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A novel WSSA technique for multi-objective optimal capacitors placement and rating in radial distribution networks

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ABSTRACT

Minimizing power loss while keeping the voltage profile within acceptable limits is a great challenge for the distribution system operators. Properly sized and optimally placed shunt capacitors (SCs) in radial distribution networks (RDNs) can enhance system efficiency and offer both technical and economic benefits. This paper presents a novel meta-heuristic technique, the weight salp swarm algorithm (WSSA) as a modified version of the original SSA algorithm by incorporating an inertia weight parameter to improve precision, speed, and consistency in solving the optimal capacitor placement (OCP) problem. The proposed method minimizes power loss, annual total costs, and improves the voltage profile of RDNs, ensuring practical applicability. Two RDNs, IEEE 33-bus and a real Iraqi 65-bus in Sadat Al-Hindiya, Babel Governorate, Iraq, were used to evaluate WSSA's performance. Comparative analysis with recently published approaches demonstrates WSSA’s superiority in reducing power loss, lowering costs, and improving voltage profiles. For the IEEE 33-bus, power loss is decreased by 34.81%, and the total cost is lessened by 29.08% (savings of $30,965.33). For the Iraqi 65-bus, WSSA reduces power loss by 32.03% and decreases the total cost by 29.51% (savings of $69,201.57). These results confirm WSSA’s effectiveness in achieving OCP with enhanced technical and economic benefits.

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1. INTRODUCTION

The increasing demand for electricity, coupled with limited expansion in generation and transmission infrastructure, poses a significant challenge to modern electrical networks. Also, the continuous advancement of human growth is causing electrical distribution networks to grow [1]. This ultimately results in the network's weakness because power loss rise, the voltage profile drastically drops, and the currents flowing through the system's branches increases over what is esteemed [2].

Enhancing radial distribution network (RDN) dependability is significant for the overall stability of the electrical power network [3]. There are various methods to improve and enhance the efficiency and performance of RDNs, including optimal distributed generation (DG) placement [4], network reconfiguration, and optimal shunt capacitors (SCs) placement [5]. Each of these methods offers distinct advantages and challenges [6].

However, DG placement helps reduce losses by generating power closer to demand [7]. Additionally, integrating DG into existing grids can be complex and costly, making it less cost-effective compared to SCs [8], [9]. Reconfiguration optimizes power flow by changing the network topology, which can reduce losses and improve voltage stability [10]. However, reconfiguration is less flexible in large networks and more resource-intensive compared to the simpler and more cost-effective solution offered by SCs [11], [12].

Among various available methods, optimally placing and sizing SCs is widely used for its ability to mitigate power losses and enhance voltage profiles through reactive power compensation [13]. Several techniques have been proposed to enhance RDN performance, with SC placement emerging as one of the most common approaches [14]. SCs are strategically placed in RDNs to reduce loss through reactive power compensation, which becomes increasingly important as energy conservation is prioritized [15], [16]. Another benefit of capacitor banks is that they can enhance the voltage profile and liberate feeder capacity for better system utilization [17].

However, improper SCs placement can result in suboptimal performance, such as higher losses and voltage drops, thereby highlighting the importance of optimizing their locations and sizes [18]. The issue of identifying optimal positions and ratings of SCs in RDNs known as optimal capacitor placement (OCP) problem, poses a significant challenge for RDN operators. This challenge arises because this problem is a combinatorial in nature and must address multiple technical objectives (power loss, voltage profile) and economic consideration (cost, maintenance) [19].

As a result, in latest years, a variety of optimization approaches have been recommended for finding the better solution for OCP problems in RDNs in order to maximize their benefits. Many methods have been developed for tackling the OCP problem, which has gotten more attention from researchers. For addressing the OCP problem, two techniques dependent on loss sensitivity factors (LSFs) for deciding optimal places and the plant growth simulation algorithm (PGSA) for calculating optimal capacitor capacities was used in [20]. However, such methods are limited to capacitor sizing alone, and a holistic solution is often not achieved.

Several other methods, such as direct search algorithm (DSA) have been applied to identify the OCP for maximizing net savings and diminishing actual power loss [21]. The mine blast algorithm (MBA) was applied to OCP problem by Elazim and Ali [22]. In the first phase, LSF is used to locate such buses, followed by MBA to optimize both the SC's capacities as well as their positions. For solving the OCP problem, Youssef *et al.* [23] combined the salp swarm algorithm (SSA) with LSF for optimal locations and sizes of SCs. In a different approach, a hybrid strategy for capacitor positioning and sizing in RDNs was proposed by combining a fuzzy expert system (FES) and the dragonfly algorithm (DA) [24].

Abdelsalam and Mansour [25] employed the sine cosine algorithm (SCA) to maximize profit through eliminating energy loss, reducing capacitor investment costs, and improving dependability. In their approach, LSF were used for finding the most sensitive buses for SCs placement, ensuring optimal capacitor placement [25]. A novel hybrid technique based on combined a genetic algorithm (GA) with a new stability index was used to solve the OCP in RDNs, aiming to reduces loss and improves voltage stability [26]. In their hybrid method, the optimal sites of the capacitors are identified by the bus voltage stability index (BVSI), while the GA is employed to calculate the optimal capacitors size. Recent studies by [27]-[29] have advanced the optimization of SC allocation by integrating them simultaneously with electric vehicle charging stations for enhancing distribution system reliability and economic performance. Their hybrid optimization approaches address both technical and financial objectives, focusing on optimal SCs assignment and sizing electric vehicle.

In light of the above discussion, a comparative summary of the most notable optimization approaches used in previous OCP studies is presented in Table 1. While these methods offer partial solutions, most studies have limitations. These limitations include the lack of consideration for bus voltage and capacitor capacity constraints, along with the omission of repair and operating costs in the overall capacitor cost estimates. Additionally, the objective functions in prior studies are typically treated independently, focusing on loss mitigation or cost reduction as separate goals, rather than integrating both into a unified framework.

Moreover, capacitor placement in many prior studies is often based on sensitivity factors such as the LSF. While these factors can provide a preliminary estimate, they have been found to be less reliable and may not always result in optimal capacitor positioning [30]. Another important limitation in the current research is the insufficient emphasis on real world or practical RDNs. Most studies are conducted on standard test RDNs, which often fail to reflect the complexities and operational challenges in actual RDNs [31].

To address the limitations of prior studies, this research proposes a novel approach that simultaneously accounts for technical and economic benefits, including power loss reduction and cost-effectiveness. In this context, the SSA, presented by Mirjalili *et al.* [32] in 2021, is a promising optimization approach encouraged by the foraging behavior of salps in oceans. SSA has confirmed effectiveness in solving diverse problems because of its easiness and minimal tuning parameters.

