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*Research Article*

# Hybrid Design of Optimal Capacitor Placement and Reconfiguration for Performance Improvement in a Radial Distribution System

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Distribution System Reconfiguration (DSR) and Optimal Capacitor Placement (OCP) are the most alternative techniques for increasing the power system generation and covering the growth of power demands. These techniques reduce the Radial Distribution System (RDS) losses and enhance the voltage profile. Combining both techniques gives better performance than using the individual technique. In this paper, two operation modes were implemented. First, the individual mode of OCP is applied. Second, the dual mode of DSR after OCP process is applied. Multiobjective functions with considering the weighting factors are used for minimizing real losses, improving voltage profile, and increasing saving cost. The optimal selections of open switches, location, and size of capacitors in the individual and dual design for RDS are achieved using four different optimization algorithms. These algorithms are Modified Biogeography-Based Optimization (MBBO) algorithm, Cuckoo Search (CS) algorithm, Modified Imperialist Competitive (MIC) algorithm, and Modified Bacterial Foraging-Based Optimization (MBFBO) algorithm. These algorithms are applied for two standard networks (IEEE 33- and IEEE 69-bus). Comparisons among the proposed algorithms are done, and the results demonstrated that the MBBO algorithm is the most strong and fast algorithm to attain the optimum solution. In addition, comparisons with literature works are done to validate the effectiveness of proposed algorithms.

## 1. Introduction

The Radial Distribution System (RDS) typology is the most convenient form from protection and control sides. This section of power system suffers from higher losses due to huge branch currents and voltage deviations that caused the power supplied to customers liable to lose the quality and efficiency. The pressure to improve overall efficiency has forced utilities to seek greater efficiency in distributions systems utilizing from communication and computing technology that allow remote supervisory and control [1]. Different solutions have been used such as optimal placement of Distributed Generators (DG) [2, 3], Optimal Capacitor Placement (OCP) [4], Distribution System Reconfiguration (DSR) [5], hybrid of DG and DSR techniques [6, 7], optimal use of electrical equipment, optimal loading transformers, and removal the harmonics in order to reduce the real power losses and enhance the voltage profile. Among them, DSR and OCP are relatively the lesser operating cost [8].

DSR is got by altering the status of closed branches and is frequently prepared for loss reduction. The DSR brings to a combinatorial optimization technique because of several restrictions that should not be infringed through discovering an optimum solution to the DSR technique for loss minimization. This search occurred through the related radial configurations [9]. This also will be more difficult if meta-heuristic algorithms are employed. However, in spite of these limitations, the DSR technique is recommended and an effective approach that required zero working cost [8].

Different works were done for DSR using different optimization algorithms, networks, and objective functions. Guardado et al. proposed an encoding scheme based on paretooptimal solutions using power losses, voltage deviations, and number of operating switches as a multiobjective optimization for DSR problem when applied to real RDS [10]. Voropai and Undraal carried out the DSR with DG problem for the power system of Mongolia with single objective function of loss reduction under normal operation condition and reliability improvement after contingency condition based on ant colony algorithm [11]. Shojaeian and Ghandehari introduced sifting algorithm for DSR with an objective of real power loss and voltage deviation reductions and applied to standard 16-bus RDS with advantage of search space reduction using the method of eliminating infeasible typologies [12]. Hong et al. presented a DSR for distribution feeder containing photovoltaic arrays using an enhanced PSO algorithm with the objective of avoidance of injection of reverse power into a substation [13]. Du et al. proposed four algorithms for DSR considering DG and applied to 33-bus standard RDS. These algorithms are an Improved Quantum Artificial Fish Swarm Algorithm (IQAFSA), Quantum Artificial Fish Swarm Algorithm (QAFSA), Basic Artificial Fish Swarm Algorithm (BAFSA), and Global Edition Artificial Fish Swarm Algorithm (GAFSA) with loss reduction as an objective function. IQAFSA has proved the efficiency over the other ones [14]. Sun and Chang discovered Improved Harmony Search (IHS) algorithm for DSR with the objective of annual cost reduction and applied it to RDS in the northern Chinese city [15]. Nguyen et al. introduced Runner-Root Algorithm (RRA) to find the optimal configuration with the objective of reduction of real power losses, Load Balance Index (LBI) among branches and Load Balance (LBF) among feeders, number of switching operations, and bus voltage deviation. This approach has been applied for 33-bus and 70-bus RDSs and provided promising results [16]. Roosta et al. presented DSR with and without DG units with the objective of loss reduction, voltage improvement, and voltage stability index (VSI) increment. These objective functions are achieved simultaneously using Harmony Search Algorithm (HSA) and applied it to unbalanced 25-bus RDS for two scenarios [17]. Shuaib et al. proposed Gravitational Search (GS) algorithm to solve the DSR problem with the objective of real power loss reduction and balancing loads on feeders. This algorithm is applied for both standard 33- and 69-bus RDSs, and results show that losses are reduced and the voltage stability increased [18]. Jahani introduced a DSR technique with multiobjective functions of reliability enhancement and power loss reduction of 33-bus RDS. After DSR technique, the results prove that power losses are reduced and reliability is improved [19]. The aforementioned previous works have several drawbacks such as large DG and photovoltaic powers are required to maintain voltage and current constraints, and also other approaches did not satisfy these constraints and have slower convergence. The objective functions in these works are either real loss reduction or voltage improvement or annual cost reduction as individual objectives and not combination of above three objectives together using weighting factors.

The OCP is a reactive power injection process to compensate lower reactive power in RDS that caused the voltage reduced, losses increased, and corresponding financial benefits [20]. This compensation increases the overall stability and power factor; therefore an optimum value and place of capacitors are necessary to realize these objectives, taking into account a lower overall cost [21]. This technique contains the locations and calculation of the magnitude and number of capacitors that required to be installed in the system. This makes OCP mixed-integer nonlinear technique that has a complex nature. In addition, the radial restrictions of RDS are added to the complexity for the problem [22]. Incorrect placing of capacitors causes problems such as significant system losses and voltage drops. Therefore, the proper selection is required to locate the capacitors [23].

Many of studies have been done for OCP using different optimization algorithms and typologies. Voltage Stability Index (VSI) is implemented to predetermine the optimal location of capacitor while the Cuckoo Search (CS) algorithm is proposed to determine the optimal size of the capacitor on IEEE 34-bus and 69-bus [24]. Flower Pollination (FP) algorithm has been proposed for the solution of OCP problem in a RDS while the objective is to minimize the total power loss and cost of capacitor installation. The FP algorithm is applied to 33-, 34-, 69-, and 85-bus RDS, and comparisons are made with other algorithms [25]. In another study, VSI and Loss Sensitivity Index (LSI) are used to determine the locations while Bacterial Foraging Algorithm (BFA) is used to calculate the optimal size for 33-bus RDS [26]. Artificial Bee Colony (ABC) algorithm is applied to improve VSI and increase the saving cost depending on LSI and VSI to allocate capacitors and tested for two power systems, 34- and 118-bus RDSs [27]. Some research studies adopted LSI to find the candidate locations for the capacitor while the PSO algorithm was used to find the optimal capacitor size with the objective of loss reduction and voltage improvement for 10-, 34-, and 85-bus RDSs. The load flow that is used in this study is Newton–Raphson Method (NRM), and only the fixed-type capacitors are taken into consideration [21]. Finally, a hybrid algorithm of fuzzy expert system and Genetic Algorithm are used to determine location and size of shunt capacitors in distorted RDSs, considering effect of harmonic distortion. This technique is applied for 34-bus RDS and real RDS in Saudi Electricity Corporation with the objective of increasing the saving cost, and results indicate its superiority for harmonic reduction and increment of the RDS efficiency [28].

