Hyper-Spherical Search Algorithm for Optimal Sizing and Allocation of Capacitors in Radial Distribution Systems

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Abstract: The target of this work is to increase the annual net saving via hyper-spherical search algorithm (HSSA). HSSA is employed to obtain the optimal sizing and allocations of the candidate buses to contribute effectively in decreasing the total costs and system losses in different distributed systems. Power loss index (PLI) is utilized to find the candidate buses with the highest possibility for capacitor banks installation. Then, the developed HSSA is employed with inequality constraints to determine the most elected buses for installing and sizing shunt capacitor banks. HSSA is tested on IEEE-15 bus, IEEE-69 bus, and IEEE-119 bus systems. Applying the developed algorithm to minimize an objective function with constraints shows its ability in dealing with different radial systems. Simulated results are presented and compared with others to verify the effectiveness of the developed HSSA.

Keywords: Hyper-spherical search algorithm, radial power systems, optimal capacitor allocation, power loss index.

NOMENCLATURE

AP: assignment probability
BFS: Backward/forward sweep
C_e: annual power loss
D_{sc}: the normalized dominant sphere center
$DSOF$: difference in set of objective function
f_{sc}: objective functions estimation at a sphere center
I_l: branch current
K_p: Total costs per kWh
K_c: Total costs per KVAr
K_I: Capital installation costs
K_o: operational costs
N: Total number of buses
N_L: total number of lines
N_{cb}: Total number of compensated buses
N_{pop}: number of population
N_{sc}: number of hyper spheres centers
N_{newpar}: number of new particles
OF: objective function
$OFDsc_{,i}$: objective function difference of a sphere center
$P_{i,center}$: particle location at the sphere center
$P_{i,particle}$: particle location at the i^{th} position
$P(i)$: real power loss reduction at bus i
PLI: power loss index
$P_{ld,i}$: demand power at bus i
$P_{Losses,i}$: power losses of line i
P_{max}: maximum real power reduction through all buses
P_{min}: minimum real power reduction through all busses
Pr_{angle}: particle angles probability
P_{slack}: active power at the slack bus
Q_1 to Q_n: shunt capacitor banks sizing estimation
$Q_{c,i}$: injected reactive power at bus i
$Q_{ld,i}$: demand reactive power at bus i
Q_{slack}: reactive power at the slack bus power
r: sphere radius of a particle
r_{min}: minimum sphere of a particle
r_{max}: maximum sphere of a particle
SC_s: hyper-sphere centers
SOF: set of objective function
V_i: voltage at bus i
X_i: decision variables

I. INTRODUCTION

For many years, optimal shunt capacitor bank (SCB) placement and sizing has become a challenge for researchers and system planners. Recently, deficiency in reactive power leads to blackouts in power systems as reported by the US Canada reviews in 2004 [1,2]. In addition, system ohmic losses are diminished by proper installation of SCBs. Furthermore, at the distribution level, system performance in terms of voltage profile, system stability, and power factor is improved. Such system blackouts and improved system behavior result in more focus SCBs optimal allocation and sizing to meet load demands of reactive power [3,4].

The procedures are designed to find a minimum value for a function to solve a problem, in which SCBs allocation and sizing are to be determined. There are plenty of published work with different algorithms along with solutions to find the most proper place and the optimal size of SCBs. The initial work on allocating SCB was proposed by analytical calculus algorithms [5]-[7]. Although analytical based methods were simple, however they require many assumptions due to load variations to solve SCBs allocation problem. Recently, heuristic based algorithms are heavily used to solve SCBs allocations. Simulating annealing algorithm (SAA) for proper allocation of SCB was introduced in [8]. However, this algorithm may get trapped and take long time in local optimization. In [9], Tabu search (TS) was presented to solve SCB placement. However, the authors of [9] employed complex fitness functions and used many decision variables to be optimized. In [10], genetic algorithm (GA) was used. GA employs penalty function methods to go to constrained solutions. If a penalty function is high, GA could be trapped in local tuning. In the other side, if it is low, GA may not be able to find a possible solution [11]. In [12,13], plant grown simulation and cuckoo search algorithms were presented to solve SCB installation. However, the authors utilized continuous values of SCB rather than discrete values. The authors of [14], used particle swarm optimization (PSO) to solve SCB allocation. However, other authors complain that this algorithm suffers from low speed convergence [3]. Bee colony algorithm was used in [15]. For the same problem, cuckoo search was introduced in [16] but it takes long time for iterations to find optimal solutions. The authors of [17] utilizes ant colony algorithm to solve the same issue. However, the probability of distribution changes every iteration, which makes it consume long time to converge. The authors of [18] utilized the firefly algorithm with loss sensitivity factors to deal with the same problem. However, they did not include maintenance and installation costs into account. Harmony search (HS) and improved harmony algorithms (IHA) were introduced in [19,3] with some modifications of the objective function between them for optimal SCB placement and sizing installation. However, large number of buses was used to compensate the reactive power.

