n' and '($n+1$)' in single line diagram shown in Fig. 1 can be calculated using Eq. (10).

$$\begin{aligned} \mathrm{VSI}_{n+1} = {} & v_n^4 - 4\{P_{n,n+1}x_{n,n+1} - Q_{n,n+1}r_{n,n+1}\}^2 \\ & - 4\{P_{n,n+1}r_{n,n+1} + Q_{n,n+1}x_{n,n+1}\}v_n^2 \end{aligned} \tag{10}$$

For stable operation of the radial distribution system the value of VSI should be greater than or equal to zero at each node. The reactive power support provided by the capacitors also helps to enhance the voltage stability of the system.

3. Shark smell optimization algorithm

3.1. Overview of shark smell optimization algorithm

Shark smell optimization algorithm [16] is a metaheuristic algorithm, which finds its inspiration from the superior hunting behavior of sharks and their ability to sense the odor of prey even from miles away. When a prey is injured and blood is injected into the water, shark smells the odor of blood and move toward the prey. The movement of shark toward prey is based mainly on concentration and gradient of blood odor in the water particles. If the concentration increases as the shark moves, the movement is true. This behavior of sharks is used in SSO algorithm. The following assumptions are made while modeling movement of sharks.

1. The prey is injured and injects blood into the sea (search environment). So, the velocity of the prey movement is low and neglected against the shark's velocity. Hence, the source (prey) is approximately assumed to be fixed.
2. The blood is regularly injected into the sea and the effect of the water flow on distortion of the odor particles is neglected.
3. There is only one blood source (i.e. one injured prey) in the search environment of the shark.

The important steps of SSO algorithm include initialization, forward movement, rotational movement and position update. In the optimization problem, the search process starts when the shark smells an odor particle and each solution represents odor particle released by prey which is a possible position of shark. The optimal solution is represented by food source (prey). The odor intensity at a position represents the quality of solution. As the blood is released in the water, shark smells the odor and moves toward the prey by moving toward high odor intensity and hence to a high quality solution. In this way, shark smell algorithm can be applied to optimal capacitor placement problem.

3.1.1. Initialization of odor particles

A population of initial solutions is generated randomly within the feasible search space. Each solution represents one odor particle which is a possible position of the shark. The initial solution of the vector is given by the following:

$$X^1 = \left[X_1^1 X_2^1 X_3^1 X_4^1 \ldots X_{NP}^1\right] \tag{11}$$

Each X_i^1 is given as,

$$\left[X_{i,1}^1\, X_{i,2}^1\, X_{i,3}^1\, X_{i,4}^1 \ldots X_{i,ND}^1\right] \tag{12}$$

$i = 1, 2, \ldots, NP; X_{i,j}$ represents jth dimension of the ith shark position.

3.1.2. Forward movement of sharks

Shark in each position moves toward stronger odor particles with a velocity 'V', to become closer to the prey. Thus, corresponding to the initial position vector, we have initial velocity vector as follows:

$$V^1 = \left[V_1^1\, V_2^1\, V_3^1 \ldots V_{NP}^1\right] \tag{13}$$

Dimensional components element is given by

$$V_i^1 = \left[V_{i,1}^1\, V_{i,2}^1\, V_{i,3}^1\, V_{i,4}^1 \ldots V_{i,ND}^1\right] \tag{14}$$

Consider the velocity of sharks at kth iteration V^k. Magnitude of each V_{ij}^k is given by

$$\left|V_{i,j}^k\right| = \min \begin{bmatrix} \left|\eta_k \cdot R1 \cdot g \cdot \frac{\partial(of)}{\partial X_j}\right| X_{i,j}^k \\ +\alpha_k \cdot R2 \cdot V_{i,j}^{k-1}, \left|\beta_k \cdot V_{i,j}^{k-1}\right| \end{bmatrix} \tag{15}$$

$j = 1, 2, \ldots, ND$; $i = 1, 2, \ldots, NP$; $k = 1, 2, \ldots, k_{max}$; $k = 1, 2, \ldots, k_{max}$; $\eta_k \in [0, 1]$.