The aforementioned literature works for OCP have some drawbacks such as break of bus voltage and capacitor size constraints, and also the maintenance and operation costs are excluded from total capacitor cost calculations. In addition, the proposed objective functions are loss reduction, saving cost augmentation, and voltage profile enhancement as individual objective functions and not combined by weighting factor. The load flow used in many of these studies is NRM which is not suitable for RDS, and the capacitor cost specified constant in dollar ($) per kilo Volt Ampere reactive (kVAr) neglecting standard cost per capacitor size. The locations of capacitors for these works have been specified depending on either VSI or LSI. However, the capacitor placement based on these indices has proven less than satisfactory and not always explains the appropriate location [29].

The process of combining the proposed two techniques (OCP and DSR) consecutively provides further enhancements in terms of losses, cost, and voltage profile. This process begins with a OCP technique and after that the DSR technique is applied for this compensated system. A few researchers adopted dual OCP-DSR technique, and de Oliveira et al. proposed the dual technique using different levels of load and dual integer point algorithm with the objective of energy loss reduction and applied it to 16-, 33-, and 85-bus RDSs [22]. Priyadarshini et al. employed OCP-DSR technique to reduce losses and cost for 33- and 77-bus RDSs using Genetic Algorithm (GA) for OCP and loop elimination approach for DSR [30]. Mohamed et al. applied heuristic Moth Swarm Algorithm (MSA) for both techniques and tested on both radial and ring distribution systems (33- and 69-bus) with loss and cost reduction as multiobjective functions [31]. The drawbacks of these works are based on using of NRM load flow, not considering voltage profile improvement as an objective function with the other objective functions such as loss and cost reduction to perform multiobjective task. Also, the voltage constraints are not confirmed and the capacitor locations depend on LSI and VSI.

In this paper, two techniques of operations have been used, individual OCP and dual OCP-DSR techniques using four different optimization algorithms to solve multiobjective functions. These functions are real power loss reduction, annual saving cost augmentation, and voltage profile enhancement while satisfying RDS constraints. These algorithms are divided into two types: first type includes MBBO [32], MIC [33, 34], and MBFBO [35–37] which are population-based evolutionary algorithms. The second type contains CS which is a metaheuristic optimization algorithm [38–41]. These algorithms are an enhanced and modified version of original algorithms to solve major drawbacks such as slowly convergence, weakly behaviour, slip in local optimum solution, and so on. These algorithms are applied to select the optimal RDS configuration, best locations, and sizes of capacitors without using LSI or other indices specified in previous studies. The two techniques and four optimization algorithms have been applied to 33- and 69-bus standard IEEE RDSs at constant and balance three-phase loads, and the results have been compared with literature works.

## 2. Materials and Methods

The implemented load flow, multiobjective functions, RDS restrictions, RDSs, and optimization algorithms used in this work are described and explained in detail in this section.

*2.1. Load Flow Proposed.* A direct approach of load flow called Direct Backward Forward Sweep Method (DBFSM) is most suitable for RDS than NRM and Gauss–Seidal Method (GSM) which is much convenient for transmission systems. This is because of lower time requirements, unbalanced load nature, lower reactance/resistance ratio ($X/R$), and the radial construction. The steps for DBFSM are explained in detail in [42].

*2.2. Objective Functions.* Real loss reduction, voltage profile, and annual cost saving improvement are used as multiobjective functions for both OCP and OCP-DSR techniques in this study. These objective functions are described below.

*2.2.1. Real Loss Reduction.* The total branch losses are determined by summing the real loss for all branches based on the resistance and current of each branch as explained in the following equations:

$$F_1 = \min\left(P_{\text{loss}T}\right), \tag{1}$$

$$P_{\text{loss}T} = \sum_{b=1}^{N_{br}} P_{\text{loss}b}\,\text{kW}, \tag{2}$$

$$P_{\text{loss}b} = I_b^2 * R_b\,\text{kW}, \tag{3}$$

where $N_{\text{br}}$, $P_{\text{loss}T}$, $P_{\text{loss}b}$, $I_b$, and $R_b$ are number of branches, total power losses and loss of branch $b$, current of branch $b$, and resistance of branch $b$, respectively.

*2.2.2. Voltage Profile Improvement.* The condition for voltage improvements is that each bus voltage should be within acceptable limits else this condition is not achieved as illustrated in the following equation:

$$F_2 = \sum_{j=1}^{N_{\text{bus}}} V_{\text{vcj}} * P_{\text{vj}}, \tag{4}$$

where $N_{\text{bus}}$, $V_{\text{vcj}}$ $P_{\text{loss}b}$, and $P_{\text{vj}}$ are number of buses, voltage violation constraint, and voltage penalty factor (equals zero if voltage limits achieved and a higher value if these limits were broken) for bus $j$, respectively.

*2.2.3. Annual Saving Cost Increasing.* The saving cost gained from loss reduction is determined from the difference between annual cost of base case $C_A^B$ and annual cost after compensation $C_A^A$ as demonstrated in the following equations:

$$C_{TcP} = \sum_{c=1}^{nc} Q_c * C_{pc}, \tag{5}$$

$$C_{Tc} = C_{TcP} + \sum_{c=1}^{nc} \left(C_{Ic} + C_{oc}\right), \tag{6}$$

$$C_A^B = C_E * T * P_{\text{loss}T}^B, \tag{7}$$

$$C_A^A = C_E * T * P_{\text{loss}T}^A + C_{Tc}, \tag{8}$$

$$F_3 = S_{\text{cost}} = C^B - C^A, \quad (9)$$

where $S_{\text{cost}}, C_E, T, P^B_{\text{loss}T}, P^A_{\text{loss}T}, C_{Tcp}, nc, C_{Ic}, C_{Oc}, Q_c$, and $C_{Pc}$ are annual saving cost, energy loss cost, time interval in hour (h), total real losses before the proposed techniques ($), total real losses after the proposed techniques ($), total capacitor purchase cost ($), candidate number of capacitors, capacitor installation cost ($/location), capacitor operational cost ($/year/location), size of capacitor $c$ (kVAr), and purchase cost of the selected capacitor ($/kVAr). $C_{Tc}$ is the total capacitor cost containing purchase, installation, and operational costs for whole injected capacitors. The values of these parameters referred to reference [24] are inserted in Table 1.

The aforementioned multiobjective functions are merged in single objective function ($F_{\text{Tot}}$) by using weighting factors based on the following equations:

$$F_{Tot} = W_1 * F_1 + W_2 * F_2 + W_3 * F_3, \quad (10)$$

$$W_1 + W_2 + W_3 = 1, \quad (11)$$

where $W_1$, $W_2$, and $W_3$ are weighting factors for total real losses, voltage profile, and annual saving cost functions, respectively.

The percentage loss reduction (% reduction) is calculated based on total power losses before and after application of the proposed techniques as follows:

$$\%\,\text{reduction} = \frac{P^B_{\text{loss}T} - P^A_{\text{loss}T}}{P^B_{\text{loss}T}} * 100\%. \quad (12)$$

Also, the percentage saving (% saving) is calculated based on annual cost before and after application of the proposed techniques as follows:

$$\%\,\text{saving} = \frac{C^B - C^A}{C^B} * 100\%. \quad (13)$$

*2.3. Restrictions.* The proper working of RDS should achieve the practical and working restrictions as explained below.

*2.3.1. Practical Restrictions.* These restrictions include voltage, current, capacitor size, and number restrictions that are also known as inequality constraints and qualified as follows:

*(1) Voltage Restrictions.* Voltage value for each bus must be within its acceptable domain to sustain power quality as

$$\left|V_{j\,\min}\right| \le \left|V_j\right| \le \left|V_{j\,\max}\right|, \quad j \in N_{\text{bus}}, \quad (14)$$

where the standard minimum and maximum voltages are 0.95 and 1.05, respectively [43].

*(2) Current Restrictions.* Branch current must not exceed about the limit value from protection side and achieve the power supply continuity as

$$\left|I_b\right| \le \left|I_{b\,\max}\right|, \quad b \in N_{\text{br}}, \quad (15)$$

where maximum branch capacity is specified in [43].