Hyper-spherical search algorithm was inspired to emulate a moving particle seeking a space bounded by a sphere [20,21]. The effectiveness and convergence of HSSA algorithm compared to other algorithms for solving some mathematical problems is proved in [22]. To the authors knowledge, few woks use HSSA to solve some engineering problems [20,23]. Moreover, it is obvious from the literature review that the utilization of HSSA to solve shunt capacitor banks allocation and sizing problem has not been investigated. This encourages the authors to utilize the HSSA to solve this problem. The SCB placement test starts by using PLI examination test to arrange the buses in descending manner. The HSSA is employed to decide the optimal allocations and size of SCBs according to minimizing the total costs. The performance of the developed algorithm in terms of total loss reduction and voltage profile improvements algorithm is applied for three different microgrid radial networks. The obtained results are compared with other works to ensure the notability of the developed HSSA in dealing with placement and sizing of SCBs in a discrete manner.

The remainder of this work is organized as follows. An overview of the HSSA is introduced in section 2. Problem description is described in section 3. SCB problem formulation is presented in section 4. Results and discussion of different tested radial systems are given in section 5. Finally, conclusions are presented in section 6.

II. OVERVIEW OF HYPER-SPHERICAL SEARCH ALGORITHM

The HSSA was introduced in [22,23] for solving some engineering problems. It was inspired as emulations for a particle looking for the best solution in a surface limited by a sphere [24]. For a fitness function $f(X_i)$ as given in Eq. 1, the target is to find optimal values for the decision variables X_i such that the parameter J is minimized.

$$J = \min f(X_i) \quad \forall\ X_i \in X \tag{1}$$

With some constraints on the decision variables, the algorithm includes four steps as follows:

1- Initialization of particles and optimization parameters.

The decision variables spread according to the inequality: $X_{i,\min} < X_i < X_{i,\max}$, i=1,2,…,n. Where, n is the number of decision variables and X_i is given as in Eq. 2.

$$X_i = [Q_1 \quad Q_2 \quad Q_3 \quad \ldots Q_n] \tag{2}$$

Herein, the number of initial population (N_{pop}), number of hyper-sphere centers (N_{sc}), r_{min}, r_{max}, Pr_{angle}, and N_{newpar} are initialized. Each solution is considered as a particle. The decision variables are chosen randomly, with their probability is chosen uniformly. At this step, the particles of the objective functions (*OF*) are evaluated. The particles are arranged in ascending manner according to the *OF* estimation. The best N_{sc} particles are set to be hyper-sphere centers (SC_s). The objective function difference (OFD_{sc}) of a sphere center is defined to distribute particles in proportional manner as in Eq. 3.

$$OFD_{sc,i} = F_{sc}(X_i) - \max\{f(X_i)\} \tag{3}$$

The normalized dominant sphere center (D_{sc}) is given as Eq. 3 in terms of the objective function difference ($OFD_{sc,i}$).

$$D_{sc} = \left| \frac{OFD_{sc,i}}{\sum_{i=1}^{N_{sc}} OFD_{sc,i}} \right| \tag{4}$$

The particles number among hyper-spheres is distributed according to Eq. 5.

$$n = round\{D_{sc}(N_{pop} - N_{sc)}\} \tag{5}$$

2- Searching

The particle searches for a better solution at a specified level limited a sphere surface having a radius of r with angles θ and φ. the radius r represents the gap between the sphere center and the particle position. The changing of the angles θ and φ results in a new movement for the particle. Each angle is varied randomly in radians with a probability Pr_{angle}. The variation of the angles is done uniformly between [0, 2π] during each iteration. After determining the particle's angles, the distance between the particle and SC is chosen randomly between [r_{min}, r_{max}]. The larger radius is given in Eq. 6, in which N equals 3 in spherical coordinates.

$$r_{\max} = \sum_{i=1}^{N} (P_{i,center} - P_{i,particle})^2 \tag{6}$$

Thus, the particle location is determined by its parameters in the hyper spherical coordinates as Q[r_{min}, r_{max}, Pr_{angle}, SC]. During the search process, the particle may find a low objective function estimation. In this case, the particle's location and coordinates will be exchanged.