The term $\frac{\partial(of)}{\partial(X_j)}\Big| X_{i,j}^k$ gives the gradient $\left(\nabla_{i,j}^k\right)$ at the position $X_{i,j}^k$. Direction (sign) of dimensional velocity $\left(V_{i,j}^k\right)$ is given by the direction of the term selected by the minimum operator in Eq. (15). The positional update equation based on the velocity vector is given by Eq. (16). For simplicity Δt_k can be taken as 1.

$$Y_i^{k+1} = X_i^k + V_i^k \cdot \Delta t_k \tag{16}$$

$i = 1, 2, \ldots, NP$; $k = 1, 2, \ldots, k_{max}$.

3.1.3. Rotational movement

Along with forward movement sharks also perform rotational movements in order to find the stronger odor particles. This behavior of sharks is modeled as local search process in the SSO algorithm. The local search is modeled as

$$Z_i^{k+1,m} = Y_i^{k+1} + R3 \cdot Y_i^{k+1} \tag{17}$$

$m = 1, 2, \ldots, M$; $i = 1, 2, \ldots, NP$; $k = 1, 2, \ldots, k_{max}$.

A closed contour could be obtained by connecting M points, simulating rotational movement of sharks.

3.1.4. Position update

New position of particles is updated according to Eq. (18).

$$X_i^{k+1} = arg\ max\left\{f\left(Y_i^{k+1}\right), \quad f\left(Z_i^{k+1,1}\right), \ldots, \quad f\left(Z_i^{k+1,M}\right)\right\} \tag{18}$$

$i = 1, 2, \ldots, NP$.

Globally best individual will be selected from the final population of shark positions X^{kmax}.

3.2. Application of shark smell optimization algorithm to capacitor placement problem

Application of SSO algorithm to the capacitor placement problem is discussed here. The available discrete sized banks could be placed at any location and could be any size. Hence, capacitor placement in a radial distribution system is a combinatorial problem. This paper reports the successful application of SSO algorithm for the capacitor placement problem to minimize the cost due to system energy loss and reactive power compensation.

Algorithm steps:

Step 1. Get system data and SSO algorithm parameters like α, β, M, NP, k_{max}, η and NC.
Step 2. Initialize $k = 1$ and initialize solution vector, X^1.

The solution can be split into two parts, first part carries the locations for capacitor banks and second part carries the integer representing size of capacitor bank to be placed. To extract the size of capacitor bank, a multiplication factor is employed. kVAr = a * 50 + 100, where, 'a' is an integer representing the size of bank.

$$X = \begin{bmatrix} 30 & 22 & 31 & \vdots & 4 & 5 & 6 \\ 12 & 30 & 11 & \vdots & 3 & 6 & 8 \\ 11 & 33 & 12 & \vdots & 3 & 1 & 4 \\ 26 & 30 & 8 & \vdots & 2 & 8 & 2 \end{bmatrix} \tag{19}$$

Each row of the solution vector is one complete solution having information on locations and sizes of capacitor banks. For example consider the first solution vector X_1 = [30 22 31: 4 5 6]. The first part gives the location and the second part gives the capacitor banks to be placed at corresponding locations. (30:4), (22:5) and (31:6) the location-bank pairs, (30:4) imply that at the 30th bus a capacitor of size 300 kVAr (4 * 50 + 100) will be placed and so for other pairs.

Step 3. Evaluate the solutions X^k using load flow and find (odors') objective function using Eq. (7).
Step 4. Calculate gradients (∇) at the position vector X^k.

The gradient is calculated by perturbing the current solution. For the gradient of first part (location) of the solution, the change in total cost with respect to change in location (same bank size) is taken. For the second part (size) the change in total cost with respect to change in bank size (at the same location) is taken as gradient. Consider a solution vector $X_i = [A\ldots:B\ldots]$ corresponding gradient can be found as $\nabla_i = [\nabla_1\ldots:\nabla_2\ldots]$, for the location-bank pair (A:B). The gradient ∇_1 and ∇_2, for the minimization function, can be calculated as shown in Eq. (20).

$$\left.\begin{aligned} \nabla_1 = \frac{\partial(of)}{\partial X}\Big|_{X_{ij}} = \left(f|_{A,B} - f|_{(A+1),B}\right) \\ \nabla_2 = \frac{\partial(of)}{\partial X}\Big|_{X_{ij}} = \left(f|_{A,B} - f|_{A,(B+1)}\right) \end{aligned}\right\} \tag{20}$$