Table 1: The values of cost parameters.

| Parameter | Value |
|---|---|
| $C_{Ic}$ ($/location) | 1600 |
| $C_{Oc}$ ($/location/year) | 300 |
| $E_c$ ($/kWh) | 0.06 |
| $T$ (h) | 8760 |

*(3) Capacitor Size and Number Restrictions.* Switched type capacitors are used and only one capacitor is allowed per bus. Capacitor size and corresponding purchase cost specified in this paper are mentioned in Table 2 [23], while the number of capacitors specified in this paper is 3 capacitors based on experience and earlier studies that satisfy the final objective function. Also, the total capacitor size ($Q_{cT}$) inserted in the system must not override the total reactive power load ($Q_L$) [31]:

$$Q_{cT} \le Q_L. \quad (16)$$

*2.3.2. Working Restrictions.* These restrictions are classified into radial structure and power balance restrictions as follows.

*(1) Radial Structure Restriction.* This condition has been confirmed by determining the determinant of the bus incidence matrix $[A]$ as given in [43].

*(2) Power Balance Restriction.* The power supplied $P_{\text{Sup}}$ to the system must provide the power demand $P_{\text{Dem}}$ and total power loss $P_{\text{loss}}$ which is given by [27]

$$P_{\text{Sup}} = P_{\text{Dem}} + P_{\text{loss}T}. \quad (17)$$

*2.4. Study Systems.* The validity of the proposed strategy and optimization algorithms are tested using different sizes of RDSs. In this study, two systems are used with a constant load mode and IEEE standard distribution systems 33- and 69-bus RDSs. The line and bus data for these systems are available in the reference [44].

*2.4.1. 33-Bus IEEE RDS.* This is a standard distribution system consisting of 32 closed branches and 5 opened branches which have switches labeled $S_1 - S_{32}$ and $S_{33} - S_{37}$, respectively, in the base case as shown in Figure 1. The base values for kilo Volt (kV) and Mega Volt Ampere (MVA) are 12.66 kV and 100 MVA, respectively, with a constant load of 3,715 kW and 2,300 kVAr. In the first proposed technique (OCP), the status of branch switches remains constant while in the second technique (OCP-DSR), the branch switches are varied.

*2.4.2. 69-Bus IEEE RDS.* This is a standard distribution system consisting of 68 closed branches and 5 opened branches which have switches labeled $S_1 - S_{68}$ and $S_{69} - S_{73}$, respectively, in base case as shown in Figure 2. The base

Table 2: Standard capacitor size and costs.

| $Q_c$ (kVAr) | $C_{Pc}$ (\$/kVAr) |
|---|---|
| 150 | 0.5 |
| 300 | 0.35 |
| 450 | 0.253 |
| 600 | 0.220 |
| 750 | 0.276 |
| 900 | 0.183 |
| 1050 | 0.228 |
| 1200 | 0.170 |
| 1350 | 0.207 |
| 1500 | 0.201 |
| 1650 | 0.193 |
| 1800 | 0.187 |
| 1950 | 0.211 |
| 2100 | 0.176 |
| 2250 | 0.197 |
| 2400 | 0.170 |
| 2550 | 0.189 |
| 2700 | 0.187 |
| 2850 | 0.183 |
| 3000 | 0.180 |
| 3150 | 0.195 |
| 3300 | 0.174 |
| 3450 | 0.188 |
| 3600 | 0.170 |
| 3750 | 0.183 |
| 3900 | 0.182 |
| 4050 | 0.179 |

values for kilo Volt (kV) and Mega Volt Ampere (MVA) are 12.66 kV and 100 MVA, respectively, with a constant load of 3,802 kW and 2,695 kVAr. In the first proposed technique (OCP), the status of branch switches remains constant while in the second technique (OCP-DSR), the opened and closed branches are varied.

*2.5. Optimization Algorithms.* The proposed algorithms of this work are explained in detail in this subsection, and the previous usages of these algorithms are also provided.

*2.5.1. Modified Biogeography-Based Optimization (MBBO) Algorithm.* It is an updated version of conventional Biogeography-Based Optimization (BBO) algorithm that was discovered in 2008 by Simon, which simulates the geographical allocation of alive organisms [32]. The original BBO has a weakness in its migration and mutation stages that affect its performance. Therefore, the modified version overrides the drawbacks of conventional form through improving and adapting the BBO approach to the DSR and OCP problems to enhance solution quality at each iteration. Conventional BBO is used for optimal placement of DG [45] and DSR [46], but the MBBO is not applied for both OCP alone, DSR alone, and dual OCP-DSR techniques.

The MBBO procedures are as follows:

(1) The final choice of the control parameters for the MBBO algorithm that is considered as the optimal choice in this study is inserted in Table 3.

(2) Determine Maintain Number $M_N$ depending on population Pop using the following equation:

$$M_N = \text{Maintain rate} * \text{Pop}. \quad (18)$$

(3) Determine Habitation Number $H_N$:

$$H_N = \text{Pop} - M_N. \quad (19)$$

(4) Calculate Emigration Value $E_v$ and Immigration Value $I_v$ consecutively for each habitat based on their maximum values ($E_V^{\max}$ and $I_V^{\max}$) as follows:

$$E_v = E_V^{\max} * \frac{1}{\text{Pop} - 1}, \quad (20)$$

$$I_v = I_V^{\max} * (1 - E_v). \quad (21)$$

(5) Evaluate Emigration Possibility $E_P$ depending on $I_v$:

$$E_P = E_v, \quad \text{if } r \le I_v, \quad (22)$$

where $r$ is a random number between 0 and 1.

(6) The steady state value of $E_P$ can be calculated depending on Emigration Possibility of each species ($E_{Ps}$) as follows:

$$E_P(\infty) = \frac{E_{Ps}}{\sum_{S=1}^{\text{Pop}} E_{Ps}}. \quad (23)$$

(7) Modernise Suitability Index $\text{SI}_i^{k+1}$ for each habitat for $i$th solution utilizing from previous $i$th solution, $j$th solution and Beta variable ($\beta$):

$$\text{SI}_i^{k+1} = \text{SI}_i^k + \beta * \left(\text{SI}_j^k - \text{SI}_i^k\right), \quad (24)$$

where the $\beta$ value is specified in Table 2.

(8) Checking the selected Mutation Possibility $M_P$ with random number ($r$), if it large or equals to $r$, then the updated $\text{SI}_i^{k+1}$ equals

$$\text{SI}_i^{k+1} = \text{SI}_i^{k+1} + E_N * r, \quad (25)$$

where $E_N$ is Elite Number.

(9) Repeat procedures 2–8 until reach maximum number of iterations ($\text{iter}_{\max}$).

(10) End.

*2.5.2. Cuckoo Search (CS) Algorithm.* It is a new meta-heuristic optimization method discovered by Yang and Deb in 2009, which is inspired from parasitic performance of cuckoo birds plus levy flight performance of other birds [38]. Each egg can be viewed as a solution which is randomly generated in the initialization process. CS algorithm has been used alone for DSR and OCP techniques, and the optimal result obtained via DSR technique demonstrated the effectiveness and robustness of this algorithm. Also, CS algorithm has been applied with different typologies and objective functions for only OCP technique, in spite of