Table 1. Summary of recent optimization techniques for solving the OCP problem in RDNs

Ref. No.	Year	System type	SC allocation strategy	Algorithm used	Technical objective (loss/voltage)	Economic objective (cost/profit)
[20]	2011	IEEE 10, 34, 85	LSF (location), PGSA (size)	PGSA	✓	✗
	2012	IEEE 69, 85	Direct search	DSA	✓	✓
[21]	2018	IEEE 10, 85	LSF (location), MBA (size+location)	MBA	✓	✓
	2018	IEEE 69, 85	LSF+SSA	Hybrid SSA-LSF	✓	✓
[22]	2019	IEEE 69	FES (location), DA (size)	Fuzzy-DA	✓	✗
	2019	IEEE 33, 69	LSF	SCA	✓	✓
[23]	2024	IEEE 69	BVSI (location), GA (size)	GA	✓	✗
	2024	IEEE 33	Combined EV & SC	Hybrid optimization	✓	✓
[24]	2024	IEEE 33	Joint electric vehicle & SC	Hybrid optimization	✓	✓
	2025	IEEE 33, 69, 85, 118, Brazil 136	Joint electric vehicle & SC	Hybrid optimization	✓	✓
This work	2025	Iraqi 65, IEEE 33	Direct (both location and size)	WLSSA	✓	✓

However, like other metaheuristic algorithms, SSA suffers from certain drawbacks, such as susceptibility to getting stuck in local optima, slow convergence in complex search spaces, and reduced performance in multi-modal optimization problems. To overcome these challenges, this research introduces a new parameter named inertia weight to improve SSA's solution precision, consistency, and convergence speed by adjusting the current solution. Based on this enhancement, an improved algorithm named the WSSA is presented and applied to the OCP problem. Therefore, this study leverages the WSSA as an optimization method to simultaneously find the optimal placement and rating of SCs. The projected approach aims for diminishing power loss, reducing the overall costs associated with SCs (purchase, installation, and operating costs), and reinforcing the system voltage profile, thus maximizing the annual cost saving (ACS) subjected to maintaining all the constraints within its permissible limits.

The OCP is presented as a multi-objective one considering loss and cost while satisfying all constraints. The power flow discussed in this research uses the backward/forward sweep (BFS) technique, which is more suitable for RDNs than other conventional load flow methods. The results gotten utilizing the WSSA technique are compared to those gotten utilizing SSA and other contemporary techniques published in the literature including novel analytic (NA) [33], locust search (LS) [34], grey wolf optimization (GWO) [35], and hunter-prey optimization (HPO) [36]. The primary contributions can be outlined as follows:

i) Comprehensive multi-objective approach: The proposed work simultaneously accounts for technical and economic advantages, including power loss reduction and cost-effectiveness. The OCP issue is considered as a multi-objective optimization task, considering both loss minimization and cost reduction, integrated into a single objective function using a weighting factor.
ii) Development of WSSA: The research introduces an enhanced optimization technique, WSSA, by incorporating an inertia weight parameter into the standard SSA. This modification improves the algorithms precision, consistency, and speed, avoiding the limitations of the basic SSA in complex and multi-modal search spaces.
iii) Novel application of WSSA to OCP in RDNs: This study applies the WSSA for tackling the OCP problem in RDNs for the first time. The method determines the best possible SC placement and rating at the same time addressing gaps in previous studies that relied on LSFs or separated objectives.
iv) Application to real and standard RDNs: The efficiency of the presented method is validated on both real-world and benchmark systems. Testing the suggested methodology on a heavily loaded Iraqi 65 bus RDN and standard IEEE 33 bus RDN.
v) Enhanced energy and economic performance: The proposed approach significantly enhances the RDN's performance by reducing power loss and ameliorating voltage profile. It also achieves substantial ACS by optimizing the siting and rating of SCs, considering purchase, installation, and operating costs.
vi) Validation through comparative analysis: The results attained using the WSSA are benchmarked against those from the basic SSA and other contemporary optimization techniques described in the literature.
vii) Practical considerations for real-world implementation: The study explicitly addresses the limitations of prior research by focusing on real, heavily loaded RDNs with significant power losses and operational challenges. This practical orientation guarantees the applicability of the proposed method to real-world RDNs.

The paper's reminder is ordered as follows. Section 2 describes the OCP problem formulation, including constraints, load flow computation utilizing the BFS method, and objective functions. The fundamental ideas of the SSA and its enhancements are described in section 3. Results from simulations and case studies are offered in section 4. Lastly, conclusions and future work are explained in section 5.

2. METHOD

This section describes and explains the load flow analysis (LFA) for RDNs, multi-objective functions, and RDNs constraints implemented in this work and described in the section below.

2.1. Load flow analysis (LFA)

This section presents a fundamental tool for evaluating the steady-state performance of the RDNs, including bus voltages, power flows, and system losses. It enables accurate assessment of network operating conditions, which is essential for planning, optimization, and reliability improvement. In this study, the LFA is performed using the FBS method, chosen for its suitability in handling the unique characteristics of RDNs, as detailed in the following subsection.

2.1.1. BFS based LFA method

Because of its flexibility and precision, BFS method is widely used for attaining the LFA calculation in RDN. It has a quick convergence property and is computationally more efficient. While Newton-Raphson, fast decoupled, Gauss-Seidel, and other traditional LFA techniques are well adapted for transmission systems, they are not often used in distribution networks due to its lower efficiency, high resistance/reactance (R/X) ratios, radial configuration [37], and other factors. The BFS algorithm consists of three simple iterative steps. These steps are described in detail in [38].

2.1.2. LFA calculation

For this study, the load flow calculations are derived from the single line diagram (SLD) of RDN display in Figure 1. The SLD serves the structural representation of the network, illustrating the arrangement of buses, branches, and connected loads. Using this schematic as the reference model, the BFS is applied to iteratively compute bus voltage, branch, currents, and power flows under the specified loading conditions.

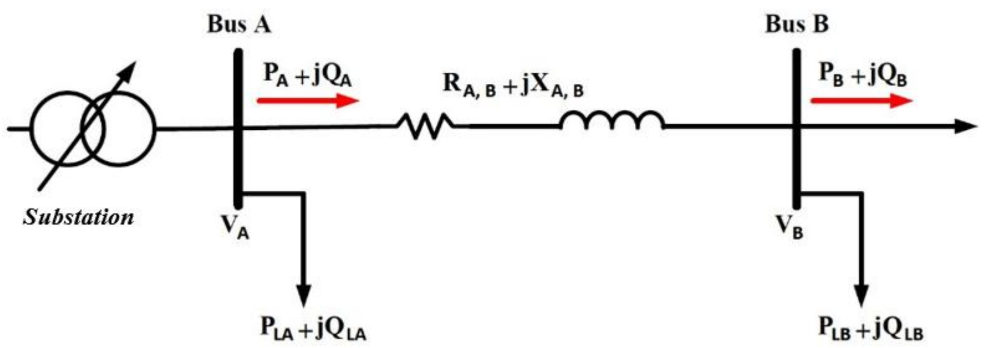

Figure 1. SLD of the RDN

From Figure 1, if A and B denote the receiving end nodes, then (1) and (2) can be utilized for computing the active (P_B) and reactive (Q_B) power flows shown in the above figure.