Step 5. Multiply ∇ by 'g' to scale the gradient. Move solution X^k to new position Y^{k+1} using Eq. (16).
Step 6. Perform rotational movements at Y_i^{k+1} using Eq. (17) and find 'M' neighbor odor positions, $Z_i^{k+1,m}$ for each X_i.
Step 7. Update sharks to new positions, choosing the best location from rotational movements and forward movement Eq. (18).
Step 8. Increment 'k'; if $k < k_{max}$, go to step 3.
Step 9. Choose the global minimum at the final position X^{kmax}.

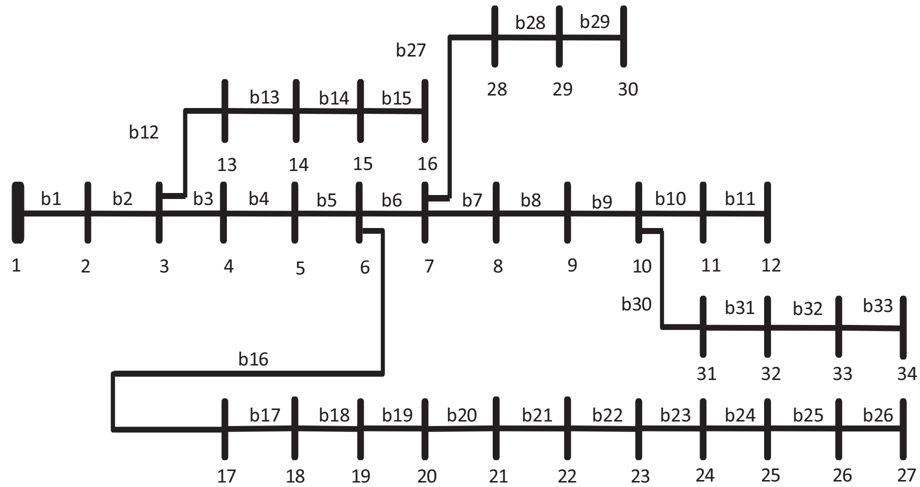

Figure 2 Single line diagram of 34-bus system.

Table 1 Compensation for 34-bus system at full load.

Method	Capacitor size in kVAr with node number	Total kVAr
SSO	800(9); 900(19); 700(25)	2400
ABC	850(19); 750(24); 700(31)	2300
HSA	800(9); 850(19); 750(24)	2400
CSA	850(9); 850(19); 700(25)	2400
GSA	800(9); 850(19); 750(24)	2400

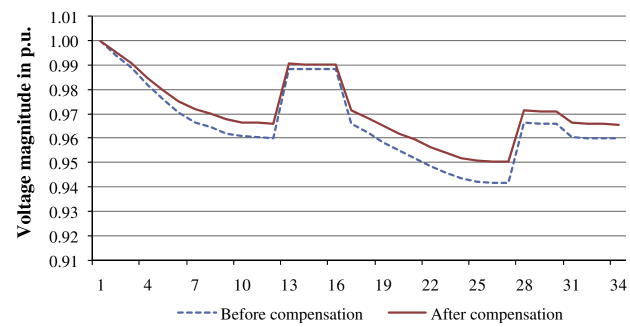

Figure 3 Comparison of voltage profile of 34-bus system at full load.

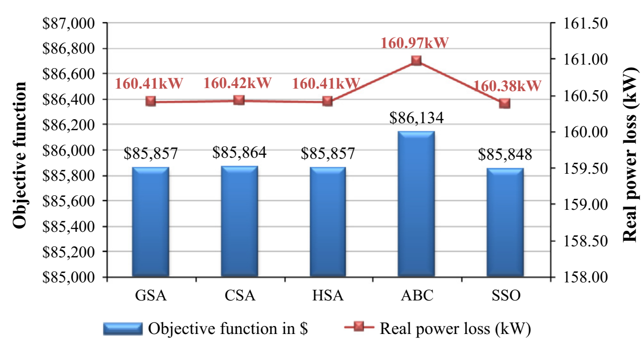

Figure 4 Comparison of proposed approach with other methods for 34-bus system at full load.