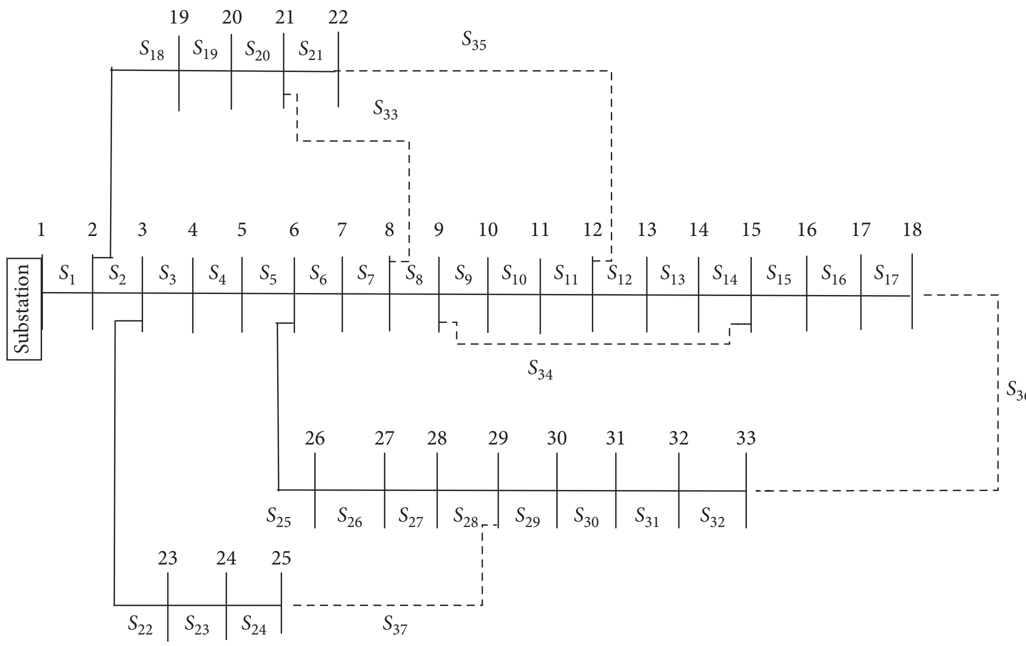


Figure 1: Single-line scheme for 33-bus RDS.

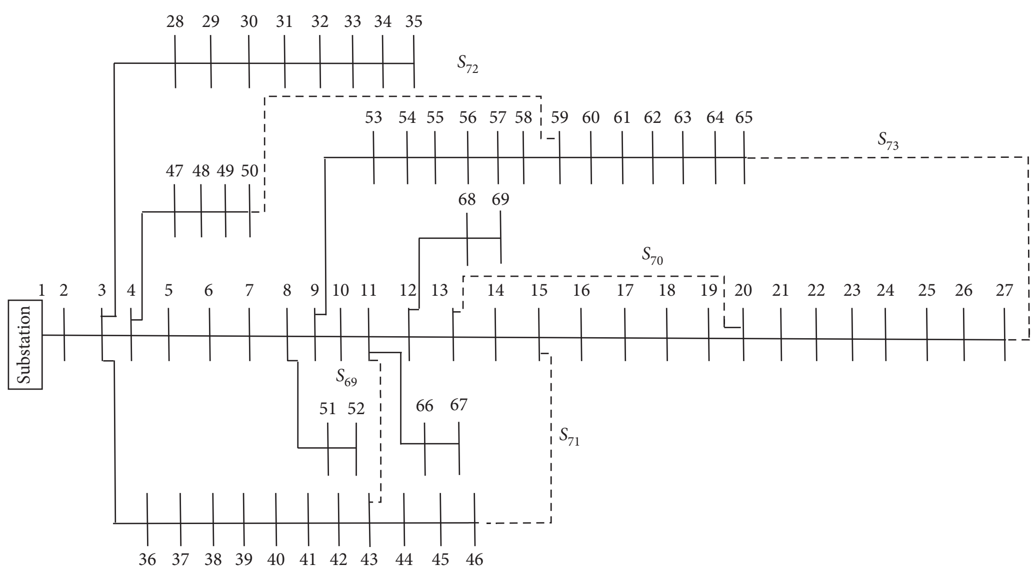


Figure 2: Single-line scheme for 69-bus RDS.

Table 3: The typical parameters of the MBBO algorithm.

| Parameter | Value |
|---|---|
| $M_P$ | 0.1 |
| $E_N$ | 2 |
| $I_V^{\max}$ | 1 |
| $E_V^{\max}$ | 1 |
| Maintain rate | 0.2 |
| $\beta$ | 0.9 |

confirming the total capacitor size restriction but did not satisfy the voltage restrictions [24, 39, 47]. In this paper, this algorithm is modified, especially the initialization process, to give better results than the original CS algorithm.

The main steps of the CS algorithm are as follows:

(1) Initialization cuckoo parameters: ranges of Host Nest number (HN) and Discover Rate Probability (DRP) are 10–50 and 0-1, respectively [39, 40]. The values of these parameters and maximum number of iterations that are used in this study are listed in Table 4.

(2) Find the fitness value for each nest value and check the constraints of optimization problem such as radial condition of RDS and other constraints. At last, select the best host nests based on the fitness value.

Table 4: Initializing parameters of the CS algorithm.

| Parameter | Value |
|---|---|
| HN | 30 |
| DRP | 0.25 |

(3) Start Levy flight phase to get the best value for each iteration as follows:

(i) Define Allocation Factor (AF) in the range (1–3) [41], Gamma Allocation (GA) function, where AF is specified and equals 3/2 in this study.

(ii) Calculate Sigma ($\mathrm{Si}_x$) for solution $x$ and Sigma ($\mathrm{Si}_y$) for solution $y$ as standard variances by the following equations:

$$\mathrm{Si}_x = \left[\frac{\mathrm{GA}(1+\mathrm{AF}) * \sin(\pi/2 * \mathrm{AF})}{\mathrm{GA}((1+\mathrm{AF})/2) * \mathrm{AF} * 2^{((\mathrm{AF}-1)/2)}}\right]^{1/\mathrm{AF}}, \quad (26)$$

$$\mathrm{Si}_y = 1. \quad (27)$$

(iii) Determine the Step Data ($\mathrm{SD}_i$) for nest ($i$) as

$$\mathrm{SD}_i = \frac{u}{|v|^{1/\mathrm{AF}}}, \quad (28)$$

where $u$ and $v$ are variables of solution $x$ and can be calculated based on random numbers ($r_x$) and ($r_y$) using the following equations:

$$v = r_y, \quad (29)$$

$$u = \mathrm{Si}_x * r_x, \quad (30)$$

where $r_x$ and $r_y$ have values which range between 0 and 1.

(iv) Calculate the Increment Value ($\mathrm{IV}_i^{\mathrm{new}}$) depending on values of $\mathrm{SD}_i$, best solution $X_{i,\mathrm{best}}$, optimal solution $X_{i,\mathrm{opt}}$, and Step Size (SZ) as

$$\mathrm{IV}_i^{\mathrm{new}} = \mathrm{SZ} * \mathrm{SD}_i * \left(X_{i,\mathrm{best}} - X_{i,\mathrm{opt}}\right), \quad (31)$$

where SZ is specified equals to 0.01.

(v) Determine the new value ($X_{i,\mathrm{new}}$) depending on $\mathrm{IV}_i^{\mathrm{new}}$ and $X_{i,\mathrm{best}}$ values using the following equation:

$$X_{i,\mathrm{new}} = \mathrm{round}\left(X_{i,\mathrm{best}} + r * \mathrm{IV}_i^{\mathrm{new}}\right), \quad (32)$$

where round is an integer number.

(4) Delete the worst values and build new ones keeping the best solutions. This phase also generates a new solution as in the Levy flight phase depending on factor $F$ which explains the ability to discover the stranger eggs that is specified as follows:

$$F = \begin{cases} 1, & \text{if } r < \mathrm{DRP}, \\ 0, & \text{else.} \end{cases} \quad (33)$$

Then, the new solution ($X_{i,\mathrm{new}}$) can be determined by using this factor as

$$X_{i,\mathrm{new}} = \mathrm{round}\left(X_{i,\mathrm{best}} + F * \Delta X_i^{\mathrm{new}}\right), \quad (34)$$

where $\Delta X_i^{\mathrm{new}}$ is similar to $\mathrm{IV}_i^{\mathrm{new}}$ in the Levy flight phase and is calculated as

$$\Delta X_i^{\mathrm{new}} = r * \left(r_{d1} - r_{d2}\right), \quad (35)$$

where $r_{d1}$ and $r_{d2}$ are random disturbances for nest positions in $X_{i,\mathrm{best}}$.

(5) Sort the solutions and find the current best solutions.

(6) The best nests with high quality of eggs (best value) will carry over to the next generation.