$$P_B = P_A - P_{LB} - R_{A,B} \times \left(\frac{P^2{}_A + Q^2{}_A}{|V_A|^2}\right) \tag{1}$$

$$Q_B = Q_A - Q_{LB} - X_{A,B} \times \left(\frac{P^2{}_A + Q^2{}_A}{|V_A|^2}\right) \tag{2}$$

The voltage of line at bus B can be calculated through utilizing (3).

$$|V_B|^2 = |V_A|^2\ 2 \times (R_{A,B} \times P_B + X_{A,B} \times Q_B) + (R^2{}_{A,B} + X^2{}_{A,B}) \times \left(\frac{P^2{}_A + Q^2{}_A}{|V_A|^2}\right) \tag{3}$$

In (4) and (5) are presented to compute the actual power loss (P_{Loss}) of the branch"A, B".

$$P_{Loss}\ (A, B) = I^2{}_{A,B} \times R_{A,B} \tag{4}$$

$$P_{Loss}\ (A, B) = \left(\frac{(P^2{}_{eff/B} + Q^2{}_{eff/B})}{|V_B|^2}\right) \times R_{A,B} \tag{5}$$

In (6) and (7) are used to determine reactive power loss (Q_{loss}) of the branch "A, B".

$$Q_{Loss}\ (A, B) = I^2{}_{A,B} \times X_{A,B} \tag{6}$$

$$Q_{Loss}\ (A, B) = \left(\frac{(P^2{}_{eff/B} + Q^2{}_{eff/B})}{|V_B|^2}\right) \times X_{A,B} \tag{7}$$

Complete actual ($P_{Loss}\ (A, B)$) and reactive ($Q_{Loss}\ (A, B)$) power losses can be determined by adding the losses of completely lines, as shown in (8) and (9).

$$P_{Total\ Loss} = \sum_{(A,B)=1}^{N(A,B)} I^2{}_{A,B} \times R_{A,B} \tag{8}$$

$$Q_{Total\ Loss} = \sum_{(A,B)=1}^{N(A,B)} I^2{}_{A,B} \times X_{A,B} \tag{9}$$

$$I^2{}_{A,B} = \frac{(P^2{}_{eff/B} + Q^2{}_{eff/B})}{|V_B|^2} \tag{10}$$

SCs increase power efficiency and reduce the overall costs associated with SCs and power loss of the RDN by injecting reactive power ($Q_{SC,B}$). The RDN in Figure 1 becomes the RDN in Figure 2 after placing SC. In (2) is being changed for this compensated RDN to (11).

$$Q_B = Q_{A,B} - Q_{LB} - X_{A,B} \times \left(\frac{P^2{}_A + Q^2{}_A}{|V_A|^2}\right) + Q_{SC,B} \tag{11}$$

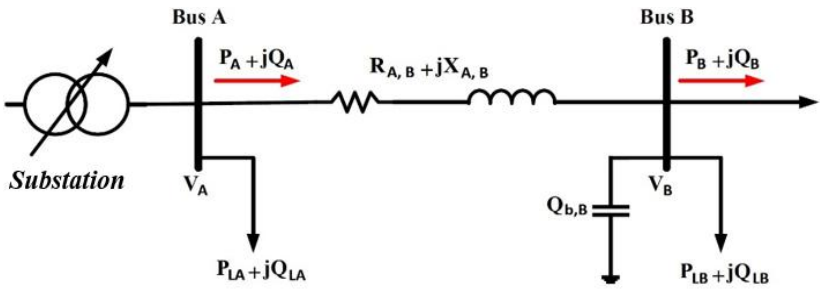

Figure 2. SLD of the compensated simple RDN with installed SC

2.2. Objective functions

Figure 3 displays the advantage of installing SCs, as considered in this work. The chief goal of objective function in the OCP issue is to lessen power loss and reduce the capacitor operation, installation, and purchase costs. As a result, the overall cost per year is reduced, and thus increasing ACS of the RDNs. The problem of OCP is viewed as a collection of multi-objective functions considering both power loss and cost, which are defined below. Though voltage profile improvement is not explicitly included in the objective function; instead, it is maintained through system constraints. Reducing power loss leads to an improved voltage profile primarily because lower losses result in less voltage drop along transmission lines and distribution feeders. With reduced current flow, resistive losses lessen, allowing the voltage at the consumer end to keep on closer to its desired level.

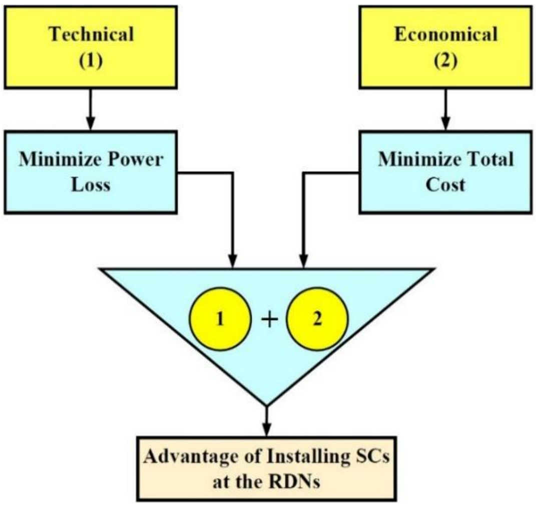

Figure 3. Advantage of installing optimal SCs at the RDNs used in this work

2.2.1. Real loss minimization

The first objective in optimum capacitor allocation is for reducing the total power loss ($P_{Total\ Loss}$). The following statement has been used to perform this objective mathematically [39].

$$F_1 = Min\ (P_{Total\ Loss}) \tag{12}$$

Where, $P_{Total\ Loss}$ is described in (8) in subsection 2.1.2.

2.2.2. Total cost minimization

The optimum capacitor allocation problem's second objective function is for minimizing the total cost per year (TC). This objective function was obtained by reducing annual energy losses cost (AELC) after compensation, which was obtained by loss minimization as well as capacitor installation, operation, and purchase costs. The following statements were used to accomplish this goal mathematically.

$$C_{TCP} = \sum_{c=1}^{nc} Q_C \times C_{PC} \tag{13}$$

$$C_{TC} = C_{TCP} + \sum_{c=1}^{nc} (C_{IC} + C_{OC}) \tag{14}$$

$$AELC = C_E \times T \times {P_{Total\ Loss}}^A \tag{15}$$

$$TC = AELC + C_{TC} \tag{16}$$

$$F_2 = Min\ (TC) \tag{17}$$

Where, C_E, T, C_{TCP}, nc, C_{IC}, C_{OC}, and Q_C, are cost of energy loss, time in hour (h), total cost ($), number of capacitors, cost of installation, cost of operation, value of capacitor (kVAR). Table 2 contains the parameter values [40]. ${P_{Total\ Loss}}^A$ denotes the total power loss after compensation. C_{PC} represents the capacitor's purchasing cost ($) per capacitor value (kVAR).