4. Simulation results

The proposed method is tested on standard IEEE 34-bus and IEEE 118-bus systems. The algorithm was developed in MATLAB environment and run in a Pentium IV, 2.1-GHz personal computer. The minimum and maximum bus voltage limits are fixed at 0.9 p.u. and 1.1 p.u. respectively. The results are obtained for three different load levels. The load levels considered are light, full and heavy with base load multiplied by factor of 0.75, 1.0 and 1.25 respectively. A fixed and switched capacitor scheme, considering variation of load levels, is provided for each system.

The loads are treated as constant power load and considered as balanced. Design period of one year is taken at full load condition for the purpose of analysis and comparison. The number of buses for compensation is selected based on the size of the system. Various constants assumed and applied in the calculations are [10]: cost of energy losses (K_e) = 0.06 $

Table 2 Comparison of performances for 34-bus system at full load.

Parameters	Uncompensated	Compensated				
		GSA	CSA	HSA	ABC	SSO
Total cost ($)	116,536	85,857	85,864	85,857	86,134	85,848
Cost reduction (%)	–	26.32	26.31	26.32	26.08	26.33
Real power loss (kW)	221.72	160.41	160.42	160.41	160.97	160.38
Loss reduction (%)	–	27.65	27.64	27.65	27.39	27.66
Reactive power loss (kVAr)	65.11	46.96	46.96	46.96	47.12	46.96
Loss reduction (%)	–	27.87	27.87	27.87	27.63	27.87
v_{min} (p.u.)	0.9417	0.9502	0.9502	0.9502	0.9500	0.9503
VSI_{min}	0.7864	0.8150	0.8152	0.8150	0.8144	0.8155

Table 3 Performance analysis of SSO for 34-bus system at nominal load (for 50 runs).

Parameter	GSA	CSA	HSA	ABC	SSO
Best objective($)	85,857.37	85,864.35	85,857.37	86,133.97	85,847.55
Worst objective ($)	86,442.86	85,959	85,887.20	86,665.42	85,865.78
Average objective ($)	86,102.22	85,907	85,869.63	86,346.22	85,854.55
Standard deviation	200.22	30.17	13.09	162.37	9.0426
Variance	40,090.75	910.62	171.40	26,364.49	81.76
Average loss	160.88	160.49	160.42	161.33	160.39
Average time taken (s)	16.19	15.51	15.07	15.62	14.74

per kW h, purchase cost of capacitor (K_c) = 25 $ per kVAr, installation cost (K_{ins}) = 1600 $ per location and operating cost (K_{ope}) = 300 $ per year per location. Depreciation factor (σ) of 10% is applied to installation and purchase cost of capacitor banks. The SSO algorithm parameters set for the system are [16]: α, η, β and g are set to 0.1, 0.9, 4 and 10^{-3} respectively and are common for both the systems.

To validate the applicability of proposed method, it is compared with the results of other classical methods such as Gravitational Search Algorithm (GSA) [19], CSA [11], Harmony Search Algorithm (HSA) [20] and ABC algorithm [9] and is applied to both the test systems under the same load conditions using the same objective function. The parameters chosen for GSA, CSA, HSA and ABC are as in [19,11,20,9].

4.1. 34-bus test system

It consists of a main feeder and 4 laterals as shown in Fig. 2. The line and load data are taken from [5]. The active and reactive loads of the system are 4636.5 kW and 2873.5 kVAr respectively. The total power loss and annual cost of operation of the system for the base case are 221.72 kW and 1, 16,536 $ respectively. The number of stages (number of iterations), k_{max} = 75, number of shark positions initialized, NP = 10, the rotational movement variable, M = 10 and the number of buses for compensation, NC = 3. The possible capacitor banks in discrete sizes are assumed to be from 150 kVAr up to 1300 kVAr in multiples of 50.