(7) Get the best results at the end of iteration.

(8) Repeat steps 2–7 until it reaches the limits of maximum iterations ($\mathrm{iter}_{\max}$).

(9) End.

*2.5.3. Modified Imperialist Competitive (MIC) Algorithm.* Imperialist Competitive (IC) algorithm is an evolutionary algorithm that was discovered by Gargari and Lucas in 2007 which is inspired by colonial simulation [33]. This algorithm wishes to reach a state that only one empire existed and its corresponding colonies have the same position and cost. A modified form (MIC) is used in this article to enhance the efficiency, convergence velocity, and accuracy of the conventional IC algorithm. The MIC algorithm improves the original IC performance by preventing premature convergence to local minima based on absorption, exchange, revolution, and competition processes. This algorithm is implemented using the following steps:

(1) Initializing process: in this process, the optimal values of MIC algorithm control parameters, such as number of countries, number of imperialists, and number of colonies, were defined and inserted in Table 5. Also, the cost and position of each imperialist and colony were initialized. The normalized power $P_N$ for each imperialist and number of colonies $N_{\mathrm{cn}}$ for empire are determined as follows:

$$P_N = \frac{C_N}{\sum_{j=1}^{\mathrm{Im}} C_j}, \quad j \in \mathrm{Im}, \quad (36)$$

$$N_{\mathrm{cn}} = \mathrm{round}\left(P_N * N_c\right), \quad (37)$$

where $C_N$, $C_j$, Im, and $N_c$ are normalize cost for each imperialist, cost of $j$th imperialist, number of imperialists, and total number of colonies, respectively.

(2) Absorption process: the colonies move toward their imperialist either in straight movement or diverted by angle ∅. The latter is better to improve the search ability around the imperialists. The new position $\mathrm{Pos}_{\mathrm{new}}$ of the colony can be updated by vector ($V$) and absorption coefficient ($\gamma$) which has a value represented in Table 5. The vector $V$ is calculated

Table 5: Optimal parameters of the MIC algorithm.

| Parameter | Value |
|---|---|
| Country number | 20 |
| Im | 10 |
| $N_c$ | 10 |
| $Z$ | 0.02 |
| RRP | 0.3 |
| $\gamma$ | 0.5 |

using position of imperialist ($\mathrm{Pos}_{\mathrm{IM}}$) and position of its corresponding colonies ($\mathrm{Pos}_c$) as

$$V = \mathrm{Pos}_{\mathrm{IM}} - \mathrm{Pos}_c. \quad (38)$$

Then, $\mathrm{Pos}_{c,\mathrm{new}}$ is calculated based on the previous position ($\mathrm{Pos}_{c,\mathrm{old}}$) as follows:

$$\mathrm{Pos}_{c,\mathrm{new}} = \mathrm{Pos}_{c,\mathrm{old}} + \gamma * \mathrm{rand}(V) * V. \quad (39)$$

The movement of colony may drift from straight line by angle $\varnothing$ that has the range corresponding to absorption angle coefficient ($\delta$) value as

$$\varnothing \in (-\delta : \delta). \quad (40)$$

(3) Exchange process: this process occurs when position or cost of the colony is better than that for the imperialist, and then the replacement occurs to update a new imperialist.

(4) Update total cost for a new united empire $T_{\mathrm{ec}}$ using cost for imperialist $C_{\mathrm{IM}}$ and the sharing cost of corresponding colonies as explained in the following equation:

$$T_{\mathrm{ec}} = C_{\mathrm{IM}} + Z * \mathrm{Ave}(C_c), \quad (41)$$

where $Z$ and $\mathrm{Ave}(C_c)$ are sharing cost and average of colony costs for the corresponding empire, respectively.

(5) Revolution process: during this process, the locations of colonies are altered randomly to enhance behavior of IC and exclude it from fall into the local minimum by using Revolution Rate Parameter (RRP) that has a range of 0.03–0.4 [34], and its optimal value is specified in Table 5. The number of revolving colonies $R_c$ equals

$$R_c = \mathrm{round}(\mathrm{RRP} * C_c). \quad (42)$$

(6) Imperialist competition process: this process aims to select the weakest colonies of weakest empires, and comparison is made between powerful empires to own these colonies. This is made depending on ownership probability $P_{\mathrm{oe}}$ for each empire that is proportional to the normalized total cost $T_{\mathrm{ecN}}$ for each empire. $T_{\mathrm{ecN}}$ is first determined as

$$T_{\mathrm{ecN}} = T_{\mathrm{ec}} - \max(T_{\mathrm{ec}}). \quad (43)$$

After that, $P_{\mathrm{oe}}$ equals

$$P_{\mathrm{oe}} = \frac{T_{\mathrm{ecN}}}{\sum_{j=1}^{\mathrm{IM}} T_{\mathrm{ecj}}}, \quad j \in \mathrm{Im}. \quad (44)$$

The vector $O$ corresponding to ownership probability for each empire generated, also a random vector $R$ of the same size is built then a vector $C$ contains the remaining empires after the collapse process as

$$C = O - R. \quad (45)$$

(7) Repeat above steps until it reaches $\mathrm{iter}_{\max}$ limit.

(8) End.

*2.5.4. Modified Bacterial Foraging-Based Optimization (MBFBO) Algorithm.* A Bacterial Foraging-Based Optimization (BFBO) algorithm is of evolutionary type, first discovered by Passino in 2002, which has removable property [35]. The bacterium represents the proposed solution for optimization problem. A modified style of this algorithm is performed to overcome the drawbacks of BFBO algorithms such as lower convergence speed and trapping in local minimum solution. This modification includes both chemotaxis and swarming processes, and this enables it to handle multiobjective functions [36]. This algorithm has been applied for DSR technique with the objective function of loss reduction and applied for optimal placement of DG [44, 48]. The steps of the MBFBO algorithm are as follows:

(1) Initialization of the MBFBO parameters: the values of these parameters are inserted in Table 6. In addition, the loops for chemotaxis, reproduction, and elimination processes have been generated.

(2) Chemotaxis process: this process was classified into tumble and swim operations. In tumble operation, the position for $i$th bacteria ($X_i^{\mathrm{New}}$) is updated based on its chemotactic step size ($C_{\mathrm{iss}}$) and direction index ($D_i$) of $c$th chemotaxis as follows [37]:

$$D_i = (r - 0.5) * 2, \quad (46)$$

$$X_i^{\mathrm{New}} = X_i^{\mathrm{old}} + \frac{D_i}{\sqrt{D_i * D_i^T}} * C_{\mathrm{iss}}. \quad (47)$$

In swim operation, swim steps $S_s$ are predefined and each bacteria move with same $C_{\mathrm{ss}}$ of previous chemotaxis, and this operation continues until it reach $S_s$ limit.

(3) Reproduction process: during this process, the health of each bacteria $C_H^i$ is determined using equation (48) and sorting it in descending order, where the ones with least health are dead while the remaining ones each split into two to keep the constant number of bacteria.

Table 6: Initial parameters for the MBFBO algorithm.

| Parameter | Value |
|---|---|
| Bacteria number | 30 |
| $N_c$ | 2 |
| $N_{re}$ | 2 |
| $P_R$ | 0.9 |
| $S_s$ | 1 |

$$C_H^i = \sum_{C=1}^{N_c} C^i, \tag{48}$$

where $N_c$ is the number of chemotaxis steps. This procedure is repeated for each of reproductive steps ($N_{re}$).

(4) Elimination process: after the reproduction step, some of the new generations move to new positions to enhance the overall performance of this algorithm depending on Removal Probability ($P_R$).

(5) Repeat steps 2–4 until it reaches $\text{iter}_{\max}$.

(6) End.

Finally, values of Pop and $\text{iter}_{\max}$ for all applied algorithms are inserted in Table 7. These values are used to give accurate and promise results over the literature studies.