Table 2. Cost parameters values [40]

Parameter	Value
C_{IC}($/Location	1600
C_{OC}($/Location/Year)	300
C_E($/kWh)	0.06
T(h)	8760

2.3. Finalized multi-objective function

The key objective of OCP is to reduce power loss and annual cost while adhering to a number of constraints. As a result, the multi-objective functions (F) were carried out using the mathematical statement in (18).

$$F = Min\ (F_1 + F_2) \tag{18}$$

Where, $F_1 = Min\ (P_{Total\ Loss})$ and $F_2 = Min\ (TC)$ as described in the previous sections (i.e. 2.2.1 and 2.2.2), respectively.

The weighted sum technique is used in this study to assess the efficacy of WSSA for determining the benefits of optimal SCs allocation and sizing. A multi-objective mathematical OCP problem is transferred to a single objective function (F) utilizing weighted sum technique. These benefits are more suitable for real world issues as (19).

$$F = Min\ (W_1 \times F_1 + W_2 \times F_2) \tag{19}$$

Where, W_1 and W_2 denote weighting factors. The above multi-function of OCP problem must be to minimize (Min) loss and costs while subjecting to a number of constraints.

2.4. OCP problem constraints

The constraints are established to ensure that RDN operates reliably and correctly after compensation. The above objective function of OCP problem should be minimized while sustaining the constraints outlined below.

2.4.1. Equality constraint

Actual and reactive power balance must be met at the RDN's substation bus. They are shown in (20) and (21), respectively [41].

$$P_{SS} = \sum_{i=1}^{N_{line}} P_{Loss}(i) + \sum_{m=1}^{N_{Bus}} P_D(m) \tag{20}$$

$$Q_{SS} = \sum_{i=1}^{N_{line}} Q_{Loss}(i) + \sum_{m=1}^{N_{Bus}} Q_D(m) - \sum_{b=1}^{N_{SC}} Q_{SC}(b) \tag{21}$$

Where, P_{SS} and Q_{SS} are the substation real and reactive power. $P_{Loss}(i)$ and $Q_{Loss}(i)$ are the real and reactive power loss at line (i) and expressed in (8) and (9). $P_D(m)$ and $Q_D(m)$ refer to the active and reactive power load at node (m). N_{SC} is the number of SC installed at the RDN and $\sum_{b=1}^{N_{SC}} Q_{SC}(b)$ denotes the total SC reactive value placed in the RDN.

2.4.2. Inequality constraints

These constraints comprise, voltage, current, capacitor value and some other constraints are as shown below:

- Voltage constraints

Voltage value (V_i) at each RDN node must remain within the permissible [V_{min} and V_{max}] limits. For voltage rise and decrease, specifications of 5% and 10% from its rated voltage are considered, respectively, as (22).

$$V_{min} \leq |V_i| \leq V_{max}, \tag{22}$$

Here, $|V_i|$ denotes the voltage value of ith bus in the RDN, which is limited to 0.90 (V_{min})–1.05 (V_{max}) p.u. in the RDN.

- Branch current constraints

From the safety hand, line current (I_{line}) value must not exceed its allowable limit ($I_{line\ max}$). This condition is required to maintain power supply stability, as shown in (23).

$$|I_{line}| \leq |I_{line\ max}| \tag{23}$$

- Capacitor number constraint: a capacitor of the switched kind is used, and each bus is limited to one capacitor.

- Total compensation constraint

According to the following equation, the total size of capacitor ($Q_{SC_{Total}}$) at the optimum position of the RDN should not supersede the total demand of reactive power ($Q_{D_{Total}}$). This relationship is expressed in (24).

$$Q_{SC_{Total}} \leq Q_{D_{Total}} \tag{24}$$

- Capacitor's rating constraint

The compensated reactive power into the RDNs via SCs is reflected as a discrete rate of 150 kVAR step. The capacitor's kVAR compensation (Q_{SC_b}) at the optimum RDN placement should be within their permissible [$Q_{SC_{min}}$ and $Q_{SC_{max}}$] bounds as (25).

$$Q_{SC_{min}} \leq Q_{SC_b} \leq Q_{SC_{max}} \tag{25}$$

2.5. Annual cost saving (ACS)

Once the presented ISSA has identified the optimum value and position of capacitors, the ACS can be determined through corresponding monetary benefits thanks to diminished active power loss, capacitor installation, operation, and purchase costs. The difference among both the total AELC of the base case (S_A^B) (before compensation) and the total cost after compensation (S_A^A) is used to calculate the ACS (S_{Cost}) achieved from objective functions minimization, as shown in the given equations:

$$S_A^B = C_E \times T \times P_{Total\ Loss}{}^{B} \tag{26}$$

$$S_A^A = AELC + C_{TC} \tag{27}$$

$$S_{Cost} = S_A^B - S_A^A \tag{28}$$

where, C_{TC} and $AELC$ are described in (14) and (15) in section (2.2.2).

2.6. Optimization process

2.6.1. Conventional SSA

The conventional SSA algorithm was proposed in 2017 [42]. Swarm salps can be scavenged in seas, and SSA simulates their process. In the deep oceans, the salp at the head of the chain will become the leader, with the remaining salps serving as followers. Because of this special behavior, the algorithm has a high degree of exploitation potential in the local range. However, the original SSA, tends to converge to a local optimum when the population leader is unable to travel to the promising areas. As a result, we suggest a method in this paper to enhance the efficiency of the SSA. The leader has a significant impact on the entire society during the leader stage [43]. The quest is directed by the chief, who keeps it going closer to the food. In (29) indicates the formula for updating location.

$$X_d^1 = \begin{cases} F_d + C_1\big((ub_d - lb_d)C_2 + lb_d\big), C_3 \geq 0 \\ F_d - C_1\big((ub_d - lb_d)C_2 + lb_d\big), C_3 < 0 \end{cases} \tag{29}$$

Where, X_d^1 and F_d represent the leader and source of food locations. ub_d and lb_d display the upper and lower boundary. C_2 and C_3 show the random numbers between [0, 1] control parameters. The factor C_1 is important in organizing exploration and extraction, as it decreases in the period [2~0]. Its meaning is as (30).

$$C_1 = 2 * e^{-(\frac{4t}{t_{max}})^2} \tag{30}$$

Where, t and t_{max} denote current and maximum iterations number. The following term is utilized to shift the follower's location.

$$X_d^i = \frac{1}{2}(X_d^i + X_d^{i-1}) \tag{31}$$

Where, X_d^i denotes the follower position and $n \geq 2$.

