Optimal Capacitor Placement in Radial Distribution System Using Chicken Swarm Optimization Algorithm

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Abstract This article presented an approach for incorporating shunt capacitor banks in radial distribution system with an aim to reduce the line losses and the total system cost. Along with the above, the optimal allocation of capacitor banks helps in improving the bus voltages and the power factor of the system. The above goal is realized by chicken swarm optimization algorithm on standard 85 and 118 bus systems. Before optimization, the possible candidate buses are obtained using power loss index, which helps in reducing search space during the algorithmic process. The obtained results are compared with other recent literatures for showing the efficacy and supremacy of the studied approach.

Keywords Chicken swarm optimization algorithm · Optimal capacitor placement · Power loss index

1 Introduction

The ever-increasing load demand causes the increase in the requirement of reactive power at load, as majority of the load have lagging power factor due to inductive nature. This causes problems like higher line losses and weak the voltage profile. For addressing the above issues, optimal capacitor placement (OCP) is considered as a concurrent topic of research in the field of electrical distribution system. The capacitor banks mainly placed near to the load and served as a reactive power source, which in result reduces the magnitude of current in distribution lines. This results in benefits such as less line losses, healthy voltage profile and improved power factor. The capacitor banks are required to be optimally positioned in terms of location, size and number for achieving the maximum benefits [1].

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Recently, a number of optimization techniques have been projected by various authors based on analytical, numerical and artificial intelligence approaches. At first, due to expensiveness of the computational tools, many authors solve the OCP problem by using analytical approaches. Later on, easy and economical availability of computing resources inspires many authors to solve the OCP problem utilizing numerical analysis methods. Afterwards, many researchers have found the application of nature inspired algorithms highly efficient in solving OCP problem as it easily converges to global optima point [2]. However, as stated in "no free lunch" theorem, a particular optimization method may not be specified as best suited for solving a specific problem, which encourages many authors to apply different approaches for solving OCP problem and evaluate the effectiveness for the same. In recent times, many approaches like cuckoo search algorithm (CSA) [3], sine cosine algorithm (SCA) [4], bacterial foraging algorithm (BFA) [5], teaching learning-based optimization (TLBO) [6], modified monkey search (MMS) algorithm [7], flower pollination algorithm (FPA) [8], artificial bee colony (ABC) optimization [9] and so on have been implemented for solving OCP problem. Chicken swarm optimization (CSO) algorithm is a simple and efficient bio-inspired algorithm proposed by Meng et al. [10] has been utilized by many researchers efficiently in solving various problems. From bibliographic review, it has been observed that the capacity of CSO algorithm has not evaluated yet for solving OCP, which motivates the authors for evaluating the efficacy of CSO algorithm for solving OCP. Furthermore, by utilizing a sensitivity analysis termed as power loss index (PLI), the weak and vulnerable buses are identified. These buses take part in the algorithm for obtaining the optimized location for capacitor banks. Discrete capacitor banks are considered in the studied optimization approach and evaluated on standard 85 and 118 bus systems.

2 Problem Formulation

For solving OCP, the objective is taken as total system cost. The total cost of the system is calculated by using Eq. (1):

$$\text{Cost} = P_{\text{P}} * \text{APL} * T + D\left(P_I * \text{NC} + P_{\text{C}} * \sum_{i}^{\text{NC}} R_{\text{C}_i}\right) + P_{\text{O}} * \text{NC} \tag{1}$$

where P_{P} represents average energy cost, APL is taken as active power line losses, P_{C}, P_{I}, P_{O} represents cost of capacitor banks in term of purchase, installation and operation, respectively, D represents depreciation factor, NC represents number of capacitors, R_{C_i} is the compensated reactive power at ith bus and T is taken as per year operating hours. The values of different parameters used in this equation are adopted from the article [3].

2.1 *Operational Constraints*

2.1.1 Bus Voltage Constraints

$$V_{\min} \le V_i \le V_{\max} \tag{2}$$

where V_i represents the ith bus voltage. $V_{\min}$ and $V_{\max}$ represents the minimum and the maximum bus voltage limit, respectively.

2.1.2 Reactive Power Compensation Constraints

$$R_{\mathrm{C}}^{\min} \le R_{\mathrm{C}_i} \le R_{\mathrm{C}}^{\max} \tag{3}$$

where $R_{\mathrm{C}}^{\min}$ and $R_{\mathrm{C}}^{\max}$ are the minimum and maximum value of allowable compensation, respectively.