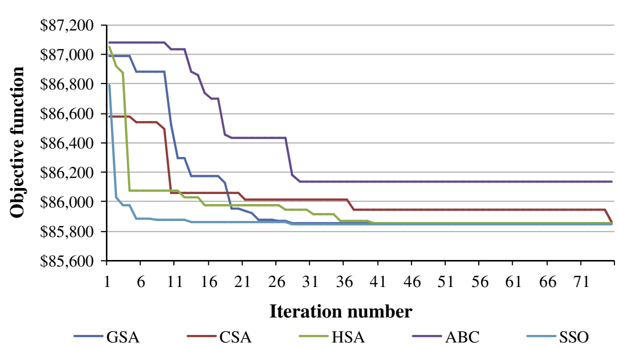

Figure 5 Convergence characteristics of SSO algorithm for 34-bus system at full load.

Table 1 shows the total kVAr injected and nodes selected for compensation by various methods. The optimal nodes and capacitor sizes obtained by the proposed algorithm are 9, 19 and 25 and 800 kVAr, 900 kVAr and 700 kVAr respectively. Total compensation of 2400 kVAr is injected at full load condition. The results of proposed approach using SSO algorithm are compared with the results of other methods and are shown in Table 2. The total power loss and annual cost of operation of the system for the optimum case are 160.38 kW and 85,848 $ respectively at full load condition. The net cost saving per year is 30,688 $. The loss and cost saving per year are 27.66% and 26.33% respectively. The minimum voltage of the system is improved to 0.9503 p.u. from 0.9417 p.u. The minimum value of VSI is 0.8155. The voltage profile of the system before and after compensation is shown in Fig. 3. It can be evidently seen from Table 2 and Fig. 4 that the proposed approach serves better cost and loss reduction compared to other methods.

The performance of the SSO and other algorithms for the 34-bus system at full load is shown in Table 3. From the table, the average cost, worst cost and best cost obtained for 50 runs are 85,854.55 $, 86,865.78 $ and 85,847.55 $ respectively. The average time taken by the CPU for the system is 14.74 s. Fig. 5 shows the convergence characteristics of SSO algorithm for this test system which is compared with the above classical algorithms. From Fig. 5 and Table 3, it is clear that the SSO algorithm outperformed the other algorithms compared.

The fixed and switched capacitor scheme to be followed at various load levels is provided in Table 4. Three fixed type

Table 4 Type and size of capacitors placed for 34-bus system at different load levels.

Capacitive compensation in kVAr					Real power loss (kW)		
Node number		9	19	25	Uncompensated	Compensated	% Loss reduction
Load level and Capacitor size in kVAr	Light(0.75)	600	650	550	121.72	88.64	27.17
	Nominal(1.0)	800	900	700	221.72	160.38	27.66
	Heavy(1.25)	1000	1200	850	355.31	256.02	27.94
Fixed	–	600 (1 No)	650 (1 No)	550 (1 No)	–	–	–
Switched	–	200 (2 Nos)	250 (1 No) 300 (1 No)	150 (2 Nos)	–	–	–