2.6.2. WSSA

Traditional SSA is prone to local minima stagnation and poor searching accuracy. For overcoming this problem and improving searching capability through both exploration and exploitation, an inertia weight mechanism w € [0,1] is introduced to the SSA, and the presented algorithm is known as WSSA [44]. This new factor in the WSSA has the benefits of getting a better searching strategy, achieving precise solutions, avoiding blindness of the search method, and accelerating speed convergence. Also, when dealing with a large number of large-scale problems, it maintains a good balance among exploration and exploitation while preserving low computational difficulty. So, the new leader's position and the new followers' position in the ISSA can be changed as shown in (32) and (33).

$$X_d^1 = \begin{cases} w \times F_d + C_1\big((ub_d - lb_d)C_2 + lb_d\big), C_3 \geq 0 \\ w \times F_d - C_1\big((ub_d - lb_d)C_2 + lb_d\big), C_3 < 0 \end{cases} \quad (32)$$

$$X_d^i = \frac{1}{2}(X_d^i + w \times X_d^{i-1}) \quad (33)$$

2.7. The implementation of WSSA to OCP problem

WSSA considers two OCP problem parameters, such as capacitor position and rating, to be control variables. As a result, and search agent's number of variables is calculated by the number of SCs. Two variables are considered for each SC: the first variable represents the position, and the second variable represents the capacity. Each search agent in WSSA, for example, is made up of two variables that are split into two sections for each SC. One is for the venue, while the other is for SC's scale. A solution corresponding to a salp is represented by these variables. The solution vector comprising position and rating of capacitor are expressed in (34). Figure 4 depicts the procedure for solving the WSSA for the OCP problem, and the WSSA flowchart is shown in this figure, illustrating the step-by-step process of the algorithm.

$$X^T = [\overline{L_{SC}}, \overline{Q_{SC}}] \quad (34)$$

Where, X^T is the control variable, L_{SC} and Q_{SC} are the location and size of capacitor. The trial-and-error technique was used for initializing WSSA control parameters. The details of WSSA parameters based two RDNs are mentioned in Table 3.

Table 3. WSSA parameters

Parameters	IEEE 33 bus	Iraqi 65 bus
Population size (N_s)	10	10
Iterations (L)	250	250
w	0.9	0.9

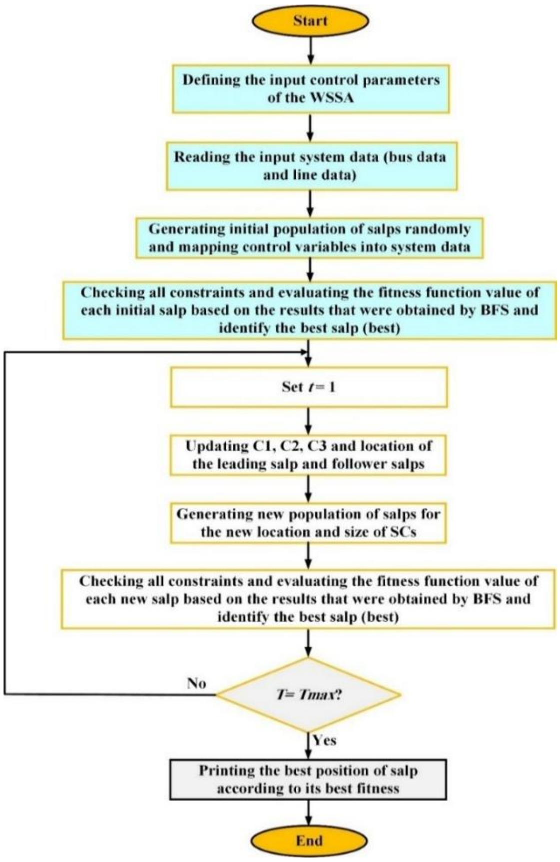

Figure 4. Flowchart of the presented WSSA implemented for OCP problem

3. RESULTS AND DISCUSSION

For evaluating the efficacy and applicability of WSSA technique in terms of minimizing power loss, reducing the total costs related with SCs, including purchase, installation, and operating costs, and improve the system voltage profile, two RDNs were used in this simulation. Due to space constraints in the paper, two RDNs, the real Iraqi 65-bus and standard IEEE 33-bus RDNs, were chosen for reporting for testing the efficacy of the proposed WSSA. The WSSA technique and the FBS is implemented in MATLAB. This study includes the total SCs costs and total cost per year (TC), and the power loss and annual cost of actual power loss (ACEL). In the following section, the numerical results of these cases are described and analyzed. The attained results by using WSSA are compared to those attained by other approaches in the literature.

3.1. Results of practical Iraqi 65 bus

The RDN, depicted in Figure 5, is an actual 65-bus from Iraq that is used as a first RDN in this paper. This RDN is a feeder originating from the secondary power station in the Sadat Al-Hindiya district, supplying electricity to the Al-Zahraa neighborhood, which is one of the districts within Sadat Al-Hindiya. This area is situated south of Al-Musayyib city in Babil Governorate, Iraq. After using the geographic position system (GPS) to determine the line length and bus locations, the system data in Table 4 is recognized [45].

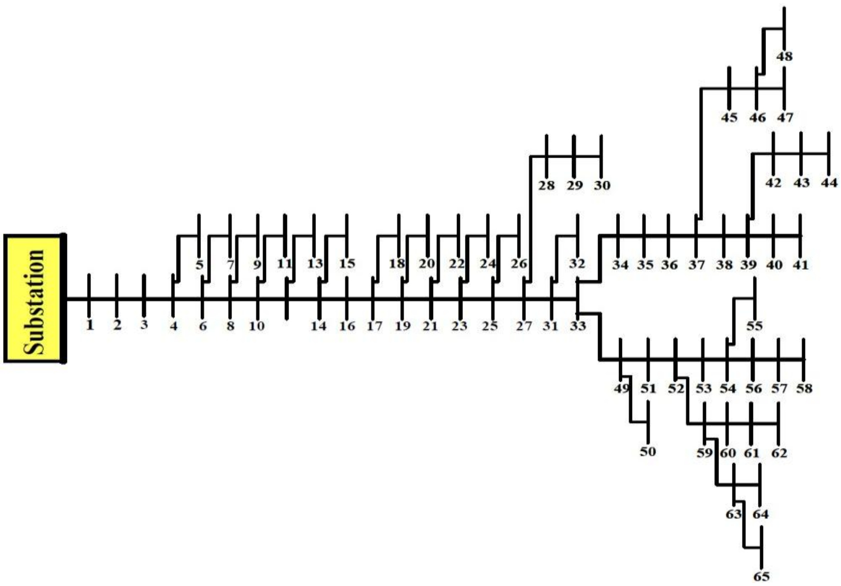

Figure 5. Practical Iraqi-65 bus RDN

The presented WSSA is satisfied on a practical Iraqi 65-bus RDN. The substation bus is the first bus in the network, and it has operating voltage of V_{Base} = 11 kV and operating apparent power of S_{Base} = 100.0 MVA. The lasting nine nodes are load nodes, with a total active and reactive power load of (S_{Load} = 5.6692 MW + J 3.5606 MVAr), respectively. Power flow by using FBS method is run before installing any SCs on said system (without compensation), the annual power loss that occurs from the normal operation of the Iraqi 65-bus system is 446.2 kW, resulting AELC of $234522.72. In addition, the minimum voltage (V_{Min}) present on the bus in this base case is 0.9066 p.u. at node 12. Alwazni and Al-kubragyi [45] contains more extensive information on the proposed 65-bus RDN.

