A Novel Quasi-opposition Based Sine Cosine Algorithm for Optimal Allocation and Sizing of Capacitor in Radial Distribution Systems

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Research Article

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A novel quasi-opposition based sine cosine algorithm for optimal allocation and sizing of capacitor in radial distribution systems

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Abstract: Increasing trend in load demand has introduced many problems in distribution systems like more line losses, low power factor, voltage fluctuations and so on. These issues have become a vital challenge for the power utilities to resolve and maintain the system under healthy conditions. For handling these issues, optimal capacitor placement (OCP) in radial distribution systems employing an optimization approach is explored in this work. The present work proposes a novel application of quasi-opposition based sine cosine algorithm for solving OCP problem. The effectiveness and superiority of the proposed algorithm is verified over other algorithms using different standard benchmark test functions. For solving OCP problem, at first, the most deserving candidate buses for the OCP are identified using a new proposed sensitivity index that helps in reducing search space for the optimization process. Thereafter, by minimizing the losses and maximizing the net annual profit of the system, the optimal location and selection of the fixed-step capacitor banks are obtained. The efficacy of the proposed algorithm has been verified by comparing the results obtained with that of other state-of-the-art algorithms on the standard IEEE 85 bus and 118 bus radial distribution test systems considering full load and variable load scenarios.

Keywords: Optimal capacitor placement, quasi-opposition based sine cosine algorithm, radial distribution system, sensitivity index

\[ \text{Symbols} \]

- \( a \): a constant number taken as 2
- \( APL_a \): active power line losses after compensation
- \( APL_b \): active power line losses before compensation
- \( BCBV \): branch current to bus voltage matrix
- \( BIBC \): bus injection to branch current matrix
- \( \cos t_a \): total cost per year after compensation
- \( \cos t_b \): total cost per year before compensation (base case)

\[ \text{Nomenclature} \]

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| Symbol | Definition |
|--------|------------|
| CVD    | cumulative voltage deviation |
| CVD_{min} | minimum cumulative voltage deviation in the system |
| CVD_{max} | maximum cumulative voltage deviation in the system |
| D      | depreciation factor |
| DLF    | direct load flow matrix |
| F_{i}^t | \( i \)th dimension value of the optimum individual at the \( t \)th iteration |
| G_{best} | best solution in terms of fitness |
| G_{i}^t | \( i \)th dimension value of the agent at the \( t \)th iteration |
| G_{o}  | initial number |
| IB_{i} | \( i \)th branch current |
| IL_{i} | \( i \)th bus load current |
| J_r    | jumping rate/jumping probability |
| K_C    | purchase cost of capacitor |
| K_I    | installation cost of capacitor |
| K_O    | operation cost of capacitor |
| K_P    | average energy cost |
| LC_{a} | sum of line currents after compensation |
| LC_{b} | sum of line currents before compensation |
| LR(i)  | loss reduction at \( i \)th bus |
| LR_{min} | minimum system loss reduction |
| LR_{max} | maximum system loss reduction |
| M      | centre of the search space |
| m      | lower limit of the search space |
| MT     | maximum number of iterations |
| n      | upper limit of the search space |
| O_{G_{o}} | opposite number |
| P_{i}  | \( i \)th bus active power load demand |
| PLI    | power loss index |
| Q_{C_{j}} | reactive power injected at the \( j \)th bus |
| Q_{C_{min}} | minimum allowable kVAr limit of capacitor banks |
| Q_{C_{max}} | maximum allowable kVAr limit of capacitor banks |
| Q_{i}  | \( i \)th bus reactive power load demand |
| QO_{G_{o}} | quasi-opposite number |
| R      | branch resistance value |
| RPL_{a} | reactive power line losses after compensation |
| RPL_{b} | reactive power line losses before compensation |
| SI     | sensitivity index |
| T      | hours per year |
| t      | current iteration number |
| V_{i}  | voltage at \( i \)th bus |
| V_{o}  | slack bus voltage |
| V_{min} | minimum allowable voltage limit |
\[ V_{max} \text{ maximum allowable voltage limit} \]
\[ VDI \text{ voltage deviation index} \]
\[ w_1, w_2, w_3, w_4 \text{ weightage factors considered for designing the objective function} \]
\[ X \text{ branch reactance value} \]
\[ Z_{mn} \text{ line impedance of the branch connected between the } m\text{th bus and } n\text{th bus} \]

1 Introduction

Distribution systems are growing larger and complex day by day with increasing load demand, which has led to more power losses. Also, most of the loads are of inductive type, hence, the requirement of reactive power at the consumer site increases, which results in poor performance of the system. Hence, it has become a major issue for the distribution companies to reduce the line losses by maintaining the system voltage and other constraints within their permissible limits. The optimal capacitor placement (OCP) is considered one of the most popular ways of resolving the above issues. Shunt capacitor placement in the distribution system acts as a source of reactive power to the load and, mainly, helps in reducing line losses, controls the voltage level, improves power factor and system stability (El-Ela et al. 2016). However, for extracting the maximum benefits, the shunt capacitors are required to be placed optimally in terms of number, location and size selection (Devabalaji et al. 2015).

In the recent past, numerous optimization methods have been projected by many researchers based on both traditional mathematics and the artificial intelligence approach. At first, for solving the OCP problem, analytical methods have been suggested by many researchers because the powerful computational tools were expensive and not readily available at that time. Neagle and Samson (1956) have proposed an analytical approach which states that to have the maximum loss reduction in a radial distribution system (RDS) with uniformly distributed load, capacitor bank needs to be placed at a location where load kVAr is twice the capacitor bank kVAr. Schmill (1965) has proposed an approach using 2/3 rule for capacitor placement at its optimal location. These methods consider the uniform distribution of load, which is an unrealistic assumption. Therefore, using the basic principles of equal area criterion and the net saving as an objective function, the OCP problem is solved by Grainger and Lee (1981) in a non-uniformly distributed load environment. Although, analytical approaches are considered simple methods, yet they may lead to inaccurate results. This may be due to the fact that the obtained values in relation to selection and location of the capacitor banks being placed may need to be rounded off owing to unrealistic assumptions like neglecting load variation and considering variables as continuous. This also may lead to problems of overvoltage and more power loss than the calculated one.