2.2 *Power Loss Index*

Some of the buses in the distribution system are more vulnerable than others and essentially needs reactive power compensation. PLI is introduced in order to sort those buses accordingly, from which some of top buses are considered for the optimization process and form which the optimized location and size of capacitor banks are found [3]. The PLI for all the system buses is calculated by utilizing Eq. (4).

$$\mathrm{PLI} = \frac{\mathrm{LR}_i - \mathrm{LR}_{\min}}{\mathrm{LR}_{\max} - \mathrm{LR}_{\min}} \tag{4}$$

where LR_i represents the loss reduction at ith bus. $\mathrm{LR}_{\min}$ and $LR_{\max}$ represents the minimum and the maximum loss reduction obtained.

2.3 *Load Flow*

In this studied work, a direct method of load flow approach is utilized for obtaining the system parameters such as line losses and bus voltages [11].

3 Overview of CSO Algorithm

CSO is a bio-inspired algorithm that imitates the behaviour of chicken swarms [10]. CSO utilizes the following approaches for finding the optimal solution. Each group of chickens consists of a rooster, few hens and chicks, in which the rooster is the dominant one and reflects the global optimal value during algorithmic process. The hens, which are considered as less fit to rooster, may follow the rooster in their subgroup for searching food. The hens may steal food found by other hens which is associated by random function. The chicks are considered as the weaker group among them and search around their mother hens for food. The equations associated with the several phases of algorithm are explained below.

3.1 Rooster Movement

The equation for obtaining the rooster position at each iteration is explained by Eq. (5):

$$Y_{i,j}^{t+1} = Y_{i,j}^{t} * \left(1 + \mathrm{randn}\left(0, \sigma^2\right)\right) \tag{5}$$

$$\sigma^2 = \begin{cases} 1, & \text{if } ft_i \le ft_l \\ \exp\left(\dfrac{ft_l - ft_i}{|ft_i| + \varepsilon}\right), & \text{otherwise} \end{cases} \tag{6}$$

where $Y_{i,j}^{t}$ is the position of solution at iteration t, $\mathrm{randn}\left(0, \sigma^2\right)$ represents Gaussian distribution with zero mean and standard deviation of σ^2, ε represents a small constant, l is the random rooster index and ft_i is the fitness value of Y_i.

3.2 Hen Movement

The positions of hens are updated by utilizing Eq. (7).

$$Y_{i,j}^{t+1} = Y_{i,j}^{t} + S_1 * \mathrm{randn} * \left(\mathrm{Y}_{\mathrm{r1,j}}^{\mathrm{t}} - \mathrm{Y}_{\mathrm{i,j}}^{\mathrm{t}}\right) + \mathrm{S}_2 * \mathrm{randn} * \left(\mathrm{Y}_{\mathrm{r2,j}}^{\mathrm{t}} - \mathrm{Y}_{\mathrm{i,j}}^{\mathrm{t}}\right) \tag{7}$$

$$S_1 = \exp\left(\frac{ft_i - ft_{r1}}{|ft_i| + \varepsilon}\right) \tag{8}$$

$$S_2 = \exp(ft_{r2} - ft_1) \tag{9}$$

3.3 Chick Movement

The positions of chicks are obtained at each iteration by using Eq. (10).

$$Y_{i,j}^{t+1} = Y_{i,j}^{t} + FL * \left(Y_{m,j}^{t} - Y_{i,j}^{t}\right) \tag{10}$$

where $m \in (1,\ \text{number of population})$ and $FL \in (0, 2)$.

4 Result and Discussion

The considered approach has been realized on 85 and 118 bus systems and the efficacy of the studied approach has been evaluated by comparing the results with different other algorithms. The compared values (line losses, bus voltages, total system cost) are obtained utilizing the load flow approach taken in this work by considering the results obtained by the respective literatures for avoiding unnecessary incongruities. The bus voltage constraint range is taken as 0.9–1.1 p.u. while the capacitor banks capacity varies within 0 to 1500 kVAr. The capacitor values are considered in discrete having step size of 50 kVAr within the allowable range. In the studied load flow approach, the voltage base value is taken 11 kV, whereas the base value of power is taken as 100 MVA. The number of iterations is taken as 100 during optimization for the present work. The important results in the tables are highlighted in bold.