Only three capacitors with values of 450, 450, and 300 kVAR are distributed at optimal positions at buses 8, 17, and 43 utilizing the presented ISSA technique. The outcomes are gotten in Table 5 and this table compares the results accomplished by proposed WSSA method with those obtained by SSA implemented for OCP on the practical Iraqi 65 Bus RDN. So, the loss ($P_{Total\ Loss}$) has been reduced to 326.5 kW by using the traditional SSA with via compensating ($\sum_{c=1}^{nc} Q_C$) 1950 kVAR. However, compared to SSA method, the proposed WSSA approach reduces $P_{Total\ Loss}$ from 446.2 to 303.24 kW as 32.03%, which enhances the minimum voltage (V_{Min}) from 0.9066 to 0.9456 p.u. and decreases total cost/year (TC) from $234522.72 to $159382.9 by reactive power injecting 1200 kVAR, resulting in better results as exposed in Table 4. The observations showed that a lesser amount of reactive power was injected via SC with the proposed approach when compared with that injected using SSA.

Table 4. Data of 65 bus local Iraqi RDN

Branch No.	Sending bus	Receiving bus	Branch data		Load at receiving end bus	
			R (Ω)	X (Ω)	P_L (MW)	Q_L (MVAR)
1	1	2	0.216363	0.264099	0.1063	0.0659
2	2	3	0.18478	0.225542	0.1063	0.0659
3	3	4	0.159363	0.194523	0.0000	0.0000
4	4	5	0.06318	0.077113	0.1700	0.1054
5	4	6	0.025650	0.031309	0.0000	0.0000
6	6	7	0.011400	0.013915	0.1063	0.0659
7	6	8	0.077663	0.094797	0.0000	0.0000
8	8	9	0.004750	0.005798	0.1063	0.0659
9	8	10	0.073625	0.089869	0.0000	0.0000
10	10	11	0.022325	0.027251	0.1063	0.0659
11	10	12	0.024938	0.03044	0.0000	0.0000
12	12	13	0.066025	0.080592	0.1700	0.1054
13	12	14	0.032300	0.039426	0.1700	0.1054
14	14	15	0.030875	0.037687	0.0000	0.0000
15	15	16	0.031588	0.038557	0.1700	0.1054
16	15	17	0.089538	0.109292	0.0000	0.0000
17	17	18	0.017100	0.020873	0.1063	0.0659
18	17	19	0.014725	0.017974	0.0000	0.0000
19	19	20	0.015675	0.019133	0.1063	0.0659
20	19	21	0.095238	0.11625	0.0000	0.0000
21	21	22	0.121838	0.148718	0.1700	0.1054
22	21	23	0.113050	0.137992	0.0000	0.0000
23	23	24	0.016388	0.020003	0.1700	0.1054
24	23	25	0.011400	0.013915	0.0000	0.0000
25	25	26	0.001663	0.002029	0.1063	0.0659
26	25	27	0.027550	0.033628	0.0000	0.0000
27	27	28	0.008550	0.010436	0.1063	0.0659
28	28	29	0.011638	0.014205	0.1700	0.1054
29	29	30	0.020900	0.025511	0.1700	0.1054
30	27	31	0.015675	0.019133	0.0000	0.0000
31	31	32	0.021613	0.026381	0.1700	0.1054
32	31	33	0.069113	0.084361	0.0000	0.0000
33	32	34	0.006175	0.007538	0.1700	0.1054
34	33	35	0.045125	0.055081	0.1063	0.0659
35	34	36	0.032063	0.039137	0.1063	0.0659
36	35	37	0.030875	0.037687	0.0000	0.0000
37	36	38	0.046550	0.056820	0.1063	0.0659
38	37	39	0.015200	0.018554	0.0000	0.0000
39	38	40	0.056763	0.069286	0.1700	0.1054
40	39	41	0.018763	0.022902	0.0000	0.0000
41	40	42	0.021138	0.025801	0.1063	0.0659
42	39	43	0.045600	0.055661	0.1700	0.1054
43	42	44	0.022088	0.026961	0.1063	0.0659
44	43	45	0.026363	0.032179	0.1700	0.1054
45	37	46	0.037525	0.045804	0.0000	0.0000
46	45	47	0.055813	0.068127	0.1063	0.0659
47	46	48	0.007600	0.009277	0.1063	0.0659
48	46	49	0.021375	0.026091	0.0000	0.0000
49	33	50	0.009975	0.012176	0.1063	0.0659
50	49	51	0.029688	0.036238	0.1700	0.1054
51	49	52	0.006413	0.007827	0.0000	0.0000
52	51	53	0.081225	0.099146	0.1700	0.1054
53	52	54	0.016150	0.019713	0.0000	0.0000
54	53	55	0.018525	0.022612	0.1700	0.1054
55	54	56	0.018763	0.022902	0.1700	0.1054
56	54	57	0.002850	0.003479	0.1063	0.0659
57	56	58	0.013538	0.016524	0.1063	0.0659
58	57	59	0.012588	0.015365	0.0000	0.0000
59	52	60	0.009500	0.011596	0.1063	0.0659
60	59	61	0.050113	0.061169	0.1700	0.1054
61	61	62	0.026125	0.031889	0.1063	0.0659
62	59	63	0.022800	0.027830	0.0000	0.0000
63	63	64	0.021138	0.025801	0.1700	0.1054
64	63	65	0.024938	0.030439	0.1700	0.1054

Furthermore, from Table 5, it is clear that the ACS (S_{Cost}) achieved by the WSSA approach is \$69201.57, which leads to a net savings of 29.51%, which is the largest of all the competitive approaches. As compared to SSA technique, the proposed WSSA algorithm is characterized by their high efficiency, which includes the lowest power losses and the highest net saving. Overall, the suggested method's real power reduction was greater than that of the other optimization technique under investigation; Table 4 summarizes the performance comparison. Based on the results of Table 4 following the implementation of the suggested WSSA, Figure 6 displays optimal locations and sizes where the SCs is locally injected within the RDN topology. Also, Table 5 demonstrates the convergence time values for the SSA and WSSA algorithms applied for tackling this problem of this study for the Iraqi 65 bus RDN. Finally, Figure 7 demonstrates the voltage profile of practical Iraqi 65 bus RDN with and without compensation obtained using the proposed WSSA-based OCP scheme solution. As seen in the diagram, the proposed solution significantly improves bus voltage profile as compared to the system without compensation and the proposed WSSA significantly improved the voltage profile compared to the traditional SSA.