Due to the easy availability of economical computing resources, different numerical programming methods have been applied to solve OCP problems. Numerical programming methods are iterative techniques used to optimize an objective function by satisfying a set of constraints. Duran (1968) uses a
dynamic programming approach for solving OCP issue considering discrete capacitor sizing and loss reduction based defined objective function. Later on, authors in (Baran and Wu 1989) have utilized a two-stage master and slave approach for solving the OCP issue. In the master stage, capacitors’ locations are obtained, whereas, type and selection of the fixed-step capacitor banks are decided under the slave stage. It is observed from the literature survey that the numerical methods take more computational time than analytical approaches and sometimes may converge to local optima as well. On the other hand, heuristic approaches are considered better than the numerical programming based approaches for finding solutions nearer to the optimal solution for capacitor placement. In (Abdel-Salam et al. 1994), the authors have investigated a heuristic approach-based allocation of capacitors by selecting sensitive nodes in terms of losses due to reactive power demand. Thereafter, the capacitor rating is obtained by maximizing active power loss reduction. Silva et al. (2008) have studied a nonlinear mixed-integer optimization technique, in which the OCP problem is solved using bus bar sensitivity index and a sigmoid function. In (Hamouda and Sayah 2013), the authors utilize heuristic search-based node stability indices for solving OCP problem by optimizing power loss and net savings. While in (Muthukumar et al. 2018), the authors have proposed a hybrid harmony search differential evolution algorithm for addressing the OCP problem.

In recent times, many nature-inspired intelligent optimization algorithms have been implemented for addressing the OCP problem. In (Kanan et al. 2011), the authors have applied a combination of fuzzy differential evolution (fuzzy-DE) and multi-agent particle swarm optimization (MAPSO) algorithms for the OCP problem by maximizing the cost function, which includes both energy cost and capacitor cost. While in (El-Fergany and Abdelaziz 2014a), the authors present an objective function comprising capacitor installation, maintenance and reactive power costs, which is minimized using the cuckoo search (CS) algorithm. El-Fergany (2014) incorporates voltage sensitivity index along with energy loss and capacitor cost in the objective function for its minimization using the artificial bee colony algorithm (ABCA). An effort in (Gampa and Das 2016) has been made by considering the minimization of multi-objective function using a combination of fuzzy-genetic algorithm, which includes different membership functions in its objective. In (Dixit et al. 2018), the authors solved the OCP problem employing a modified Gbest-guided artificial bee colony (MGABC) algorithm by taking a combination of power loss, total cost and voltage deviation as the objective function for the optimization. Whereas, a combined optimization approach (COA) of salp swarm algorithm and loss sensitivity indices has been proposed in (Youssef et al. 2018) by considering total system cost and active power losses as the objective function. In (Olabode et al. 2019), the firefly algorithm (FA) and voltage sensitivity index (VSI) based approaches are utilized to solve the OCP problem for a Nigerian distribution system. The OCP issue is solved using a discrete version of the vortex search algorithm (DVSA) with the objective of minimizing the total system cost in (Gil-González et al. 2020). In this method, a Gaussian distribution is combined with an exponential function to maintain a balance between exploitation and exploration phases of the algorithm, thus, assisting it in obtaining a
solution near to global optima value. The authors in (Al-Ammar et al. 2021) have proposed a multi-objective salp swarm algorithm (MOSSA) for solving the OCP issue, which generates a set of pareto optimal solutions. Thereafter, a final optimum solution is derived from these pareto optimal solutions using a fuzzy based method. The OCP problem is considered as a nonlinear mixed integer programming problem in the work carried out in (Riaño et al. 2021), which is solved using Chu and Beasley genetic algorithm (CBGA). Whereas, in (Mtonga et al. 2021), the authors employ the multiverse optimizer (MO) for the OCP issue. The approach used offers reduced total system cost and improved system performance. As per the “No Free Lunch” theorem, there exist no optimization techniques that may be stated as best suited for solving a given optimization problem. Therefore, different state-of-the-art optimization techniques have been proposed by many researchers for solving OCP problem such as clustering based optimization (CBO) (Vuletic and Todorvski 2014), teaching learning based optimization (TLBO) (Sultana and Roy 2014), bacterial foraging optimization algorithm (BFA) (Devbalaji et al. 2015), penalty free genetic algorithm (PFGA) (Vuletic and Todorovski 2016), evolution algorithm (EA) (El-Fergany 2013), plant growth simulation algorithm (PGSA) (Rao et al. 2011), gravitational search algorithm (GSA) (Shuaib et al. 2015), modified monkey search optimization (MMSO) technique (Duque et al. 2015), particle swarm optimization (PSO) approach (Lee et al. 2015), improved harmony algorithm (IHA) (Ali et al. 2016), crow search algorithm (CSA) (Montazeri and Askarzadeh 2019), flower pollination algorithm (FPA) (Abdelaziz et al. 2016) and so on. It is observed that most of these techniques are less sensitive to initial solution and may easily escape local optima.

Sine cosine algorithm (SCA) algorithm, a simple and powerful swarm intelligence based optimization technique introduced by Mirjalili (2016), has been implemented by many researchers in the past for solving various complex engineering/non-engineering problems and outperforms many algorithms in terms of results obtained. However, similar to other swarm intelligence algorithms, SCA suffers poor optimization precision and slow convergence speed while solving complex problems of large-scale electrical power systems (Elaziz et al. 2017). Therefore, in (Elaziz et al. 2017), an opposition based learning (OBL) technique is proposed in order to improve the performance of SCA. In opposition based approach, the initial population is generated from the pool of both current and opposite solution vectors, which enhances the searching efficiency of the basic algorithm. However, quasi-opposition based learning (QOBL) technique, developed by authors in (Rahnamayan et al. 2007), is considered more superior to the OBL approach. In the past, algorithms blended with QOBL concept have been implemented by many researchers for solving different real-world problems and the improvement in terms of result has been observed in comparison to their basic form and the form with the OBL concept (Shiva et al. 2015; Roy and Sarkar 2014). This motivates the authors in the present work to make a maiden attempt towards implementation of QOBL concept in the basic SCA with an aim to enhance its convergence speed in finding global optimal solution. The concept of QOBL is integrated with the fundamental SCA and this new hybrid manifested algorithm
is termed as quasi-opposition based sine cosine algorithm (QOSCA). In the present work, the capability of the proposed QOSCA is effectively exploited for solving the OCP problem. Before that, the performance capability of the proposed QOSCA is verified by applying it to the different unimodal and multimodal benchmark test functions and compared the output results obtained with other optimization algorithms.