3- Recovery of dummy particles

The set SCs with largest *OF* are not expected to reach a global minimum because of their inappropriate space. Such particles hyperspheres should be varied. Dump particles shown in Fig. 1 are allocated to new spheres according to set of objective function (*SOF*) estimations given in Eq. 7.

$$SOF = f_{sc} + \gamma\ mean(f_{particles\ of\ SC}) \tag{7}$$

The particles are arranged according to *SOF* in ascending manner. The parameters of the HSSA developed model is given the Appendix. To allocate to the resulting particles to new SCs, the difference in SOF ($DSOF$) is defined as follows.

$$DSOF = SOF - max_{group}\{SOF\ groups\} \tag{8}$$

The SC with highest DSOF loses its dummy particles. The outputs with highest *DSOF* are assigned to new SCs. The assignment probability (*AP*) of the new SC is given in Eq. 9.

$$AP = \left| \frac{DSOF}{\sum_{i=1}^{N_{SC}} DSOF_i} \right| \quad (9)$$

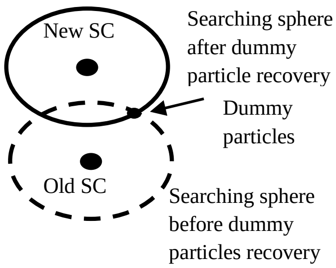

Fig. 1 Dummy particles recovery

4- New particles generation

After every search, the SC position and particles are interchanged. Then, some particles may find a position having a low value of *OF* estimation value than its SC. In this step, the particles (N_{newpar}) with inappropriate *OF* estimation will be eliminated. Such particles are replaced by a new group of particles with the same number N_{newpar} described in step one.

5- Convergence checking

The process continuous until all particles in the best SC have same objective function value. The algorithm is terminated if the maximum number of iterations is reached or the *OF* has the smallest threshold changes during its estimation [11]. Fig. 2 illustrates how HSSA is employed to solve capacitor allocation and sizing.

III. PROBLEM DESCRIPTION

Shunt capacitor bank sizing and placement within radial microgrids provide an effective way to decrease ohmic power losses and consequently saves net annual cost. The developed work in this study presents an optimal planning to allocate SCBs and estimate their corresponding size. Fig. 2 shows a flow chart of HSSA algorithm and load flow study to solve SCBs allocations and sizing. To prove the economical viewpoint saving, it is required to run load flow analysis and estimate the ohmic loss reduction due to SCBs reactive power compensation. In this study, the back/forward sweep (BFS) method is employed for load flow analysis. The testing starts by a test procedure named power loss index (PLI) to determine the candidate buses for SCBs allocation. HSSA is employed to determine the place and size of the SCBs. The goal is to minimize total active power loss and installation of SCBs costs.

IV. PROBLEM FORMULATION

The optimal capacitor allocation in radial distributed systems or microgrids is solved in discrete estimations according to Eqs. 1 and 2. The purpose of the problem is to minimize total yearly operational costs for capacitor installation and power losses. This section introduces the problem formulation.

A. Power loss index (PLI)

In this study, PLI is employed to specify the highest priority buses for capacitor placement, which results in less time consumption for optimization procedures. This PLI method includes injecting reactive power at each bus except the slack bus. The injected power should be a fraction from the total reactive power demand at each bus. The PLI is given in Eq.10.

$$PLI(i) = \frac{P(i) - P_{\min}}{P_{\max} - P_{\min}} \quad (10)$$

All designations are given in the nomenclature. The highest buses in terms of PLI index will be inserted to the HSSA to optimally fix SCBs placement and sizing.