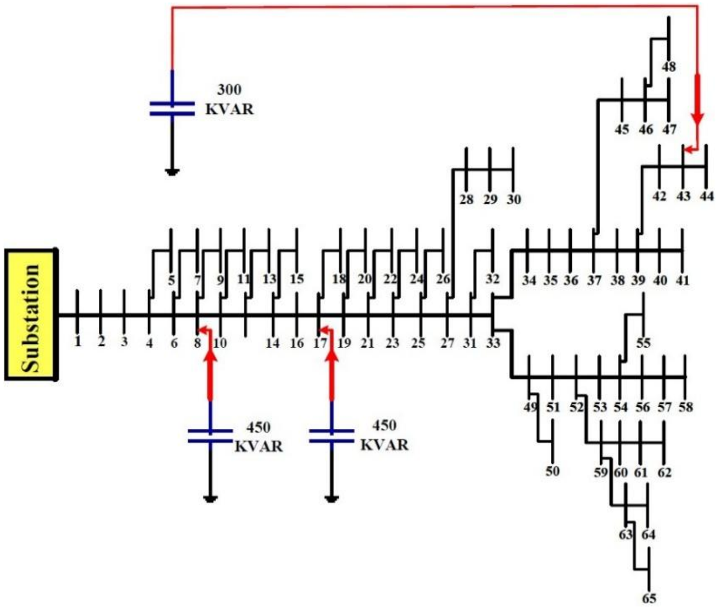

Figure 6. Practical Iraqi-65 bus RDN showing the locations and sizes of SCs for reactive power compensation

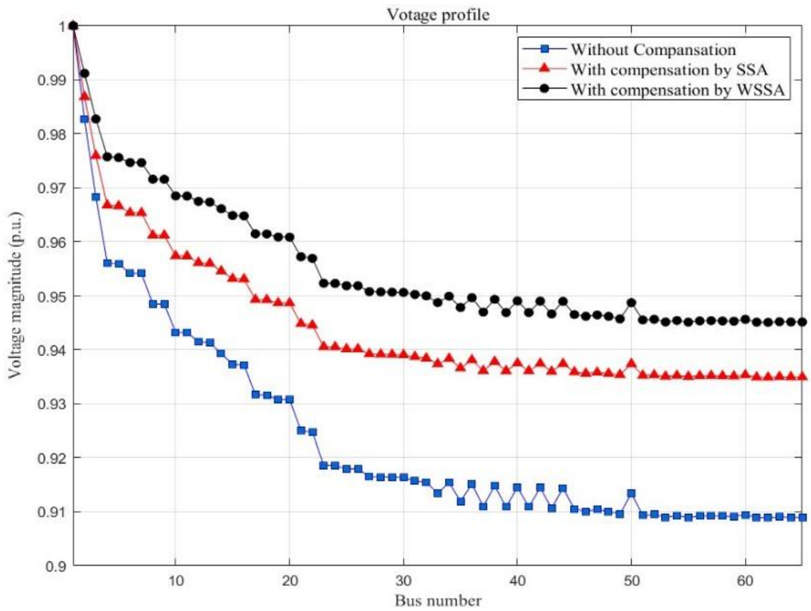

Figure 7. Voltage profile of practical Iraqi 65 bus with and without SCs

Table 5. Experimental results of practical Iraqi-65 bus RDN

Items	Base case	SSA	WSSA
Year	-	2025	2025
L_{SCs} (bus no.)	-	27, 43, 54	8, 17, 43
Q_{SCs} (in kVAR)	-	600, 450, 900	450, 450, 300
V_{Min}	0.9066	0.9340	0.9456
Total kVAR	-	1950	1200
$P_{Total\ Loss}$	446.2	326.5	303.24
C_{TC} (\$) (A)	-	6110.55	5938.2
$AELC$ (\$) (B)	234522.72	171608.4	159382.9
TC (C = A+B (\$))	-	177718.95	165321.14
S_{Cost}(\$) (D=234522.72-C)	-	56803.77	69201.57
% reduction (P_{Loss})	-	26.82	32.03
% savings (E=D/234522.72)	-	24.22	29.51
Convergence time (sec.)	-	27.2	21.6

3.2. Results of standard IEEE 33 bus

This network was presented for assessing the effect of the presented WSSA on a standard RDN. This network has 33 buses, 32 distribution branches, with one main substation and three laterals as exposed in Figure 8. The total power loads of this system are (2.3+J 3.715) MVA. All calculations are done in p.u. using the system's-based voltage (V_{Base}) and apparent base power (S_{Base}), which are 12.66 kV and 100 MVA, respectively. The detailed system data are recorded in detail in [46]. Because of high inductive loads, the end buses of this RDN have low voltages. The $P_{Total\ Loss}$ is calculated at 202.67 kW with the V_{Min} at node 18 of (0.9131 p.u.) and the total AELC is 106527 $ after executing the load flow estimation using the FBS method and without placing any capacitor banks in the RDN (base case).

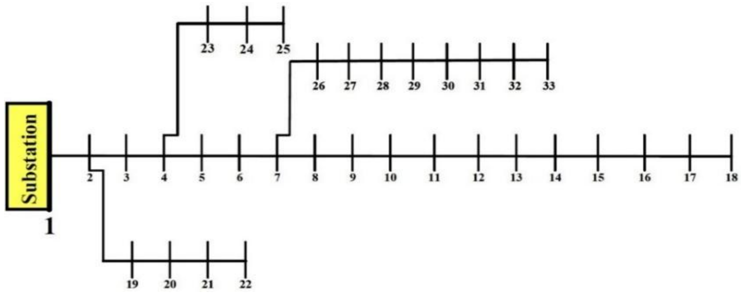

Figure 8. Standard IEEE 33 bus RDN

The presented WSSA-based OCP approach chose bus numbers 8, 10, and 29 as optimal nodes to position the SCs, in this case of optimal capacities 300, 150, and 1050 kVAR, respectively, as exposed in Table 6. Also in the same table, the proposed WSSA was compared to the results obtained utilizing other recent techniques available in the literature, such as NA [33], LS [34], GWO [35], and HPO [36]. From the same table, after compensating the reactive power to this RDN by using WSSA, the $P_{Total\ Loss}$ is diminished from 202.67 to 132.12 kW, which is the minimum of all aforementioned algorithms reported in the literature, corresponding to a 34.81% active power loss rate, which is the largest of all aforementioned algorithms published in the literature. The observations showed that a lesser amount of reactive power was injected via shunt capacitor with the proposed approach when compared with that injected using SSA. Even though the amount of injected power with the use NA was lesser, yet loss reduction achieved using WSSA was much better than that of NA.

These results demonstrate the better value when it is compared with 33.63% of GSA, 31.55% of NA, 31.3% of LS, and 33.51% of GWO. As compared to the other recent techniques in Table 6, this result is the greatest value. Furthermore, the V_{Min} at node 18 is reinforced from 0.9131 to 0.9506 p.u. after compensation by WSSA, which is within the voltage limits. Also, the WSSA has reduced the total cost/year from 106527$ (base case) to 75561.67$ (after compensation). Moreover, as shown in Table 5, when compared to the system without compensation, the ACS (S_{Cost}) after compensation by the WSSA approach maximizes to 34%, the highest of all comparative approaches.