As surfaced in the literature, it is observed that most of the researchers follow a two-step approach for solving the OCP problem. At first, the weak and more deserving buses for capacitor placement are identified using different sensitivity analysis methods. In the second step, among the identified deserving buses, the optimal location and the selection of fixed-step capacitor banks are found utilizing optimization techniques. The sensitivity analysis reduces search space for the optimization process and also decreases the chances of being converged to local optima. The authors in (Rao et al. 2011) use loss sensitivity factor (LSF) for selecting candidate buses for the optimization method. Whereas, in (El-Fergany and Abdelaziz 2014a), power loss index (PLI) has been utilized to find potential weak buses for OCP using CS algorithm. A comparative study between LSF and PLI has been carried out in (El-Fergany 2013). In (El-Ela et al. 2016), two loss sensitivity indices have been used for selecting weak buses for further treatment using the ant colony optimization (ACO) approach. Based on loss sensitivity and voltage sensitivity indices, a new

| Table 1 | A summary of the published literatures in comparison to the presented work |
|---------|--------------------------------------------------------------------------------|
| References | Techniques | Sensitivity analysis technique | Loading condition | Objective functions |
| Rao et al. 2011 | PGSA | LSF | Fixed | ✓ |
| Kannan et al. 2011 | Fuzzy-DE and fuzzy-MAPSO approach | Fuzzy | Fixed | ✓ |
| El-Fergany 2013 | EA | PLI and LSF | Fixed | ✓ |
| El-Fergany and Abdelaziz 2014a | CS algorithm | PLI | Multiple | ✓ |
| El-Fergany 2014 | ABCA | LSF | Multiple | ✓ |
| Sultana and Roy 2014 | TLBO | LSF | Multiple | ✓ | ✓ |
| Vuletic and Todorovski 2014 | CBO | LSF | Multiple | ✓ |
| Devabalaji et al. 2014 | BFA | LSF and VSI | Multiple | ✓ |
| Duque et al. 2015 | MMSO | - | Fixed | ✓ |
| Lee et al. 2015 | PSO | - | Fixed | ✓ | ✓ |
| Shuaib et al. 2015 | GSA | LSF | Fixed | ✓ |
| Abdelaziz et al. 2016 | FPA | LSF, VSI | Multiple | ✓ |
| Ali et al. 2016 | IHA | LSF, VSI | Multiple | ✓ |
| Gampa and Rao 2016 | Fuzzy-GA | LSI, VSI | Multiple | ✓ | ✓ | ✓ |
| Vuletic and Todorovski 2016 | PFGA | - | Multiple | ✓ |
| Dixit et al. 2018 | MGABC | LSF | Multiple | ✓ |
| Muthukumar et al. 2018 | HSA and DE | LSF | Multiple | ✓ |
| Youssef et al. 2018 | SSA | LSF | Multiple | ✓ |
| Olabode et al. 2019 | FA | VSI | Fixed | ✓ |
| Montazeri and Askarzadeh 2019 | CSA | PLI, LSF | Fixed | ✓ |
| Gil-González et al. 2020 | DVSA | - | Fixed | ✓ |
| Al-Ammar et al. 2021 | MOSSA | - | Fixed | ✓ | ✓ | ✓ |
| Riaño et al. 2021 | CBGA | - | Fixed | ✓ |
| Mtonga et al. 2021 | MO | LSF | Fixed | ✓ |
| Proposed method | QOSCA | PLI, VDI | Multiple | ✓ | ✓ | ✓ |

In the 5th column, the A, B, C, D parameters refer to the system cost, active power line losses, reactive power line losses and system line currents as objective functions, respectively; and in the 3rd column an entry ‘-’ means not applicable.
sensitivity analysis is proposed in (Gampa and Das 2016). In (Montazeri and Askarzadeh 2019), a modified power loss index has been implemented.

From Table 1, it may be observed that the majority of approaches considered minimization of total system cost and active power line losses as their objective function to solve the OCP problem. Reactive power line losses and line current capacity are mostly considered as constrained parameters or for sensitivity analysis, while these parameters are very rarely considered as the objective function for algorithmic processes. Therefore, in the present work, all of these parameters are taken into account in formulating the objective function. Apart from this, in the present work, a new index for sensitivity analysis is proposed for selecting weak and deserving candidate buses for OCP in the adopted standard IEEE 85 and 118 bus radial distribution systems. The new sensitivity index is constituted considering PLI and voltage deviation index (VDI) by giving equal priority to both of them. The proposed sensitivity index is used to sort the buses in terms of suitability for the capacitor placement. Following this, the possible bus locations are presented to the SCA and the proposed QOSCA for assessing the optimal location and selection of capacitor banks. Discrete and switchable capacitor banks are considered for different loading conditions. The output results yielded using the proposed approach for different standard IEEE test systems are compared with results reported in the other published literature. The results obtained confirm the superiority of the proposed approach. In order to further confirm the robustness of the proposed approach in solving the OCP problem, Wilcoxon’s signed rank test is conducted. The main contributions of the paper are listed below.
(a) An improved version of SCA, referred as QOSCA, is proposed for the first time.
(b) The performance of the proposed QOSCA is tested over different benchmark test functions.
(c) The OCP issue within the adopted radial distribution test systems is solved using SCA and the proposed QOSCA.
(d) A new sensitivity analysis is proposed for selecting the most deserving candidate buses for OCP.
(e) Different loading conditions are taken into consideration to make the approach more realistic.
(f) The proposed methodology is statistically analyzed using Wilcoxon's signed rank test to prove its robustness in solving the OCP problem.

The remaining paper is structured as follows. In Section 2, the formulation of the objective function considering different constraint factors is presented. The proposed sensitivity index analysis is illustrated in Section 3. The adopted load flow algorithm is described in Section 4. Section 5 explains the proposed QOSCA. Simulation results are presented in Section 6 followed by conclusion in Section 7.

2 Problem formulation

The main objective of OCP in a radial distribution system is to decrease the line losses by bringing bus voltages within the allowable limit and, thus, maximizing the net annual profit of the system. In this work, the objective is formulated by (1)
\[
\text{minimize } \left( \frac{\cos t_a * w_1}{\cos t_b} + \frac{APL_a * w_2}{APL_b} + \frac{RPL_a * w_3}{RPL_b} + \frac{LC_a * w_4}{LC_b} \right)
\]

where, \(\cos t_a\) and \(\cos t_b\) are the total cost per year, \(APL_a\) and \(APL_b\) are the active power line losses, \(RPL_a\) and \(RPL_b\) are the reactive power line losses and, \(LC_a\) and \(LC_b\) are the sum of line currents of the distribution system. Here, suffixes ‘a’ and ‘b’ represent before and after compensation, respectively. The best value of weightage factors are selected based on the number of trial runs and finalized as \(w_1 = 0.55\), \(w_2 = 0.15\), \(w_3 = 0.15\) and \(w_4 = 0.15\). For calculating the cost of the system, an expression shown in (2) is used

\[
\text{Cost} = K_P * APL * T + D \left( K_I * NC + K_C * \sum_{i=1}^{NC} Q_{Ci} \right) + K_O * NC
\]

where, \(NC\) is the number of capacitor banks. The value and the notational description of all other constants are given in Table 2 and are taken from the work presented in (El-Fergany and Abdelaziz 2014b).