4.1 Case Study 1: 85 Bus Test System

The required values of data regarding the test system are taken from the literature presented in [12]. The total active load is 2570.28 kW, whereas the total reactive load of the system taken is 2622.2 kVAr. At first, the PLI value is obtained for all the buses and sorted accordingly. For this case study, the buses are organized as 54, 55, 51, 76, 69, 74, 39, 72, 66, 28, 62, 38, 61, 60, 59, 82, 37 …. The top 16 buses (user defined) are participated in the optimization process as possible location for capacitor placement. After executing the CSO algorithm, the optimal result is obtained as given in Table 1 and is consists of 5 different capacitor locations with total shunt compensation of 2000 kVAr. The size and location of each capacitor banks along with the respective bus voltage and line loss reduction are stated in Table 1. It may be observed form Table 1 that the total profit obtained using the proposed algorithm is better than the other compared approaches, which is taken as the optimization objective. The other parameters like line losses and bus voltages are comparable with other presented approaches (Fig. 1).

Table 1 Summaries of optimal results for IEEE 85 bus test system

Items	Un-compensated	Compensated			
		BFA [5]	TLBO [6]	MMS [7]	CSO (studied)
Capacitor location (size in kVAr)	-	9 (840) 34 (660) 60 (650)	15 (150) 23 (300) 26 (300) 32 (150) 36 (150) 38 (150) 45 (150) 52 (150) 57 (300) 61 (150) 64 (300) 73 (150) 82 (150)	10 (150) 14 (300) 17 (150) 20 (300) 26 (300) 28 (150) 32 (150) 45 (150) 49 (300) 60 (450) 68 (150) 73 (150) 84 (150)	**28 (600)** **55 (350)** **60 (550)** **69 (200)** **82 (300)**
Total kVAr	-	2150	2550	2850	**2000**
APL (kW)	316.135	152.903	143.244	145.231	**150.036**
% Loss reduction	-	51.63	54.69	54.06	**52.54**
RPL (kVAr)	198.613	94.728	89.694	90.981	**93.281**
$V_{\min}$ (p.u.)	0.871	0.919	0.924	0.927	**0.919**
Net savings ($)	-	73,184.74	70,061.51	67,517.14	**74,201.39**
% saving	-	44.04	42.16	40.63	**44.66**

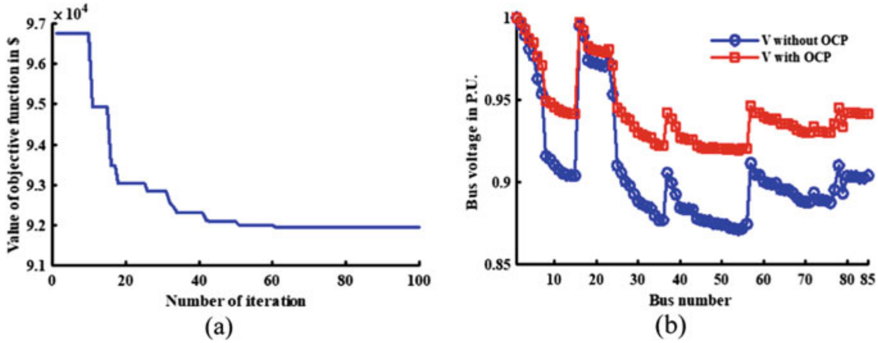

Fig. 1 Results obtained for case study 1. **a** Convergence profile of objective function and **b** Improvement in voltage profile after OCP

4.2 *Case Study 2: 118 Bus Test System*

The required values of data regarding the test system are taken from the literature presented in [13]. The total active load is 22,709.71 kW, whereas the total reactive load of the system taken is 17,040.97 kVAr. After carrying out the power loss index

Table 2 Summaries of optimal results for IEEE 118 bus test system

Items	Un-compensated	Compensated			
		FPA [8]	ABC [9]	CSA [3]	CSO (studied)
Capacitor location (size in kVAr)	-	39 (1500) 43 (600) 70 (500) 74 (1050) 86 (900) 91 (1500) 107 (700) 109 (500) 118 (1050)	32 (850) 35 (1050) 40 (1300) 50 (800) 70 (550) 73 (1300) 79 (1200) 105 (700) 106 (250) 109 (800) 110 (1200)	32 (1500) 39 (1500) 40 (550) 70 (950) 74 (750) 86 (1050) 108 (1500) 118 (1200)	**32 (1000)** **39 (950)** **40 (650)** **43 (300)** **72 (1350)** **76 (200)** **86 (800)** **91 (1300)** **107 (950)** **118 (1500)**
Total kVAr		8300	10,000	9000	**9000**
APL (kW)	1297.413	855.690	856.548	862.031	**847.001**
% Loss reduction	-	34.05	33.98	33.56	**34.72**
RPL (kVAr)	978.715	646.636	641.96	647.969	**635.637**
V_{min} (p.u.)	0.869	0.907	0.909	0.906	**0.906**
Net savings ($)	-	185,089.61	174,898.64	178,876.78	**185,536.758**
% saving	-	27.14	25.65	26.23	**27.21**