In addition, when comparing to some other recent techniques available in the literature, a closer review of Table 5 reveals that presented WSSA-based OCP approach results in the greatest reduction in $P_{Total\ Loss}$ and cost TC with greatest increase in net savings (S_{Cost}), demonstrating the competitiveness of presented WSSA-based OCP approach. In all the magnitude of reduction in real power with the WSSA was better compared to other methods investigated in the literature. A summary of this performance comparison is exposed in Table 6. Based on the results of Table 5, following the application of the suggested WSSA, Figure 9 illustrates different ideal locations and sizes of SCs injected locally inside the RDN topology. Table 6 shows the convergence times of SSA and WSSA for the IEEE 33-bus RDN in solving OCP problem.

Furthermore, as shown in Figure 10, the integration of capacitors significantly improves the voltage profile. The figure also illustrates the voltage performance of a 33-bus system with and without compensation obtained through the proposed WSSA-based OCP. A comparison with the traditional SSA demonstrates the superior effectiveness of the presented approach.

Table 6. Experimental results of IEEE node-33 RDN

Items	Base case	NA [37]	LS [38]	GWO [39]	HPO [40]	SSA	WSSA
Year	-	2017	2018	2019	2023	2025	2025
L_{SCs} (bus no.)	-	14, 30, 32	12, 25, 30	8, 13, 20	12, 24, 30	10, 13, 30	8, 10, 29
Q_{SCs} (in kVAR)	-	550, 480, 330	450, 350, 900	450, 300, 900	450, 450, 1050	450, 750, 900	300, 150, 1050
V_{Min}	0.9130	0.9428	0.9291	0.9400	-	0.9500	0.9506
Total kVAR	-	1360	1700	1650	1950	2100	1500
$P_{Total\ Loss}$	202.67	138.72	139.23	134.07	138.43	141.27	132.12
C_{TC} (\$) (A)	-	9780	10800	6083.55	6167.1	6185.55	6119.4
$AELC$ (\$) (B)	106527	72911.23	73179.28	70468.5	72758.8	74251.51	69442.27
TC (C = A+B (\$))		82691	83979	76552.05	78925.9	80437.062	75561.67
S_{Cost}(\$) (D = 106527-C)	-	23836	22548	29975	27601.09	26089.94	30965.33
% reduction (P_{Loss})	-	31.55	31.3	33.51	31.69	30.03	34.81
% savings (E = D/106527)	-	22.37	21.16	28.13	25.9	24.5	29.08
Convergence time (sec.)	-	-	-	-	-	21.8	19.2

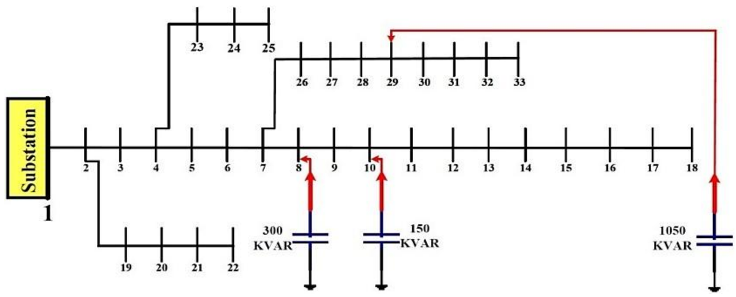

Figure 9. Standard IEEE-33 bus RDN after adding SCs for reactive power compensation

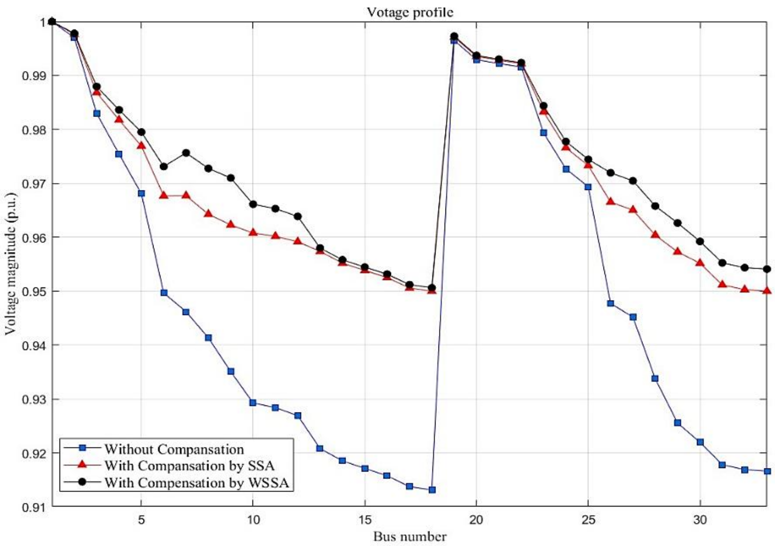

Figure 10. Voltage profile of IEEE 33 bus before and after SCs

4. CONCLUSION

Maintaining appropriate power quality in a cost-effective manner during different operating conditions is a significant obstacle for RDN operators. In this paper, the effective meta-heuristic WSSA was used as a novel optimization technique for identifying OCP in RDNs in order to preserve power efficiency. Multi-objective functions for the OCP problem were set, including improving the voltage profile, decreasing system losses, and lowering the RDN's annual total cost (TC), thereby maximizing the net savings (S_{Cost}). To evaluate superiority of WSSA, it was verified on IEEE 33-bus and on a real Iraqi 65-bus RDNs using MATLAB/simulation program. According to the obtained results, installing SCs in RDNs at the optimum position and rating reduces power loss (P_{Loss}), enhanced annual net cost savings, and improved voltage profile. So, it is concluded that strategically positioned SCs in RDN can boost the distribution network's reliability, stability, and performance. To highlight the advantages and superiority of the presented WSSA method, the results of it were compared to those attained by other recent approaches in the literature. The comparative results with other approaches in the literature confirms that the presented WSSA approach has high accuracy for solving OCP problem which leads to maximize the technical and economic benefits of the two RDNs. The main points that are noteworthy are listed as follow: i) This paper does not incorporate an optimal node selection strategy for reactive power compensation based on loss sensitivity factors; ii) Reactive power compensation resulted in a 32.03% power loss reduction and a 29.51% economic benefit for the real Iraqi 65-bus RDN, while attaining 34.81% power loss reduction and a 29.08 % financial profit for the IEEE 33-bus RDN; and iii) The results clearly indicate that WSSA achieves better performance than the other algorithms in power loss reduction and financial benefits across both RDNs.

For future work, WSSA could be applied to optimize STATCOM parameters for improved voltage profiles and explore the simultaneous installation of DG and SCs for a more comprehensive evaluation of RDN competitiveness. Another avenue for future research is evaluating WSSA's long-term performance, particularly its ability to handle dynamic changes in load profiles and varying network conditions, ensuring robustness and scalability.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration. As the sole author of this paper, Omar Muhammed Neda was responsible for all listed contributions as indicated in the table below.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Omar Muhammed Neda	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Author state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [OMN], upon reasonable request.

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