2.1 Operational constraints

While employing the adopted optimization techniques, certain constraint factors need to be ensured that they exist within the allowable range at each iteration. The constraints that are taken for the current work are presented below.

2.1.1 Bus voltage constraint

The voltage at each bus must be within their reasonable minimum and the maximum limits as stated by (3)

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

where, \(V_i\) is the voltage at \(i\)th bus and \(V_{\text{min}}\) and \(V_{\text{max}}\) are the minimum and the maximum allowable voltage limits, respectively.

2.1.2 Capacitor size constraint

The reactive power injection by the capacitor banks must exists within their minimum and the maximum limits as given by (4)

\[
Q_{C_{\text{min}}} \leq Q_{C_j} \leq Q_{C_{\text{max}}}
\]

where, \(Q_{C_j}\) is the reactive power injected at the \(j\)th bus and \(Q_{C_{\text{min}}}\) and \(Q_{C_{\text{max}}}\) denote the minimum and the maximum allowable kVAR limits of capacitor banks, respectively.
3 Identification of potential buses

The main aim of identifying potential buses is that it significantly cuts the search space for the optimization process. In this paper, a new sensitivity index has been proposed for identifying potentially weak buses which are more sensitive for capacitor placement than others. This process reduces overall system loss and notably improves the voltage profile of the system. Here, in this analysis, equal preference is given to both reductions of line losses and bus voltage deviation. Separately, PLI and VDI are calculated for each bus and, finally, sensitivity index for all the buses are calculated giving equal weightage to both. The proposed sensitivity index (SI) is given by (5)

\[ SI = PLI \times 0.5 + VDI \times 0.5 \] (5)

where, PLI and VDI are expressed by (6) and (7), respectively.

\[ PLI = \frac{LR(i) - LR_{min}}{LR_{max} - LR_{min}} \] (6)

The loss reduction (LR) is obtained for each bus by compensating the total reactive load at that bus considering one bus (except slack bus) at a time. \( LR_{min} \) and \( LR_{max} \) are the minimum and the maximum system loss reduction, respectively. After calculating LR, PLI for every bus is obtained using (6). The VDI component of (5) is given by (7).

\[ VDI = \frac{CVD(i) - CVD_{min}}{CVD_{max} - CVD_{min}} \] (7)

The VDI is found for every bus except slack bus. \( CVD_{min} \) and \( CVD_{max} \) are the minimum and the maximum cumulative voltage deviation (CVD) in the system, respectively. The CVD is defined by (8)

\[ CVD = \begin{cases} 0 & \text{if } 0.95 \leq V_i \leq 1.0 \\ \sum_{i=1}^{NB} 1 - V_i & \text{else} \end{cases} \] (8)

where, \( NB \) is the total number of network buses. CVD for each bus is calculated by compensating total reactive load at that bus by taking one bus at a time except slack bus. Thereafter, VDI is calculated for each bus using (7).

4 Load flow

In a radial distribution system, the buses are connected end to end and has only one feeder end. Also, it has high resistance (\( R \)) to reactance (\( X \)) ratio, which makes the traditional load flow approaches like the Newton-Raphson method, Gauss-Seidal method and other load flow approaches less efficient and convergent. Various load flow methodologies have been proposed by many researchers for addressing the above-mentioned issue in the recent past. In (Shen et al. 2018), a methodology is presented that utilizes the
graph theory based power flow approach for solving the load flow problem of radial and mesh structure distribution systems. A modified backward-forward sweep method based load flow is proposed in (Montoya et al. 2020) that utilizes branch-to-node incidence matrix and is suitable for both radial and mesh distribution systems. A new successive approximations based load flow approach is presented in (Herrera-Briñez et al. 2021). Its comparative performance study with the existing backward-forward sweep load flow approach is also demonstrated in order to establish the equivalence of the suggested methodology with the existing method. In this work, a direct approach based on (Teng 2003) is applied for finding load flow solution of the studied radial distribution systems. This method utilizes two different matrices named as bus injection to branch current (BIBC) matrix and the branch current to bus voltage (BCBV) matrix for determining load flow solutions. The procedure of the adopted load flow algorithm is elaborated thoroughly below by considering a simple 6 bus radial distribution system as shown in Fig. 1.

![Single line diagram of a simple distribution system](image)

From Fig. 1, the \(i\)th branch currents (\(IB_i\)), in terms of \(i\)th bus load currents (\(IL_i\)) may be stated in matrix form by (9). 

\[
\begin{bmatrix}
IB_1 \\
IB_2 \\
IB_3 \\
IB_4 \\
IB_5 \\
IB_6
\end{bmatrix} =
\begin{bmatrix}
1 & 1 & 1 & 1 & 1 & 0 \\
0 & 1 & 1 & 1 & 1 & 0 \\
0 & 0 & 1 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
IL_1 \\
IL_2 \\
IL_3 \\
IL_4 \\
IL_5 \\
IL_6
\end{bmatrix}
\]  

(9)

In generalized form, (9) may be written as (10). 

\[
\begin{bmatrix}
IB_1 \\
IB_2 \\
IB_3 \\
IB_4 \\
IB_5 \\
IB_6
\end{bmatrix} = [BIBC][IL]
\]  

(10)

The relation between the branch current and the bus voltage may be stated in matrix form by (11). 

\[
\begin{bmatrix}
V_1 \\
V_2 \\
V_3 \\
V_4 \\
V_5 \\
V_6
\end{bmatrix} =
\begin{bmatrix}
Z_{12} & 0 & 0 & 0 & 0 & 0 \\
Z_{12} & Z_{23} & 0 & 0 & 0 & 0 \\
Z_{12} & Z_{23} & Z_{34} & 0 & 0 & 0 \\
Z_{12} & Z_{23} & Z_{34} & Z_{45} & 0 & 0 \\
Z_{12} & Z_{23} & 0 & 0 & Z_{36} & 0 \\
Z_{12} & Z_{23} & 0 & 0 & 0 & Z_{36}
\end{bmatrix}
\begin{bmatrix}
IB_1 \\
IB_2 \\
IB_3 \\
IB_4 \\
IB_5 \\
IB_6
\end{bmatrix}
\]  

(11)
In (11), $Z_{mn}$ signifies the line impedance of the branch connected between the $m$th bus and $n$th bus of a radial distributed system and may be represented as $Z_{mn} = R_{mn} + jX_{mn}$. In generalized form, (11) may be written as (12).