Table 7: Setting of parameters for applied algorithms.

| Proposed algorithms | Parameter | |
|---|---|---|
| | Pop | $\text{iter}_{\max}$, (RDS) |
| MBBO | 30 | |
| CS | 30 | 50, (33-bus) |
| MIC | 20 | 100, (69-bus) |
| MBFBO | 30 | |

## 3. Results and Discussion

The proposed four algorithms were carried out under the MATLAB environment (Release 2018b), and these algorithms were applied for two techniques (OCP and OCP-DSR) for 33- and 69-bus RDSs. The duration of the test is one year using constant power load. The results of these algorithms during this test are inserted in the following tables and figures.

*3.1. IEEE-33 Bus RDS.* The results for the application of proposed algorithms on this system for both OCP and OCP-DSR techniques are inserted in Tables 8 and 9, respectively. Figures 3 and 4 show the voltage profile for 33-bus RDS with OCP and OCP-DSR, respectively, which provide that the voltage enhanced in the dual technique is better than the individual technique, and the voltage constraints are also confirmed using these techniques. The convergence graph of real losses for the four algorithms using two techniques is shown in Figures 5 and 6, respectively, which explained a significant reduction obtained using the OCP-DSR technique.

Also, these tables contain comparisons with literature works with the same multiobjective functions such as Locust Search (LS) [49], Novel Analytic (NA) [50], Gravitational Search Algorithm (GSA) [51], Flower Pollination Algorithm (FPA) [52], Moth Flame Optimization (MFO) [53], and Improved Binary Particle Swarm Optimization (IBPSO) [54] algorithms.

From Tables 8 and 9, it is concluded that the proposed algorithms achieved better performance for losses, voltage profile, and cost aspects. The results proved the superiority of proposed algorithms, and the dual OCP-DSR technique provided better performance than individual OCP technique as explained in Table 9. Also, this table contains comparison with literature work that showed the total capacitor size and number restrictions were violated in the previous study and confirmed in proposed algorithms. Also, in spite of larger number and sizes of capacitors for the literature work, the MBBO and CS algorithms achieved significant reduction in losses with more saving. This proves the superiority and effectiveness of these algorithms for proper selection of size and location of capacitors.

*3.2. IEEE 69-Bus RDS.* The capacitor size and location are optimally implemented using the four proposed algorithms for the OCP technique in this system. Table 10 demonstrates the results for these algorithms with OCP technique and confirmed the better performance for the MBBO algorithm over the other proposed algorithms. Also, this table contains comparisons with LS [49], GSA [51], FPA [52], MFO [53], and Logistic Map Differential Evolution (LMDE) [55] algorithms and indicated the superiority of the proposed algorithms in terms of losses, voltages, and saving cost over these works.

The second approach utilizing from DSR technique is applied to a compensated system known as dual OCP-DSR technique. The results are given in Table 11 which explain a further reduction in the real losses and more improvement of voltage and saving cost if compared with using the individual OCP technique. Also, this table contains comparisons with Fuzzy Multiobjective Approach (FMOA) [56] and indicates the superiority of the proposed algorithms in terms of losses, voltages, and saving cost. The literature work broke the voltage constraints, therefore, in spite of more loss reduction but did not confirm the RDS restrictions as done with proposed algorithms. The corresponding voltage profile and convergence graph for losses are shown in Figures 7–10, respectively.

From Tables 8–11 and Figures 3–10, it can be seen that the proposed algorithms have achieved a better performance in the dual OCP-DSR technique as compared with an individual OCP technique. The MBBO algorithm has high ability compared with the other algorithms in terms of the quality of solution and computational efficiency. A comparison with literature works has been done for individual and dual approaches that used the same objective functions and case studies. This comparison proved that the proposed algorithms achieved the voltage constraints which were broken in some literature works. In addition, the losses and

Table 8: Results and comparisons of IEEE-33-bus RDS without and with individual OCP technique.

| Parameters | Without OCP | Literature algorithms | | | | | Proposed algorithms | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | LS [49] | NA [50] | GSA [51] | FPA [52] | MFO [53] | IBPSO [54] | MBBO | CS | MIC | MBFBO |
| Year | — | 2018 | 2017 | 2015 | 2016 | 2018 | 2014 | 2019 | 2019 | 2019 | 2019 |
| $Q_c$ (kVAr) | — | [450, 350, 900] | [550, 480, 330] | [350, 450, 800] | [250, 400, 950] | [450, 300, 900] | [900, 300, 300, 300, 300, 600, 600] | [750, 450, 600] | [300, 750, 600] | [750, 150, 750] | [900, 600, 750] |
| Location | — | [12, 25, 30] | [14, 30, 32] | [26, 13, 15] | [6, 9, 30] | [8, 13, 30] | [1, 3, 14, 22, 24, 30, 31] | [27, 30, 24] | [8, 30, 23] | [27, 2, 24] | [5, 27, 2] |
| $Q_{cT}$ (kVAr) | — | 1700 | 1360 | 1600 | 1600 | 1650 | 3300 | 1800 | 1650 | 1650 | 2250 |
| $C_{Tc}$ ($) | — | 10800 | 9780 | 6151.5 | 6091 | 6083.55 | 14148.7 | 6152.85 | 6144 | 6189 | 6203.7 |
| $P_{\text{loss}T}$ (kW) | 202.6771 | 139.23 | 138.72 | 134.5 | 134.47 | 134.0725 | 134.2 | 108.6105 | 123.4426 | 126.3468 | 125.755 |
| $V_{\min}$ (p. u.) | 0.91306 | 0.9291 | 0.9428 | 0.9672 | 0.9365 | 0.94 | 0.9389 | 0.95 | 0.95 | 0.95 | 0.95 |
| $V_{\max}$ (p. u.) | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| % reduction | — | 31.3 | 31.556 | 33.638 | 33.65 | 33.8502 | 33.7863 | 46.412 | 39.0939 | 37.661 | 37.953 |
| $C_A$ ($) | 106527 | 83979 | 82691 | 76845 | 76768 | 76552 | 84684 | 63239 | 71025 | 72597 | 72301 |
| $S_{\text{cost}}$ ($) | — | 22548 | 23836 | 29682 | 29759 | 29975 | 21843 | 43289 | 35502 | 33930 | 34227 |
| % saving | — | 21.1660 | 22.3760 | 27.8630 | 27.9360 | 28.1384 | 20.5050 | 40.6366 | 33.3268 | 31.8510 | 32.1299 |
| Pop | — | 20 | NR* | 2000 | 25 | 20 | NR* | 30 | 30 | 20 | 30 |
| $\text{iter}_{\max}$ | — | 1000 | NR* | 400 | 100 | 20 | NR* | 50 | 50 | 50 | 50 |

NR*: not reported.

Table 9: Results and comparisons of IEEE-33-bus RDS without and with dual OCP-DSR technique.

| Parameters | Without OCP-DSR | Literature | Proposed algorithm | | | |
|---|---|---|---|---|---|---|
| | | IBPSO [54] | MBBO | CS | MIC | MBFBO |
| Year | — | 2014 | 2019 | 2019 | 2019 | 2019 |
| Tie-switches | [33, 34, 35, 36, 37] | [7, 10, 34, 36, 37] | [7, 11, 34, 36, 28] | [8, 5, 37, 30, 12] | [9, 25, 14, 33, 37] | [8, 37, 14, 7, 36] |
| $Q_c$ (kVAr) | — | [900, 300, 300, 300, 300, 600, 600] | [750, 450, 600] | [300, 750, 600] | [750, 150, 750] | [900, 600, 750] |
| Location | — | [1, 3, 14, 22, 24, 30, 31] | [27, 30, 24] | [8, 30, 23] | [27, 2, 24] | [5, 27, 2] |
| $Q_{cT}$ (kVAr) | — | 3300 | 1800 | 1650 | 1650 | 2250 |
| $C_{Tc}$ ($) | — | 14148.7 | 6152.85 | 6144 | 6189 | 6203.7 |
| $P_{\text{loss}T}$ (kW) | 202.6771 | 95.91 | 83.469 | 95.6628 | 97.6377 | 97.3076 |
| $V_{\min}$ (p. u.) | 0.91306 | 0.9658 | 0.9559 | 0.9704 | 0.95 | 0.95 |
| $V_{\max}$ (p. u.) | 1 | 1 | 1 | 1 | 1 | 1 |
| % reduction | — | 52.678 | 58.8167 | 52.8003 | 51.8259 | 51.9888 |
| $C_A$ ($) | 106527 | 64559 | 50024 | 56424 | 57507 | 57349 |
| $S_{\text{cost}}$ ($) | — | 41968 | 56503 | 50103 | 49020 | 49179 |
| % saving | — | 39.3970 | 53.0410 | 47.0331 | 46.0165 | 46.1657 |
| Pop | — | NR* | 30 | 30 | 20 | 30 |
| $\text{iter}_{\max}$ | — | NR* | 50 | 50 | 50 | 50 |

cost are better in this work. Then, the approach of selecting the capacitor location using intelligent algorithms gives robust and accurate results than using conventional indices such as LSI and VSI.