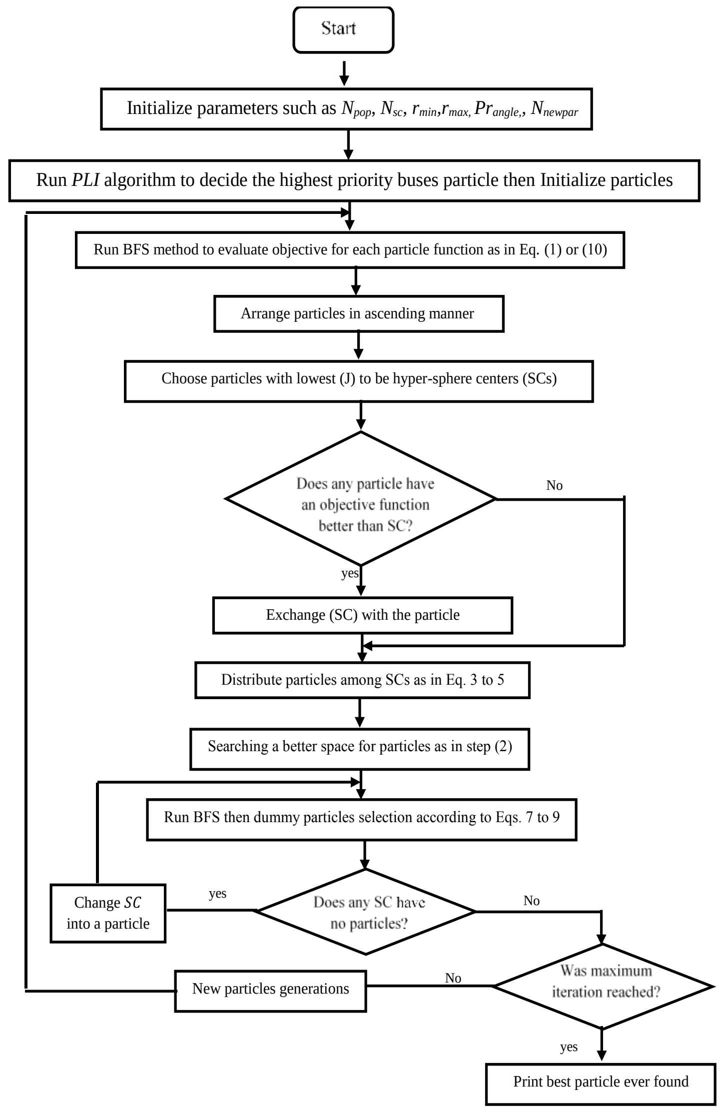

Fig. 2 SCBs flow chart using HSSA

B. Objective (fitness) function

The objective of capacitor allocation and sizing is to minimize the annual energy losses with consideration of capacitor installation and size costs. The objective function given in Eq. 1 can be tailored as follows:

$$J = min\ [K_p C_{losses} + D\left(K_I \sum_{i=1}^{N_{Cb}} i + K_c \sum_{i=1}^{N_{cb}} Q_{c,i}\right) + K_o N_{cb}] \quad (11)$$

The terminology in Eq. 11 accounts for annual ohmic loss, installation and running costs, and the total operational costs of the estimated reactive power. All parameters are given in Table I [3,15].

Table I Cost function parameters

Parameter	Value	unit
K_p	0.06	$/kWh
T	0.8760	H
D	0.2	-
K_c	25	$/kVAr
K_o	300	$/year/location
K_i	1600	$

C. Constraints

The real power and reactive power constraints are given in the quality and inequality functions in Eqs. 12 to 14 respectively.

$$P_{slack} = \sum_{i=1}^{N} P_{ld,i} + \sum_{j=1}^{N_L} P_{losses,i} \tag{12}$$

$$Q_{slack} = \sum_{i=1}^{N} Q_{ld,i} + \sum_{i=1}^{N_L} Q_{losses,i} - \sum_{i=1}^{N_{cb}} Q_{c,i} \tag{13}$$

$$Q_{c,\min} \le Q_{c,i} \le Q_{c,max} \tag{14}$$

The estimation of the reactive power is given in discrete values with a step of 50kVAr [3]. In addition, this power should be less than half the total reactive power demand as in Eq. (15).

$$\sum_{i=1}^{N_{cb}} Q_{c,i} \le 0.5 \sum_{i=1}^{N} Q_{ld,i} \tag{15}$$

The voltage magnitude constraints at each bus are restricted by the following inequality, in which the minimum and maximum voltage limits lie in the interval [0.9,1.05].

$$V_{\min} \le V_i \le V_{\max} \quad \forall i \in N \tag{16}$$

In order to keep transmission line complex power capacities within their constraints, the current through any line is limited by the inequality in Eq. 17.

$$I_{l,\min} \le I_{l,i} \le I_{l,\max} \quad \forall i \in N_L \tag{17}$$

V. RESULTS AND DISCUSSION

In this section, the notability of the developed HSSA to find optimal locations and sizing of SCBs for different radial systems is investigated. Three different radial distribution networks are considered: IEEE-15, IEEE-69, and IEEE-119. The developed algorithm has been developed via Matlab ver 2015 [25].

A. IEEE-15 bus radial system

HSSA is applied firstly for IEEE-15 bus system shown in Fig. 3. The data of this system was found in [26]. The total network loads are 1752kVA with power factor equals 0.7. Total losses without SCB reactive power compensation are 61.95kW. In this article, the PLI are initially used to select the candidate buses for SCBs placement as shown in Fig. 4. The buses with largest values can be ordered as follows: 15, 11, 4, 7, 6, 12, 14, 3, 8, 13,…2 . Then, the proposed HSSA is applied to decide the optimal allocation and SCBs sizing. This can be achieved by installing 800kVAr at four buses (150kVAr at 15, 250kVAr at 14, 200kVAr at 4 and 200kVAr at 7).