$$[\Delta V] = [BCBV][IB]$$  \hspace{1cm} (12)

Using (10) and (12) we may write,

$$[\Delta V] = [BCBV][BIBC][IL]$$

$$= [DLF][IL]$$  \hspace{1cm} (13)

The distribution load flow solution is obtained by solving (14) and (15), iteratively, till the sum of change in voltage ($V$) at each bus is less than $10^{-8}$.

$$I_{il}^t = \left(\frac{P_i + jQ_i}{V_i^t}\right)^*$$  \hspace{1cm} (14)

$$[V^{t+1}] = [V^o] + [DLF][I_{il}^k]$$  \hspace{1cm} (15)

Where, $P_i$ and $Q_i$ are the $i$th bus active and reactive power load demands, respectively. $t$ is the current iteration count and $V^o$ is the slack bus voltage (considered as 1 p.u.). The total line losses of a system is calculated using (16) and (17)

$$APL = \sum_{i=1}^{NB-1} I_{bi}^2 R_i$$  \hspace{1cm} (16)

$$RPL = \sum_{i=1}^{NB-1} I_{bi}^2 X_i$$  \hspace{1cm} (17)

5 SCA and QOSCA

5.1 SCA

SCA is initially proposed by Mirjalili in 2016 (Mirjalili 2016). It is a stochastic population based optimization technique that uses sine and cosine mathematical functions for producing new updated solutions. At first, the initial population matrix is randomly created taking different constraints factors into consideration. After that, the fitness value of each generated population is evaluated using the proposed objective function stated in (1) and the best solution in terms of fitness is selected as $G_{best}$. The solutions are then improved using (18). If the current best solution in terms of fitness is superior than the previous
best solution, then it is considered as the new $G_{best}$. After the completion of all steps involved in the algorithm, the best solution is considered as the desired output.

$$G_{i}^{t+1} = \begin{cases} 
G_{i}^{t} + k_{1} \cdot \sin(k_{2}) \cdot |k_{3}F_{i}^{t} - G_{i}^{t}|, & k_{4} < 0.5 \\
G_{i}^{t} + k_{1} \cdot \cos(k_{2}) \cdot |k_{3}F_{i}^{t} - G_{i}^{t}|, & k_{4} \geq 0.5 
\end{cases}$$

(18)

Where, $t$ is the current iteration number, $G_{i}^{t}$ is the $i$th dimension value of the agent at the $t$th iteration and $F_{i}^{t}$ is the $i$th dimension value of the optimum individual at the $t$th iteration. $k_{1}$, $k_{2}$, $k_{3}$ and $k_{4}$ are the random numbers. $k_{1}$ is defined as $k_{1} = a - t \frac{a}{MT}$. Where, $MT$ is the maximum number of iteration and $a$ is a constant taken as 2.

5.2 QOSCA

OBL is a concept developed by Tizhoosh (2005), has been utilized by many authors for improving the convergence rate of the different computational optimization methods. In OBL, the concept of both current and the opposite solutions are considered together for generating new solutions. In many literatures, it has been verified that the opposite candidate solution has a better probability of getting closer to the optimum solution than the random solutions. In order to explain the mathematics behind OBL in detail, the concept of opposite number and the opposite point are described below.

5.2.1 Opposite number

Let us consider the initial population as a real number $G_{o}$ lying within the interval $[m,n]$. Then, the opposite number $OG_{o}$ is defined by (19).

$$OG_{o} = m + n - G_{o}$$

(19)

5.2.2 Opposite point

Let us consider a point in $d$-dimensional search space $G(G_{1},G_{2},\ldots,G_{d})$ lying within the interval $[m_{i},n_{i}]$; $i = \{1,2,\ldots,d\}$. Then, the opposite point $OG$ is defined by (20).

$$OG_{i} = m_{i} + n_{i} - G_{i}$$

(20)

The concept of OBL has been implemented for SCA in (Elaziz et al. 2017) by Elaziz et al. and the considerable improvement in the desired results is shown. However, Rahnamayan et al. (2007) have suggested the concept of QOBL, which is considered as more superior in terms of performance than OBL. The concept of quasi-opposite number and the opposite point are described below.
5.2.3 Quasi-opposite number

Let us consider the initial population as a real number \( (G_o) \) existing within the interval \([m,n]\). Then, the quasi-opposite number \( (QOG_o) \) is defined by (21).

\[
QOG_o = \text{rand}\left(\frac{m+n}{2}, m+n-G_o\right)
\] (21)

The pseudo code for finding quasi opposite number is given in Algorithm 1.

---

**Algorithm 1**: Pseudo code for quasi-opposite number

\[
M = \frac{(m+n)}{2};
\]
% M is the center of search space

if \((G_o < M)\)  
\[
QOG_o = M + (G_o - M) \times \text{rand}(0,1);
\]
else  
\[
QOG_o = G_o + (M - G_o) \times \text{rand}(0,1);
\]
End

---

5.2.4 Quasi-opposite point

Let us consider, a point in \(d\)-dimensional search space \( G(G_1, G_2, \ldots, G_d) \) lying within the interval \([m_i, n_i]\); where \(i = \{1, 2, \ldots, d\}\). Then, the quasi-opposite point \( (QOG) \) is defined by (22).

\[
QOG_i = \text{rand}\left(\frac{m_i+n_i}{2}, m_i+n_i-G_i\right)
\] (22)

The pseudo code for finding quasi opposite point is given in Algorithm 2.

---

**Algorithm 2**: Pseudo code for quasi-opposite point

\[
M_i = \frac{(m_i+n_i)}{2};
\]

if \((G_{o_i} < M_i)\)  
\[
QOG_{o_i} = M_i + (G_{o_i} - M_i) \times \text{rand}(0,1);
\]
else  
\[
QOG_{o_i} = G_{o_i} + (M_i - G_{o_i}) \times \text{rand}(0,1);
\]
End

---

5.2.5 Quasi-opposition based population initialization

In case of having no prior knowledge about the solution(s), a better starting population may be generated utilizing the QOBL concept. The steps for QOBL are specified below.
(a) The initial population is generated using random function.
(b) Quasi-opposite population is calculated using (22).
(c) Both random and quasi-opposite populations are combined and according to their fittest objective value, the best $N$ solutions are considered as the initial population.

5.2.6 Quasi-oppositional generation jumping

The concept of quasi-opposition based population generation is implemented in order to increase the diversity among them, which may lead the evolutionary process to jump to a new fitter candidate solution. While executing the algorithm, a concept similar to the quasi-opposition based initial population generation is employed to the current population within the iterative loop. On the basis of jumping rate/jumping probability $\left( J_r \right)$, a new quasi-opposite population is generated using (22). But here, instead of taking the predefined minimum and the maximum boundary limits, the lowest and the highest value of each variable in the current population are taken for the calculation. The pseudo code of the proposed QOSCA is presented as Algorithm 3.