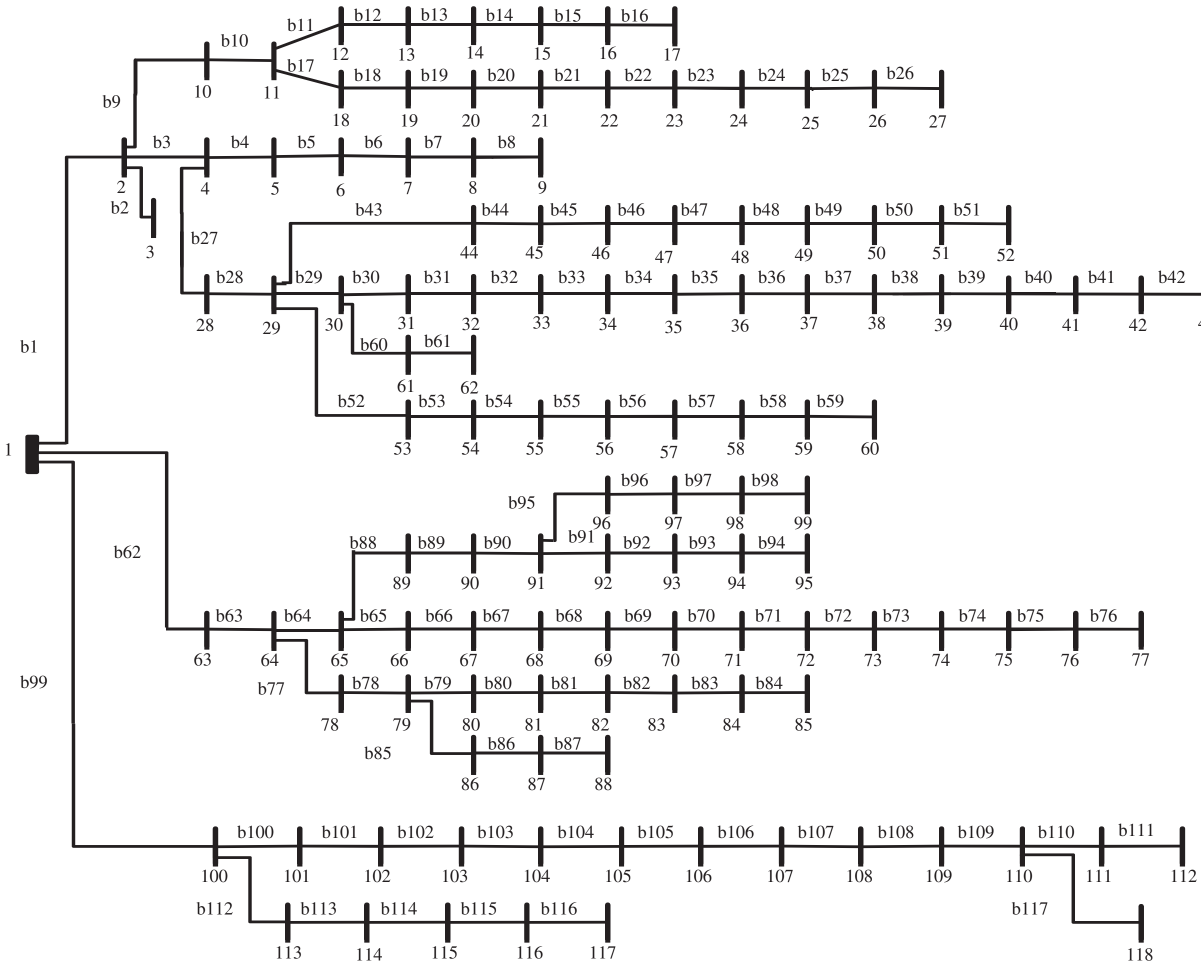

Figure 6 Single line diagram of 118-bus system.

Table 5 Compensation for 118-bus system at full load.

Method	Capacitor size in kVAr with node number	Total kVAr
SSO	1350(6); 1350(21); 1100(32); 1300(39); 900(40); 950(47); 1300(73); 1550(82); 800(90); 1100(109); 1200(110)	12,900
ABC	1100(20); 1200(34); 1450(41); 1000(70); 650(75); 1250(80); 350(84); 1300(99); 1400(102); 1100(103); 1450(108)	12,250
HSA	1000(20); 800(26); 1200(34); 1450(39); 850(44); 950(61); 1400(72); 1450(81); 1150(97); 1400(108); 1450(118)	13,100
CSA	850(24); 550(32); 700(38); 1500(40); 1500(46); 1100(73); 400(78); 1100(86); 1450(96); 1400(106); 1500(110)	12,050
GSA	400(43); 800(96); 450(61); 1250(37); 750(80); 950(72); 850(110); 800(112); 400(85); 1050(55); 350(35)	8050

capacitors of size 600 kVAr, 650 kVAr and 550 kVAr are placed at nodes 9, 19 and 25 respectively. Switched capacitors of sizes 200 kVAr * 2, 250 kVAr and 300 kVAr and 150 kVAr * 2 are placed at nodes 9, 19 and 25 respectively and are switched according to the prevailing load condition. The loss and percent loss reduction at the various load levels are also presented. The analyses clearly indicate the suitability of proposed approach to the capacitor placement problem for cost reduction in RDS.