A comparison was made among the developed algorithm and the previous works form the literature to solve SCB placement and sizing. This comparison is tabulated in Table II. From Table II, it is clear that the total losses are decreased to 31.01kW with percentage of reduction of 51.578%. In addition, the annual cost is reduced to 22782$ with improving the net saving to 30.04%, which is the most valuable result among the others. Fig. 5 shows the buses voltage profile improvement. The *OF* performance against number of iterations is shown in Fig. 6. The objective function convergence takes 17 iterations to reach the optimal estimations. The first 17 iterations take 5.12s using an intel-core CPU of i3 with 3.6GHz speed.

Nobility of HSSA over others

To prove the notability of the developed HSSA, the obtained results are compared with previous works that achieve good results from the literature. From the data given in Table II, HSSA gives better results compared to others. This can be achieved by installing of 800kVAr at four buses, which is the smallest value compared what is achieved in [30]. The power losses reduction achieves 49.99% compared to 50.86% in [27]. The spectacular appeal of HSSA is the net saving per year. The developed HSSA shows the best net saving among the others with a value of 9781.4$/year with the percentage of saving reaches 30.04%. It is obvious from the above results that the developed HSSA is a strong competitive to other algorithms.

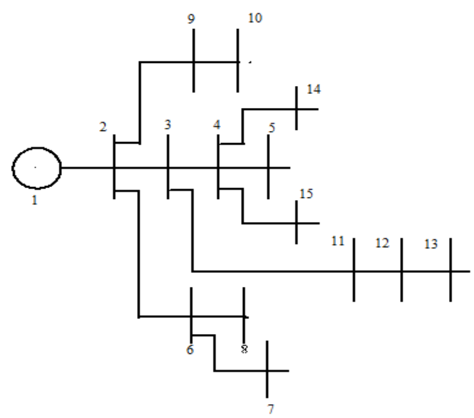

Fig. 3 One line diagram of IEEE-15 bus system

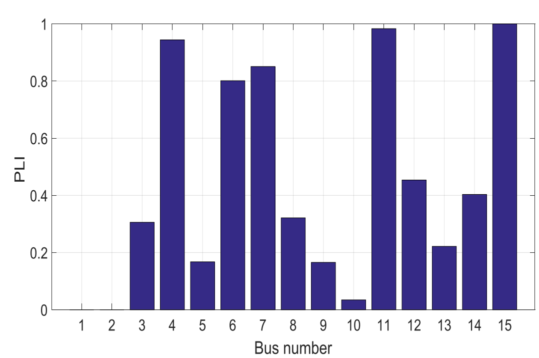

Fig. 4 PLI of IEEE-15 bus system

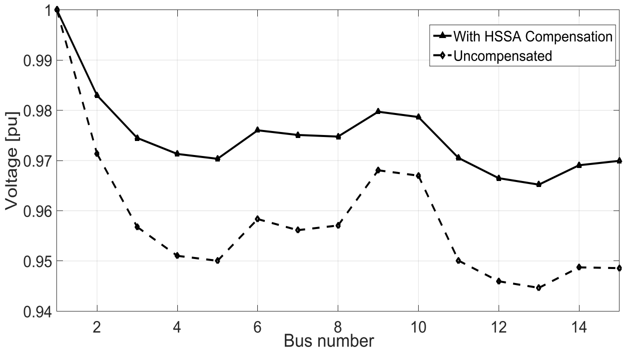

Fig. 5 Improvement in IEEE 15 bus system voltages due to HSSA compensation

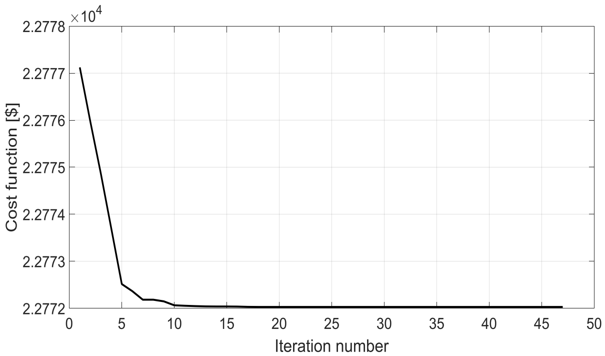

Fig. 6 Objective function variation for IEEE 15 bus system

B. IEEE-69 bus radial system

The second scenario employing HSSA is the IEEE-69 bus system as shown in Fig. 7. The data of this system are given in [26]. Total losses without SCB reactive power compensation are 224.89kW. Fig. 8 shows the buses according to PLI index. They can be arranged as follows: 61, 64, 59, 65, 21, 12, 11, 62, 18, 17,…, 16. Then, the proposed algorithm is applied by selecting the optimum positions and capacitor values depending on the HSSA method. This is achieved by installing of 1400kVAr at two buses (1050kVAr at 61 and 250kVAr at 21).