---

**Algorithm 3**: Pseudo code for the proposed QOSCA

**Step 1** Set the parameters: the minimum and the maximum boundary limit of the parameters, number of iterations, population size.

**Step 2** Initialize the population matrix by utilizing random function.

**Step 3** Quasi oppositional initialization

```matlab
for i = 1 : N % N is the number of population
    for j = 1 : d % d is the dimension size of the function
        \text{OG}_{o_i,j} = m_j + n_j - G_{o_i,j};
        M_{i,j} = \left( m_j + n_j \right) / 2;
        \text{if} \ (G_{o_i,j} < M_{i,j})
            QOOG_{o_i,j} = M_{i,j} + \left( \text{OG}_{o_i,j} - M_{i,j} \right) \times \text{rand}(0,1);
        \text{else}
            QOOG_{o_i,j} = \text{OG}_{o_i,j} + \left( M_{i,j} - \text{OG}_{o_i,j} \right) \times \text{rand}(0,1);
        \text{end} % end of if loop
    end % end of for loop
end % end of for loop
```

Select the $N$ fittest individuals from the union of the initial population and quasi-oppositional initial population and find the fittest solution and $g_{\text{best}}$.

**Step 4** Starting of the iterative loop

```matlab
while (i < maximum iteration)
    \text{$k_1$} = a - t \frac{a}{MT} ; \ % \text{MT} \text{ is the maximum number of iteration and } a = 2
    for i = 1 : N
        for j = 1 : d
```

14
\[ \begin{align*}
k_2 &= 2\pi \times \text{rand}(0,1) ; \\
k_3 &= 2 \times \text{rand}(0,1) ; \\
k_4 &= \text{rand}(0,1) ; \\
\text{if } k_4 < 0.5 \\
G'_{\text{new},i,j}^t &= G_{i,j}^t + k_1 \times \sin(k_2) \times \left| k_3 F_i^t - G_{i,j}^t \right| ; \\
\text{else} \quad G'_{\text{new},i,j}^t &= G_{i,j}^t + k_1 \times \cos(k_2) \times \left| k_3 F_i^t - G_{i,j}^t \right| ; \\
\text{end } \% \text{ end of if loop} \\
\text{if } f(G_{\text{new}}_i > G_i) \\
G_i &= G_{\text{new}}_i ; \\
\text{end } \% \text{ end of if loop} \\
\text{end } \% \text{ end of for loop} \\
\text{end } \% \text{end of for loop} \\
\text{Step 5 Starting of quasi-oppositional generation jumping} \\
\text{if } (\text{rand}(0,1) < J_r) \\
\text{for } i = 1 : N \\
\text{for } j = 1 : d \\
OG_{i,j} = m_{i,j}(gn) + n_{i,j}(gn) - G_{i,j} ; \\
% \text{ } m_{i,j}(gn) \text{ is the minimum value of the } j\text{th variable of } i\text{th parameter in the current iteration (gn)} \\
% \text{ } n_{i,j}(gn) \text{ is the maximum value of the } j\text{th variable of the } i\text{th parameter in the current iteration} \\
M_{i,j} = \left( m_{i,j}(gn) + n_{i,j}(gn) \right) / 2 ; \\
\text{if } (G_{i,j} < M_{i,j}) \\
QOG_{i,j} = M_{i,j} + (OG_{i,j} - M_{i,j}) \times \text{rand}(0,1) ; \\
\text{else} \quad QOG_{i,j} = OG_{i,j} + (M_{i,j} - OG_{i,j}) \times \text{rand}(0,1) ; \\
\text{end } \% \text{end of if loop} \\
\text{end } \% \text{end of for loop} \\
\text{end } \% \text{end of for loop} \\
\text{Select } N \text{ fittest population and keep track of the best solution.} \\
\text{end } \% \text{end of while loop} \\
\text{Step 6 Obtained the current best solution as the desired solution.} \\
\end{align*} \]

6 Result and discussion

Firstly, the effectiveness in the performance of QOSCA is evaluated by applying it to five different standard unimodal and multimodal benchmark test functions. Later, the performance of the proposed QOSCA in solving the OCP problem is verified considering different standard radial distribution test systems. In the present work, IEEE standard 85 bus and 118 bus test systems with different loading
conditions are considered for OCP and these are presented as a different case study. As reactive power compensation varies with different loading conditions, hence, switchable capacitor banks are considered for the placement at the right location. The search space for the optimization process has been reduced significantly by detecting the potentially weak buses using sensitivity analysis. Based on the calculated value of the proposed sensitivity index, the buses are sorted in descending order of their sensitivity value and a fixed number of buses (user-defined) from the top are selected as an input to the proposed optimization approach for OCP. The values of the constants used for cost calculations are given in Table 2. The bus voltage constraint limit is taken as 0.9 p.u. to 1.1 p.u. The allowable capacitor bank size limit varies between 0 to 1500 kVAr in the step of 50 kVAr. The optimal results obtained employing other optimization techniques (as reported in literature) are utilized in the adopted load flow algorithm for the performance comparison with respect to the approach proposed in this work. This is done to avoid unnecessary incongruities. The code for SCA and the proposed QOSCA have been realized using MATLAB®. For both IEEE 85 and IEEE 118 bus test systems, the population size is taken as 50. The results of importance are

| S. No. | Parameter description | Value |
|--------|----------------------|-------|
| 1      | Average energy cost ($K_p$) | $0.06/kWh |
| 2      | Depreciation factor ($D$) | 20% |
| 3      | Purchase cost ($K_C$) | $25/kVAr |
| 4      | Installation cost ($K_I$) | $1600/location |
| 5      | Operation cost ($K_O$) | $300/year/location |
| 6      | Hours per year ($T$) | 8760 |

Table 3
Details of benchmark test functions (Nematollahi et al. 2017)

| Name      | Range     | Dimension | Formulation                                      | Min |
|-----------|-----------|-----------|-------------------------------------------------|-----|
| Sphere    | [-100,100]| 30        | $f_1(n) = \sum_{i=1}^{d} n_i^2$                  | 0   |
| Schwefel 2.22 | [-10,10] | 30        | $f_2(n) = \sum_{i=1}^{d} |n_i| + \prod_{i=1}^{d} |n_i|$ | 0   |
| Schwefel 1.2 | [-100,100]| 30       | $f_3(n) = \sum_{i=1}^{d} \left( \sum_{j=1}^{i} n_j \right)^2$ | 0   |
| Rastrigin | [-5.12,.12]| 30       | $f_4(n) = \sum_{i=1}^{d} n_i^2 - 10\cos(2\pi n_i) + 10$ | 0   |
| Ackley    | [-32,32]  | 30        | $f_5(n) = -20\exp\left(-0.2\sqrt{\frac{1}{N} \sum_{i=1}^{d} n_i^2}\right) - \exp\left(\frac{1}{N} \sum_{i=1}^{d} \cos(2\pi n_i)\right) + 20 + e$ | 0   |
highlighted in bold in their respective tables associated with each of the studied cases and an entry of ‘-’ in each table means not applicable.