4.2. 118-bus test system

It consists of 118 buses and 117 branches as shown in Fig. 6. The line and load data are taken from [21]. The active and

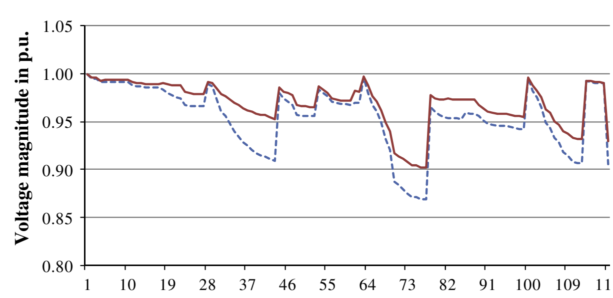

Figure 7 Comparison of voltage profile of 118-bus system at full load.

Table 6 Comparison of performances for 118-bus system at full load.

Parameters	Uncompensated	Compensated				
		GSA	CSA	HSA	ABC	SSO
Total cost ($)	682,281	474,824.32	446,613.58	444,845.66	459,625.97	443,028.34
Cost reduction (%)	–	30.40	34.54	34.80	32.63	35.06
Real power loss (kW)	1298.10	892.95	837.37	833.51	862.03	830.15
Loss reduction (%)	–	31.21	35.49	35.79	33.59	36.04
Reactive power loss (kVAr)	978.72	668.98	622.93	621.07	639.72	621.51
Loss reduction (%)	–	31.64	36.35	36.54	34.63	36.49
v_{min} (p.u.)	0.8688	0.8932	0.9000	0.9033	0.9092	0.9145
VSI_{min}	0.5697	0.6365	0.6562	0.6659	0.6833	0.6995

reactive loads of the system are 22,709.70 kW and 17,041.10 kVAr respectively. The total power loss and annual cost of operation of the system for the base case are 1298.10 kW and 6, 82,281 $ respectively. The number of stages used (number of iterations), k_{max} = 75, number of shark positions initialized, NP = 20, the rotational movement variable, M = 20 and the number of buses for compensation, NC = 11. The possible capacitor banks in discrete sizes are assumed to be from 150 kVAr up to 1500 kVAr in multiples of 50.

Table 5 shows the total kVAr injected and nodes selected for capacitor placement by various methods. The optimal nodes and capacitor sizes obtained by the proposed algorithm are 6, 21, 32, 39, 40, 47, 73, 82, 90,109 and 110 and 1350 kVAr, 1350 kVAr, 1100 kVAr, 1300 kVAr, 900 kVAr, 950 kVAr, 1300 kVAr, 1550 kVAr, 800 kVAr, 1100 kVAr and 1200 kVAr respectively. Total compensation of 12,900 kVAr is injected at full load condition. The voltage profile of the system before and after compensation is shown in Fig. 7. The performance of SSO algorithm on 118-bus system is compared with the above mentioned classical algorithms and is shown in Table 6. The total power loss and annual cost of operation of the system for the optimum case are 830.15 kW and 4, 43,028.34 $ respectively at full load condition. The net cost saving per year is 2, 39,252.66 $. The loss and cost saving per year are 36.04% and 35.06% respectively and found to be better than other methods. The minimum voltage of the system is improved to 0.9145 p.u. from 0.8688 p.u. The minimum value of VSI is 0.6995. It can be seen from Table 6 and Fig. 8 that the proposed approach serves better cost and loss reduction compared to other methods even in a large scale system.

The performance of the SSO algorithm for the 118-bus system at full load condition is shown in Table 7. From the table, the average cost, worst cost and best cost obtained during 50 runs are 4, 45,123.26 $, 4, 45,973.47 $ and 4, 43,028.34 $ respectively. The average time taken by the CPU for the system is 71.75 s. Fig. 9 shows the comparison of convergence characteristics of SSO algorithm with other algorithms for this

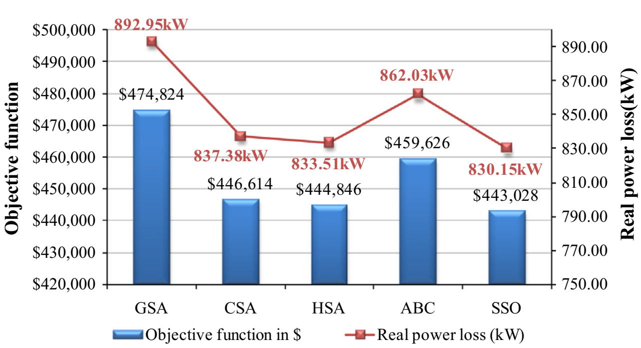

Figure 8 Comparison of proposed approach with other methods for 118-bus system at full load.