This comparison is given in Table III. It can be noticed that the value of total losses are decreased to 147.7kW with percentage of reduction of 34.32%. In addition, the developed algorithm is capable to reduce annual costs to 85865.21$. The corresponding net saving records 27.35%, which is the best one. This improvement is achieved by installing of 1400kVAr at two buses. It is clear that the buses voltage profile is improved as shown in Fig. 9. The lowest bus voltage is improved to 0.9290pu.

Nobility of HSSA over others

In order to ascertain the reliability and effectiveness of the proposed algorithm, a comparison was made among the developed algorithm and the previous methods to solve this capacitor allocation problem. From the data given in Tables III, HSSA competes other algorithms. The power losses reduction achieves 34.32% compared to 35.38% in [3].

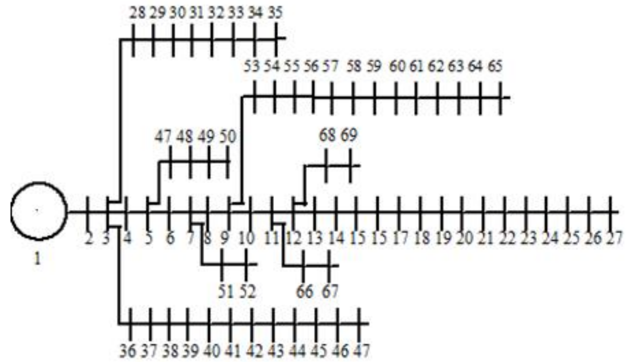

Fig. 7 One line diagram of IEEE 69-bus system

Total kVAr compensation obtained by HSSA is 1400kVAr, which is the smallest value compared to 1700kVAr as achieved in [3]. Again, the biggest appeal of HSSA is the net saving per year. The developed HSSA shows the highest net saving among the others with a value of 32334.3$/year. The percentage of saving reaches 27.35%. From the investigation of the IEEE-69 bus network, HSSA capability to solve SCBs allocation and sizing is proved with the least value of annual cost.

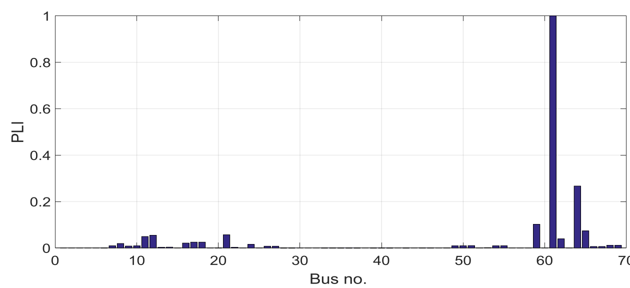

Fig. 8 PLI of IEEE-69 bus system

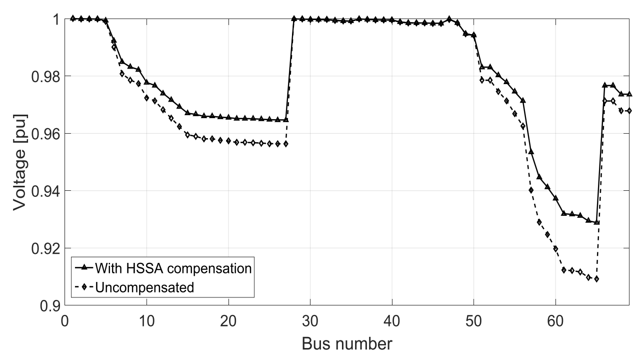

Fig. 9 Improvement in IEEE-69 bus system voltages due to HSSA compensation

C. IEEE-119 bus radial system

HSSA is applied for the IEEE-119 bus system shown in Fig. 10. The data of this system are given in [33]. The total network loads are 28392.42kVA. The total power of such network is 22709kW. Total losses without SCB reactive power compensation are 1294.35kW. The PLI results for candidate bus arrangement to SCB placement are shown in Fig. 11. According to PLI values, the buses are arranged as follows 116, 52, 77, 73, 114, 112, 74, 117, 56, 115, 101, 79, 33, 83, 113, 53, 100, 75, 32, 107, 61, 89, 42, …,92, 104.