6.1 Case study 1: Mathematical benchmark problems

The proposed QOSCA is tested on five different benchmark test functions. The benchmark functions consist of different unimodal and multimodal test functions and the details of the same are given in Table 3. For evaluating the effectiveness of the proposed QOSCA, a comparative analysis with other established algorithms in terms of the mean and standard deviation of the obtained results are illustrated in Table 4. 30 different trial runs are considered for calculating the mean and standard deviation value of the outputs. While executing the proposed algorithm, the population size is considered as 40, whereas, the number of iterations is taken as 500. From Table 4, it may be seen that for all the five benchmark functions, QOSCA gives better results than other algorithms. The improved performance of QOSCA over SCA in terms of

![Comparative convergence curve obtained using SCA and the proposed QOSCA for different benchmark functions](image)

**Fig. 2** Comparative convergence curve obtained using SCA and the proposed QOSCA for different benchmark functions (a) Sphere, (b) Schwafel 2.22, (c) Schwafel 1.2, (d) Rastrigin and (e) Ackley
convergence profile corresponding to different benchmark functions is shown in Fig. 2. From Table 4 and Fig. 2, it may be concluded that QOSCA offers better results than the basic SCA.

6.2 Case Study 2: IEEE 85 bus test system

In this case study, the line and load data of the standard IEEE 85 bus test system are taken from the work of (Das et al. 1995). The single line diagram of the IEEE 85 bus test system is shown in Fig. 3. The total base load of this studied system is given as (2570.28+j2622.2) kVA. While performing the simulation, the system base value for voltage and power is considered as 11 kV and 100 MVA, respectively. After executing the load flow algorithm, the uncompensated active and reactive power line losses of the

![Fig. 3 Single line diagram of standard IEEE 85 bus test system](image)
considered system are obtained as 316.135 kW and 198.613 kVAr, respectively. Further, sensitivity analysis is carried out and the buses are sorted (based on calculated index value) in their preference order for capacitor placement as 54, 55, 51, 76, 69, 74, 39, 72, 66, 28, 38, 61, 60, 82, 80 and so on. From the results found, the top 16 buses are nominated as potential buses for capacitor placement. Among these suitable buses, optimal location and selection of the fixed-step capacitor banks for their placement are found utilizing the proposed QOSCA. In this case study, three different loading conditions (represented as load factor in Table 6) have been considered and the results obtained are compared with those yielded using other reported algorithms. The comparative convergence profiles obtained using SCA and QOSCA are shown in Fig. 4a. The comparative improvement in system bus voltages before and after the compensation is displayed in Fig. 4b. Table 5 presents the comparison between different parameters’ values obtained using the proposed QOSCA and the other adopted state-of-the-art algorithms. For full load condition, the QOSCA finds 5 best locations (i.e., bus number 28, 54, 60, 69 and 80) for capacitor placements with a total compensation of 2100 kVAr. As a result, the active and reactive power line losses of the system are reduced to 149.182 kW and 92.654 kVAr, respectively. While, the minimum bus voltage of the system (associated with the bus number 54) is increased from 0.871 p.u. to 0.921 p.u. The net annual profit using the cost formula is obtained as $74150.217, which is better among other compared algorithms and, thus, proves the superiority of the proposed algorithm over the others. The time required to execute the SCA and QRSCA for solving the OCP problem are found as 7.31 s and 14.14 s, respectively (see Table 5). It is to note here that the elapsed time is dependent on a variety of factors such as the characteristics of the computers used

| Parameters | Uncompensated results | Compensated results |
|------------|-----------------------|---------------------|
| Capacitor locations and their sizes | | |
| Capacitor size | 15(150) | 9 (840) |
| Capacitor size | 23(300) | 34(660) |
| Capacitor size | 26(300) | 60(650) |
| Capacitor size | 32(150) | 34(400) |
| Capacitor size | 36(150) | 54(150) |
| Capacitor size | 38(150) | 58(350) |
| Capacitor size | 45(150) | 64(500) |
| Capacitor size | 52(150) | 83(250) |
| Capacitor size | 57(300) | 61(300) |
| Capacitor size | 61(150) | 68(300) |
| Capacitor size | 64(300) | 80(300) |
| Capacitor size | 73(150) | |
| Capacitor size | 82(150) | |
| Total kVAr | 2550 | 2150 |
| APL (kW) | 316.135 | 143.244 |
| % Loss Reduction | - | 54.69 |
| RPL (kVAr) | 198.613 | 94.728 |
| Vmin (p.u.) | 0.871 | 0.924 |
| Net savings ($) | - | 70061.51 |
| % saving | - | 42.16 |
| Elapsed time (in s) | 18.38 | 8.69 |

Table 5
Summaries and results for IEEE 85 bus test system under full load condition

- Uncompensated results
- Compensated results
- TLBO (Sultana and Roy 2014)
- BFA (Devabalaji et al. 2015)
- IHA (Ali et al. 2016)
- ACO (El-Ela et al. 2016)
- COA (Youssef et al. 2018)
- SCA (Studied)
- QOSCA (Proposed)
to execute the simulations, the population size of the adopted algorithms, and so on, which may differ in different published literature. The computational time taken by the proposed approach is in the range of one minute, which can be considered as efficient as per metaheuristic standards (Montoya et al. 2020a). Comparison of output results obtained utilizing the proposed and other state-of-the-art algorithms (as reported in earlier works) under different loading conditions is presented in Table 6.