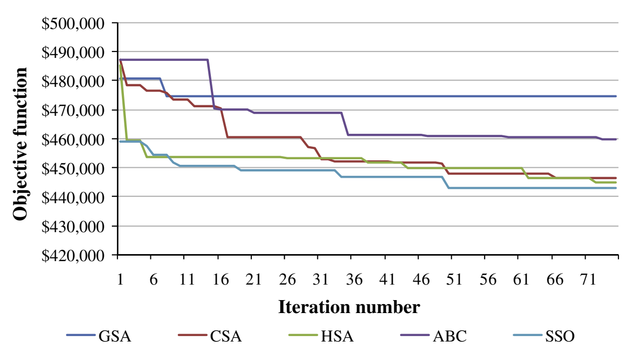

Figure 9 Convergence characteristics of SSO algorithm for 118-bus system at full load.

Table 7 Performance analysis of SSO for 118-bus system at nominal load (For 50 runs).

Parameter	GSA	CSA	HSA	ABC	SSO
Best objective ($)	474,824.32	44,6613.58	444,845.66	459,625.97	443,028.34
Worst objective ($)	492,322.52	450,418.27	449,704.52	484,046.08	445,973.47
Average objective ($)	480,491.91	448,916.25	446,164.99	471,688.56	445,123.26
standard deviation	5087.53	1166.13	1500.59	9562.02	941.76
Variance	25,883,005.75	1,359,881.00	2,251,777.80	91,432,280.47	886,927.28
Average loss	902.71	842.17	836.41	885.78	834.44
Average time taken (s)	88.17	75.44	73.08	73.18	71.75

Table 8 Type and size of capacitors placed for 118-bus system at different load levels.

Capacitive compensation in kVAr												
Node number		6	21	32	39	40	47	73	82	90	109	110
Load level and Capacitor size in kVAr	Light (0.75)	1250	850	1100	950	550	850	1100	900	800	700	1050
	Nominal (1.0)	1350	1350	1100	1300	900	950	1300	1550	800	1100	1200
	Heavy (1.25)	1500	1150	1400	1450	1150	1300	1450	1450	1200	1500	1450
Fixed	–	1250 (1 No)	850 (1 No)	1100 (1 No)	950 (1 No)	550 (1 No)	850 (1 No)	1100 (1 No)	900 (1 No)	800 (1 No)	700 (1 No)	1050 (1 No)
Switched	–	100 (1 No) 150 (1 No)	200 (1 No) 300 (1 No)	300 (1 No)	150 (1 No) 350 (1 No)	250 (1 No) 350 (1 No)	100 (1 No) 350 (1 No)	150 (1 No) 200 (1 No)	100 (1 No) 550 (1 No)	400 (1 No)	400 (2 No)	150 (1 No) 250 (1 No)

system. From Fig. 9 and Table 7, it is evident that the proposed method is better than the other methods in terms of quality of solutions. This analysis implicates the suitability of proposed approach in a large scale system.

The fixed and switched capacitor scheme to be followed at various probable load factors is provided in Table 8. The power loss during light load for uncompensated and compensated systems is found to be 697.29 kW and 444.64 kW, respectively. Similarly the power loss during heavy load for uncompensated and compensated systems is 2134.38 kW and 1346.02 kW, respectively.

5. Conclusion

In this paper, a recently developed metaheuristic shark smell optimization algorithm has been applied to find the optimal location and size of capacitors to be placed in radial distribution system with the objective of minimizing the cost due to energy loss and reactive power compensation of distribution system. Computational results showed that the performance of the SSO algorithm is better than the other classical algorithms compared. The bus voltage profile is also improved. This work can also be implemented to any large scale practical radial distribution network. The fixed and switched capacitor scheme to be followed during various load factors is also provided. Capacitor bank sizes have been taken as a discrete variable, which is an added advantage for the practical applicability of the solution. The advantage of SSO algorithm lies in the fact that it gives optimum results with simpler formulation satisfying the constraints.

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