Table II Comparison results of IEEE-15 bus system

Items	Un-compensated	PSO [14]	FGA [27]	In [28]	DE [29]	In [30]	IHA [3]	Developed HSSA
Total losses (kW)	61.95	32.7	30.4411	32.6	32.3	33.2	31.1255	31.01
Loss reduction (%)	-	47.22	50.86	47.38	47.86	46.41	49.76	49.99%
Minimum voltage	0.9424	-	0.9677	-	-	-	0.9658	0.9662
Total kVAr	-	1192	1100	1193	1132	900	950	800
Annual cost ($/year)	32563.4	24387.1	24599.8	24339.6	24496.8	24429.9	22969.56	22782
Net saving $/year)	-	8176.3	7963.6	8223.8	8066.4	8133.5	9593.84	9781.4
% saving	-	25.11	24.46	25.26	24.77	24.98	29.46	30.04

Table III Comparison results of IEEE-69 bus system

Items	Un-compensated	PSO [14]	FGA [30]	In [31]	DE [32]	IHA [3]	Developed HSSA
Total losses (kW)	224.89	152.48	156.62	148.48	151.37	145.32	147.7
Loss reduction (%)	-	32.2	30.4	34.0	32.7	35.38	34.32
Minimum voltage	0.9092	-	0.9396	0.9305	0.9311	0.937	0.9290
Total kVAr	-	1621	1600	1800	1450	1700	1400
Annual cost $/year)	118200.0	90108.5	92179.5	88901.1	89913.4	86122.1	85865.21
Net saving $/year)	-	28096.3	26025.3	29303.7	28291.4	32082.7	32334.3
% saving	-	23.77	22.02	24.79	23.93	27.14	27.35

Table IV Comparison results of IEEE-119 bus system

Item	Un-compensated	ABC [16]	CSA [15]	HS [19]	IHA [3]	Developed HSSA
Total losses (kW)	1294.38	845.39	858.89	926.1	843.14	834.05
Loss reduction (%)	-	33.99	33.64	28.26	34.85	34.87
Minimum voltage	-	0.90886	0.9060	-	0.9020	0.9073
Total kVAr	-	10000	9000	9928	9800	8850
Annual cost ($/year)	680310.36	50588.7	501392.6	549418.2	497737.5	488077.63
Net saving ($/year)	-	174423	178917.8	130892.2	182572.8	192232.73
% saving	-	25.64	26.3	19.24	26.8	28.26

Table V Optimal location and sizing of SCBs in kVAr for IEEE-119 bus

Bus number	116	52	83	74	42	101	79	113
kVAr	1450	2150	1050	1150	900	800	500	850

Table VI Effectiveness of HSSA

IEEE system	Best ever found from Table II,III,V		Developed HSSA		*% of increasing of net saving with HSSA
15 bus	9593.84	29.46%	9781.4	30.04%	2%
69 bus	32082.7	27.14%	32334.3	27.35%	0.8%
119 bus	182572.8	26.8%	192232.73	28.26%	5.1%
*% of increasing of net saving with HSSA= (Best ever found from Table III, V, VII - Developed HSSA)/ Best ever found from Tables II,III,V.					

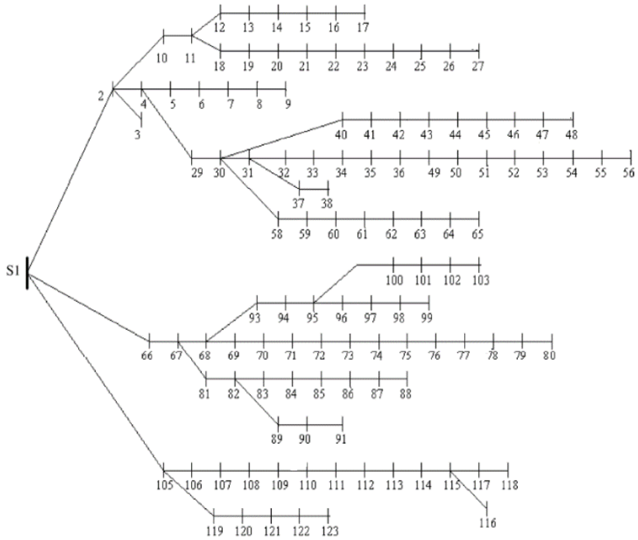

Fig. 10 One line diagram of IEEE-119 bus system [33]