calculation, the buses are arranged as 118, 39, 74, 70, 109, 107, 71, 111, 43, 110, 86, 76, 32, 91, 108, 40, 85, 72, 31 …. The top 18 buses are selected as the potential location for OCP and take part in the optimization for finding the best location. Thereafter, the CSO algorithm yields ten different locations for capacitor allocation with overall compensation of 9000 kVAr. The obtained result for CSO algorithm is given in detail in Table 2 and compared with the other algorithms. It may be observed from Table 2 that along with the total annual profit, the obtained result produces the maximum reduction in line losses and shows good improvement in voltage profile. This proves the superior efficacy of the proposed approach over the other compared algorithms (Fig. 2).

5 Conclusion

In the current study, the optimum allocation and sizing of shunt capacitor banks are obtained by realizing CSO algorithm for 85 and 118 bus test systems. By considering the total system cost as the objective, the optimization process is carried out. The effectiveness and supremacy of the studied approach is demonstrated by obtaining the maximum benefits in terms of cost which is found better than some other recent optimization technique outputs.

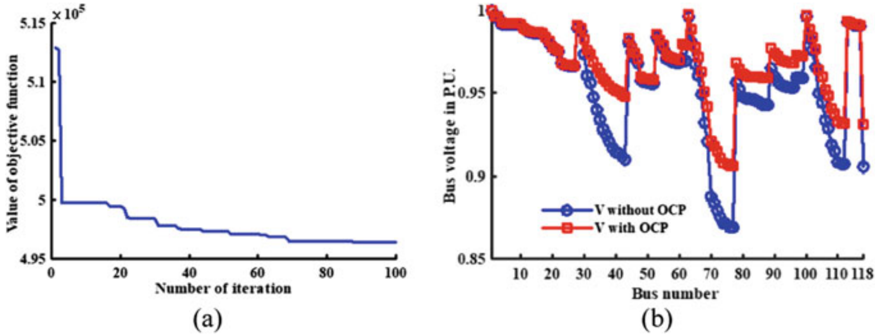

Fig. 2 Results obtained for case study 2. **a** Convergence profile of objective function and **b** improvement in voltage profile after OCP

References

1. El-Ela AA, El-Sehiemy RA, Kinawy AM et al (2016) Optimal capacitor placement in distribution systems for power loss reduction and voltage profile improvement. IET Gener Trans Distrib 10(5):1209–1221
2. Aman MM, Jasmon GB, Bakar AHA, Mokhli H, Karimi M (2014) Optimum shunt capacitor placement in distribution system—a review and comparative study. Renew Sustain Energy Rev 30:429–439
3. El-Fergany AA, Abdelaziz AY (2014) Capacitor allocation in radial distribution networks using cuckoo search algorithm. IET Gener Trans Distrib 8(2):223–232
4. Biswal SR, Shankar G (2018) Optimal sizing and allocation of capacitors in radial distribution system using sine cosine algorithm. In: IEEE international conference power electronics drives energy system (PEDES), IEEE, pp. 1–4
5. 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
6. Sultana S, Roy PK (2014) Optimal capacitor placement in radial distribution systems using teaching learning based optimization. Int J Electr Power Energy Syst 54:387–398
7. Duque FG, Oliveira LW, Oliveira EJ et al (2015) Allocation of capacitor banks in distribution systems through a modified monkey search optimization technique. Int J Electr Power Energy Syst 73:420–432
8. Abdelaziz AY, Ali ES, Elazim SMA (2016) Optimal sizing and locations of capacitors in radial distribution systems via flower pollination optimization algorithm and power loss index. Int J Eng Sci Technol 19(1):610–618
9. El-Fergany AA, Abdelaziz AY (2014b) Artificial bee colony algorithm to allocate fixed and switched static shunt capacitors in radial distribution networks. Electr Power Comp Syst 42(5):427–438
10. Meng X, Liu Y, Gao X, Zhang H (2014) A new bio-ınspired algorithm: chicken swarm optimization. In: International conference in swarm intelligence, pp. 86–94
11. Teng JH (2003) A direct approach for distribution system load flow solution. IEEE Trans Power Deliv 18(3):882–887
12. Das D, Kothari DP, Kalam A (1995) Simple and efficient method for load flow solution of radial distribution networks. Int J Electr Power Energy Syst 17(5):335–346
13. Zhang D, Fu Z, Zhang L (2007) An improved Tabu search algorithm for loss minimum reconfiguration in large-scale distribution systems. Electr Power Syst Res 77:685–694