## 4. Conclusions

The effective RDS has lower real losses, better voltage profile, and more saving cost that must be achieved together. DSR and OCP techniques are the most economic solutions for the aforementioned problems and perform fast convergence. In this work, two approaches that have been used to get bigger profit are individual OCP and dual OCP-DSR techniques to select the best locations and sizes of capacitors in addition to modifying the network configuration without using LSI and VSI factors. Four different optimization algorithms, MBBO, CS, MIC, and MBFBO, are used for solving the optimization problem via MATLAB 2018b software. The load flow proposed in this paper is DBFSM instead of NRM and GSM to calculate total real losses, each bus voltage, and branch currents. The two IEEE-33 and 69-bus RDSs are used to prove the efficiency of each algorithm. The results of these algorithms for two techniques and systems are compared among each other. The comparison results demonstrate the superiority of the MBBO algorithm over the other algorithms in terms of lower real losses, better voltage profile, and saving cost. This algorithm achieved percentage reduction of 46.412% and 58.8167% for 33-bus RDS while it

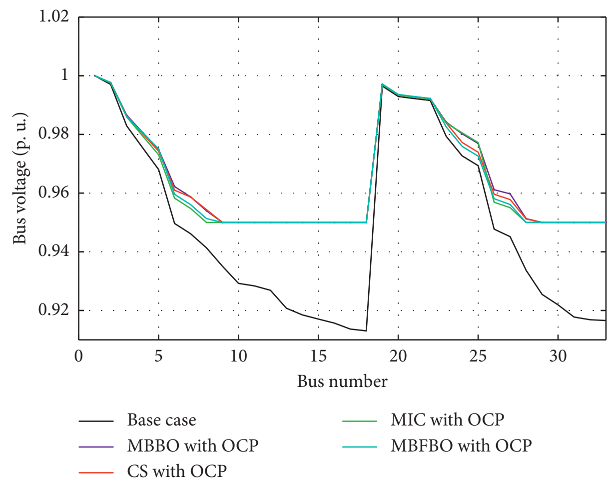


Figure 3: Voltage profile for 33-bus RDS using OCP technique.

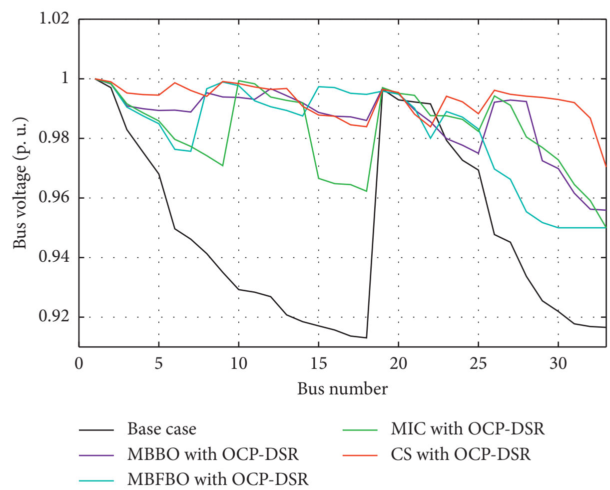


Figure 4: Voltage profile for 33-bus RDS using OCP-DSR technique.

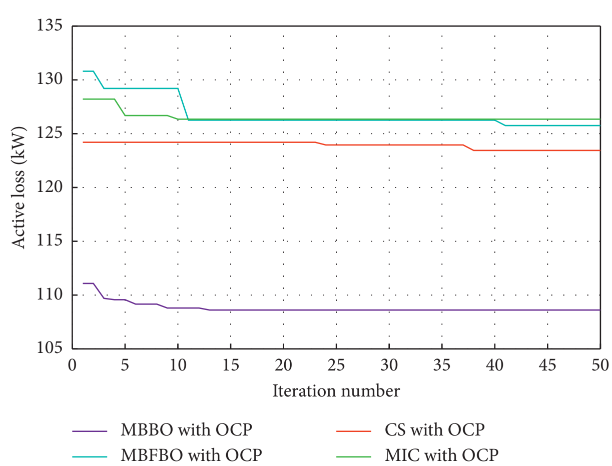


Figure 5: Convergence loss graph for 33-bus RDS using OCP technique.

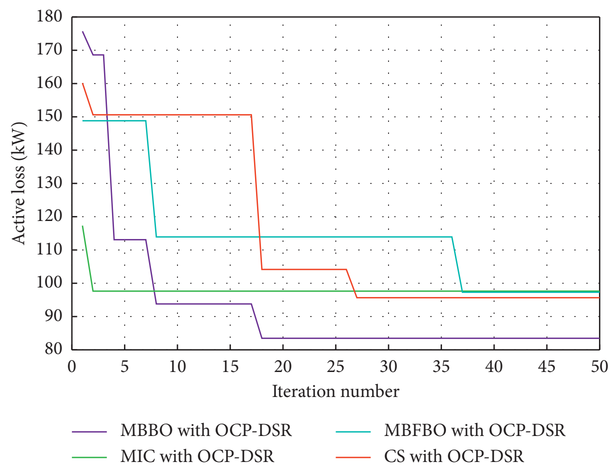


Figure 6: Convergence loss graph for 33-bus RDS using OCP-DSR technique.

Table 10: Results and comparisons of IEEE 69-bus RDS without and with individual OCP technique.

| Parameters | Without OCP | Literature algorithms | | | | | Proposed algorithms | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | LS [49] | GSA [51] | FPA [52] | MFO [53] | LMDE [55] | MBBO | CS | MIC | MBFBO |
| Year | — | 2018 | 2015 | 2016 | 2018 | 2019 | 2019 | 2019 | 2019 | 2019 |
| $Q_c$ (kVAr) | — | [350, 1200] | [150, 150, 1050] | [1350] | [300, 1350] | [200, 250, 250, 600, 300] | [300, 900, 150] | [450, 600, 900] | [1350, 150, 450] | [600, 300, 300] |
| Location | — | [17, 61] | [26, 13, 15] | [61] | [17, 61] | [21, 59, 61, 62, 65] | [12, 60, 21] | [15, 50, 61] | [59, 69, 15] | [59, 68, 20] |
| $Q_{cT}$ (kVAr) | — | 1550 | 1350 | 1350 | 1650 | 1600 | 1350 | 1950 | 1950 | 1200 |
| $C_{Tc}$ ($) | — | 8450 | 6089.4 | 2179.45 | 6084.45 | 10012 | 6044.7 | 6110.55 | 6168.3 | 6042 |
| $P_{\text{loss}T}$ (kW) | 224.9606 | 146.61 | 145.9 | 150.28 | 145.6945 | 146.31 | 61.5959 | 90.8139 | 120.6084 | 101.8776 |
| $V_{\min}$ (p. u.) | 0.90901 | 0.93 | 0.9519 | 0.9333 | 0.9330 | 0.9310 | 0.96 | 0.96 | 0.9501 | 0.955 |
| $V_{\max}$ (p. u.) | 1 | 1 | 1 | 1 | 1 | 0.9999 | 1 | 1 | 1 | 1 |
| % reduction | — | 34.8285 | 35.1441 | 33.197 | 35.235 | 34.95 | 72.6192 | 59.6312 | 46.3869 | 54.7131 |
| $C_A$ ($) | 118239 | 85508 | 82774 | 81167 | 82661 | 86913 | 38420 | 53842 | 69560 | 59589 |
| $S_{\text{cost}}$ ($) | — | 32731 | 35465 | 37073 | 35578 | 31326 | 79820 | 64397 | 48679 | 58650 |
| % saving | — | 27.6820 | 29.9943 | 31.3543 | 30.0899 | 26.4937 | 67.5073 | 54.4634 | 41.1700 | 49.6029 |
| Pop | — | 20 | 2500 | 25 | 20 | NR* | 30 | 30 | 20 | 30 |
| $\text{iter}_{\max}$ | — | 1000 | 750 | 100 | 20 | 100 | 100 | 100 | 100 | 100 |