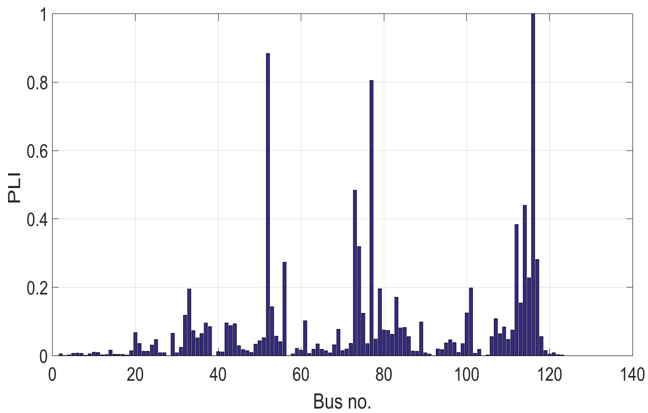

Fig. 11 PLI of IEEE-119 bus system

With Applying the developed HSSA, Optimal location and sizing of SCBs are determined as in Table IV. The losses are reduced to 834.05kW. This represents a percentage of reduction of 34.87%. The annual cost decreases to 488077.63$. The resultant net saving percentage is enhanced by 28.26%. In addition, it is clear that the buses voltage profile is improved as shown in Fig. 12.

Nobility of HSSA over others

The notability of the developed HSSA is proved through the obtained results as given in Table IV. The results are compared with previous works that achieve high-qualified results from the literature. From the data given in Table VI, HSSA gives competitive results compared to others. The power losses reduction achieves 34.87% compared to 28.26% in [19]. Total kVAr compensation obtained by HSSA is 8850kVAr at only eight buses as in Table V, which is the smallest value, compared to what is achieved in [15]. The developed HSSA shows the best net saving among the investigated others with a value of 192232.72$/year with the percentage of saving reaches 28.26%. It is clear from the above results that the developed HSSA lends itself as strong competitive to other algorithms.

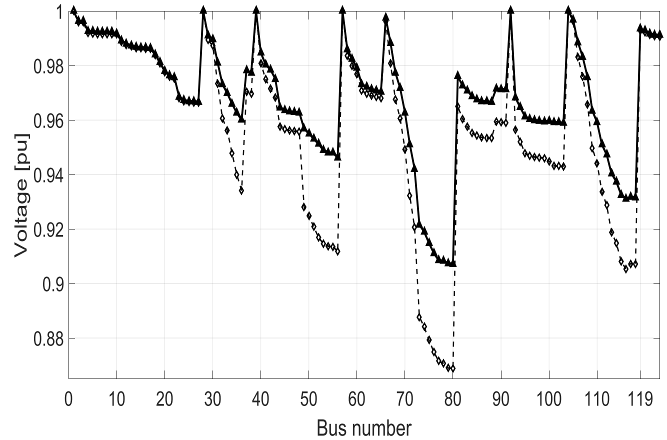

Fig. 12 Improvement in IEEE-119 bus system voltages due to HSSA compensation

D. HSSA effectiveness outline

From the different investigated radial systems above, HSSA shows strong contribution in achieving the study target, which aims primarily to increase the annual net cost saving. Table VI highlights the effectiveness of the developed HSSA compared to the best results ever obtained through the investigated state-of-the-art works from the literature. It is clear from Table VI that HSSA shows good results in increasing the net saving. It reaches 5.1% net saving for the IEEE-119 bus.

VI. CONCLUSIONS

In this research, hyper-spherical search algorithm (HSSA) has been utilized to estimate the optimal size and allocation of shunt capacitor banks. The effectiveness of HSSA is demonstrated through different radial distribution systems. Simulation results reveal that the developed algorithm is effective to offer an optimal scheduling of SCBs estimation in order to maximize net annual saving. From the above development, comparison results, and discussions, the following conclusions are drawn. (1) The developed algorithm allows the SCB estimation to be evaluated in an economic and high-qualified way. (2) The effectiveness of the developed HSSA to estimate the optimal size and allocation of SCBs to maximize net annual costs is achieved compared to best results ever obtained through the stat-of-the-art works. It reaches 5.1% for IEEE-119 bus system. (3) The algorithm is effective and can be cooperated with different radial distributed power systems to achieve SCBs operation and reduce total ohmic losses.

APPENDIX

Number of particles (N_{pop})=200; Maximum number of iterations=200; N_{sc}=50; γ=0.1; r_{min}=0.0, r_{max}=1.1; N_{newpar}=10, difference between SCs in two successive iteration=0.000001.

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