### Table 6
Results of IEEE 85 bus test system for different loading conditions

| Load factor | Parameters | Uncompensated results | Compensated results | QOSCA (Proposed) |
|-------------|------------|------------------------|---------------------|------------------|
|             |            | IHA (Ali et al. 2016)  | QOSCA (Proposed)    |                  |
|             |            | Values                 | Location (Size (in kVAR)) | Values | Location (Size (in kVAR)) |
| 1           | APL (kW)   | 316.135                | 147.605             | 5 locations     | 149.182  |
|             | RPL (kVAR) | 198.613                | 91.832              |                 | 92.654   |
|             | Vmin (p.u.)| 0.871                  | 0.924               |                 | 0.921    |
|             | Net savings ($) | -                     | 72989.368         |                 | 74150.217 |
| 0.75        | APL (kW)   | 166.967                | 88.620              | 8(250)           | 87.263   |
|             | RPL (kVAR) | 104.953                | 54.110              | 29(350)          | 53.893   |
|             | Vmin (p.u.)| 0.907                  | 0.933               | 58(350)          | 0.939    |
|             | Net savings ($) | -                     | 31449.183         |                 | 33282.496 |
| 0.5         | APL (kW)   | 70.099                 | 38.075              | 8(200)           | 39.093   |
|             | RPL (kVAR) | 44.083                 | 23.363              | 29(350)          | 23.947   |
|             | Vmin (p.u.)| 0.940                  | 0.999               | 58(350)          | 0.956    |
|             | Net savings ($) | -                     | 10471.814         |                 | 10806.987 |

**Net injected kVAR**

- Fixed (location, kVAR): (28,600), (69,250)
- Switched (location, kVAR): (28,150), (54,300), (60,500), (69,150), (80,350)

![Fig. 4](image_url)

**Fig. 4** Results obtained for IEEE 85 bus test case (a) comparative convergence profiles obtained using SCA and the proposed QOSCA and (b) comparison of bus voltages before and after the compensation
6.3 Case Study 3: IEEE 118 bus test system

The data of the standard IEEE 118 bus test system are adopted from (Zhang et al. 2007) with the total base load of the system given as \((22709.71+j17040.97)\) kVA. The system base value for voltage and power are considered the same as that of case study 2. The single line diagram for the present case study is shown in Fig. 5. Employing load flow algorithm, the active and reactive power line losses are obtained as 1297.413 kW and 978.715 kVAr, respectively. In this case study as well, as an outcome of sensitivity analysis, the buses are ranked in their preference order for capacitor placement as 39, 118, 74, 70, 109, 86, 71, 107, 43, 111, 32, 110, 91 and so on. Out of these, the top 18 bus locations are selected and are given as inputs to the proposed QOSCA. Thereafter, the QOSCA further obtains the best locations for the capacitors placement along with their sizes. Three different loading conditions are considered in this case study. The results obtained using QOSCA for different loading conditions are analyzed by comparing it with those yielded using other algorithms. The convergence profile in terms of the objective function is shown in Fig. 6a. The comparative improvement in the system bus voltages before and after compensation is depicted in Fig. 6b. Table 7 presents the comparison between different parameters’ values obtained using the proposed QOSCA and the other adopted algorithms. After performing the optimization process for full load condition, the QOSCA finally finds 9 optimal locations for the capacitor placement with a total compensation of 9650 kVAr. Following this, the active and reactive power line losses of the system are reduced to 841.259 kW and 630.331 kVAr, respectively (refer Table 7). Also, the minimum bus voltage (i.e., for the bus number
77) of the system is improved from 0.869 p.u. to 0.906 p.u. The net annual savings calculated using the cost formula is obtained as $185924.52, which is better with respect to other methodologies. The time required to execute the SCA and QRSCA for solving the OCP problem for this test case are observed to be 12.22 s and 20.34 s, respectively. Comparison of output results obtained utilizing the proposed and other state-of-the-art algorithms under different loading conditions is presented in Table 8.

![Fig. 6](image_url)  
Fig. 6 Results obtained for IEEE 118 bus test case (a) comparative convergence profiles obtained using SCA and the proposed QOSCA and (b) comparison of bus voltages before and after the compensation
For both test cases (85 and 118 bus radial distribution systems), a non-parametric statistical test known as Wilcoxon's signed rank test is used to verify the robustness of the proposed QOSCA for solving the OCP issue as described in (Montoya et al. 2020a, Saha et al. 2017). This study aids in determining how similar the obtained results are, implying that they are statistically comparable. For performing this test, 100 independent trial runs have been executed for both the test cases and the respective outcomes are shown in Table 9.

For the 85 bus test system, after performing the specified independent evaluations, the minimum and the maximum value of the results are obtained as 0.5549 and 0.5649, respectively. The mean and standard deviation values are found to be 0.5615 and 0.0023, respectively. The Wilcoxon’s signed rank test is performed using these data sets, from which the $p$-value in this test case is obtained as 3.8952e-18, which is much lower than the desired value of 0.05. Similarly, for the 118 bus test system, the minimum and the maximum value of the results are obtained as 0.7167 and 0.7346, respectively. The mean and standard deviation values are observed to be 0.7221 and 0.0004, respectively. The $p$-value is found as 3.8966e-18.
and is well within the acceptable limit of 0.05 in this case as well. Furthermore, for both the test case studies, the standard deviation values are observed to be very small, demonstrating that the solution converges to the global optimal value for the vast majority of the time. This demonstrates the robustness of the proposed approach for solving the OCP problem.

7 Conclusion

In this paper, a novel QOSCA is proposed, which utilizes the concept of the quasi-oppositional based learning approach in order to enhance the performance of the basic SCA. For investigating the effectiveness and superiority of the proposed algorithm, its comparative performance analysis with other algorithms using standard benchmark functions is presented. Thereafter, SCA and QOSCA are effectively employed to find the optimal location and selection of fixed-step capacitor banks for IEEE standard 85 bus and 118 bus radial distribution systems. The objective function considered for the algorithmic process comprises of net annual cost, active and reactive power line losses and line currents. The net annual cost includes the cost of energy, the cost of purchase of capacitors and their installation and maintenance costs as well. A new sensitivity index based analysis is proposed for reducing the search space during the optimization process. The supremacy of the proposed algorithm for solving the OCP problem has been verified by comparing its results obtained under different loading scenarios with that of the other recently surfaced state-of-art algorithms. The results obtained employing the proposed method are quite promising in terms of the net annual profit obtained and simultaneous reduction in line losses and enhancement in bus voltage profiles of the system. Furthermore, the robustness of the proposed method in solving the OCP issue of both the studied cases is verified employing a statistical analysis approach based on Wilcoxon’s signed rank test. The results found demonstrates that over a number of independent trial runs, the proposed algorithm converges to the global optimal value in each run with a very little deviation. Finally, it may be concluded from the results obtained that the proposed QOSCA shows improved convergence towards the global optima in comparison to other counterparts.

Compliance with ethical standards

Conflict of interest All authors declare that they have no conflict of interest.

Ethical approval This research does not involve any harmful impact to human participants and/or animals.

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