Table 11: Results and comparisons of IEEE 69-bus RDS without and with dual OCP-DSR technique.

| Parameters | Without OCP-DSR | Literature | | Proposed algorithms | | |
|---|---|---|---|---|---|---|
| | | FMOA [56] | MBBO | CS | MIC | MBFBO |
| Year | — | 2013 | 2019 | 2019 | 2019 | 2019 |
| Tie-switches | [69, 70, 71, 72, 73] | [69, 70, 57, 64, 12] | [58, 42, 19, 60, 45] | [49, 10, 59, 45, 19] | [70, 58, 49, 69, 14] | [10, 19, 14, 60, 54] |
| $Q_c$ (kVAr) | — | 400 | [300, 900, 150] | [450, 600, 900] | [1350, 150, 450] | [600, 300, 300] |
| Location | — | 61 | [12, 60, 21] | [15, 50, 61] | [59, 69, 15] | [59, 68, 20] |
| $Q_{cT}$ (kVAr) | — | 400 | 1350 | 1950 | 1950 | 1200 |
| $C_{Tc}$ ($) | — | 2001.2 | 6044.7 | 6110.55 | 6168.3 | 6042 |
| $P_{\text{loss}T}$ (kW) | 224.9606 | 95.1 | 54.9369 | 80.4276 | 102.846 | 80.6144 |
| $V_{\min}$ (p. u.) | 0.90901 | 0.9450 | 0.97336 | 0.97189 | 0.97447 | 0.98651 |
| $V_{\max}$ (p. u.) | 1 | 1 | 1.0016 | 1 | 1 | 1.0005 |
| % reduction | — | 57.725 | 75.5793 | 64.2482 | 54.2827 | 64.1651 |
| $C_A$ ($) | 118239 | 51986 | 34920 | 48383 | 60224 | 48413 |
| $S_{\text{cost}}$ ($) | — | 66253 | 83320 | 69856 | 58015 | 69826 |
| % saving | — | 56.0331 | 70.4674 | 59.0803 | 49.0659 | 59.0550 |
| Pop | — | NR* | 30 | 30 | 20 | 30 |
| $\text{iter}_{\max}$ | — | NR* | 100 | 100 | 100 | 100 |

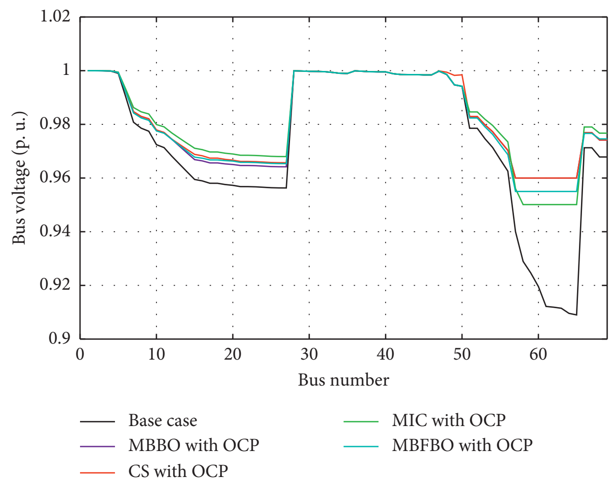


FIGURE 7: Voltage profile for 69-bus RDS using OCP technique.

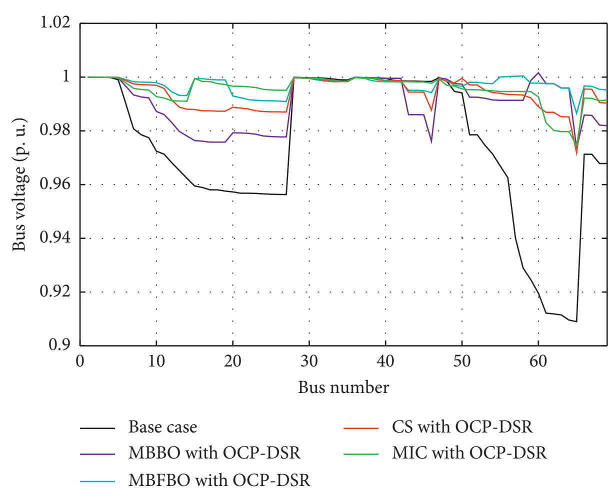


FIGURE 8: Voltage profile for 69-bus RDS using OCP-DSR technique.

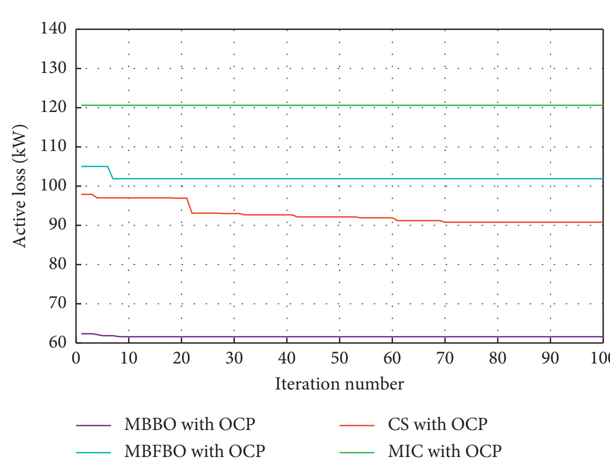


FIGURE 9: Convergence loss graph for 69-bus RDS using OCP technique.

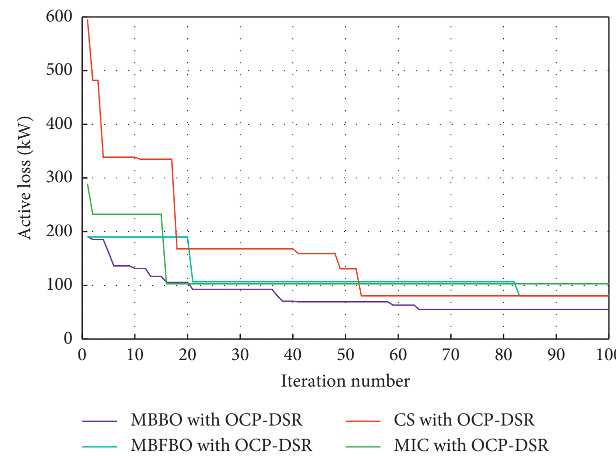


FIGURE 10: Convergence loss graph for 69-bus RDS using OCP-DSR technique.

achieved reduction of 72.6192% and 75.5793% for 69-bus RDS using individual and dual techniques, respectively. This algorithm achieved percentage saving of 40.6366% and 53.041% for 33-bus RDS while it achieved saving of 67.5073% and 70.4674% for 69-bus RDS using individual and dual techniques, respectively. Also, a comparison with literature works has been done to validate the proposed algorithms. Finally, the dual OCP-DSR technique has higher ability than the individual OCP technique in reduction of total losses, improving both voltage profile and annual saving cost of the 33-bus and 69-bus systems.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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