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Impact of DGs on the Reactive Power-Supported Optimal EDN for Profit Maximisation

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***Abstract*—Significant issues such as high-Power Loss (P_{Loss}) and drop in node voltages in Electric Distribution Networks (EDNs) can be well mitigated using renowned techniques such as Alteration of Electric Distribution Network Switches (AEDNS), Optimal Capacitor Support (OCS), and Integration of Dispersed Generation (IDG), which are identified as the most economical and efficient approaches. This study presents the optimisation of AEDNS with and without OCS considering four different scenarios to maximise the profit through reduction in P_{Loss}, which is regarded as the first-step process. To further increase profit, IDG was integrated into the EDNs after the combined optimisation of OCS and AEDNS. In this work, Levy Flight Mechanism (LFM) was incorporated into the Seagull Optimisation Algorithm (SOA) and applied to solve the objective function based on economics. The effectiveness of the presented methodology was evaluated and confirmed using a real 59-bus in Cairo, Egypt, EDN, as well as a conventional 33-bus test system. For each scenario, the P_{Loss} reductions and net profit of the proposed methodology were contrasted with those obtained from previously reported approaches. The collected findings show that by optimising AEDNS, OCS, and IDG, the established methodology effectively yields more economic gain for all scenarios.**

***Index Terms*—Alteration of electric distribution network switches; Electric distribution network; Integration of dispersed generation; Optimal capacitor support.**

I. INTRODUCTION

The goal of any distribution power utility is to provide end consumers with a consistent power supply while ensuring lower operating costs and adequate power quality. Several studies reported that the loss of I^2R in EDN accounts for roughly 13 % of the total energy output. [1]. Similarly, to reduce T&D losses in India, reforms in the electric power sector were implemented after the year 2000, due to which the total Power Loss (P_{Loss}) dropped from 37 % to 24.6 % in 2001-02 [2]. Improvement in EDN performance necessitates appropriate planning to increase utility efficiency, i.e., how effectively the P_{Loss} gets minimised is the responsibility of the distribution utilities, thereby reduction in economic loss.

In general, most EDNs have sectionalising and tie-switches whose states decide the topological configuration of the EDN. However, the topological structure must be ensured to be radial. Alteration of Electric Distribution Network Switches (AEDNS) is one of the traditional techniques followed since the 1980s. The alteration of these switches will reduce power losses, improve bus voltage profile, load balancing, network reliability and security improvement, productivity enhancement, economy growth and service restoration (under contingency), etc. The primary objective of the distribution utilities is to determine a suitable topological configuration utilising soft computing approaches to obtain the best results. On the other hand, an inappropriate topological structure will reverse the target of the objectives. Numerous research papers solved using AEDNS have been reported in the last four decades [3]–[6].

A portion of the reactive power demand of the Main Power Source (MPS) has been reduced by Optimal Capacitor Support (OCS) locally near the loads in the radial EDN. Maximising power saving, improving the node voltage profile, reducing the release of feeder capacity, reducing the thermally limited apparatus load, loading congestion, improving the MPS power factor, etc. are some of the advantages of OCS. Thus, more real power output can be transferred to the end users. Achieving maximum cost savings as a result of reduction in P_{Loss} concurrent with capacitor purchase cost determines the capacity, number, and type of capacitor installed in the optimal buses. Capacitors installed on nonoptimal buses will reverse the objective. For the past four decades, many investigations based on OCS in EDNs have been focussed on [7]–[10].

Although the intentions of both AEDNS and OCS are the same, the properties are different and have limitations. In the scenario of heavy reactive power demand, the effect of AEDNS in reducing the I^2R loss is very less. Alternatively, optimally adding capacitors to the EDN reduces I^2R loss and improves the node voltage profile by reducing the reactive power flow in the EDN. However, this method is unsuccessful when dealing with large reactive power demands. Therefore, optimising of AEDNS and OCS one after the other will result in a greater reduction in I^2R loss followed by an increase in node voltage to the highest extent possible, thus generating economic savings.

The selection of the optimum nodes for OCS, accompanied

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by its sizing concurrently using AEDNS, is a nonlinear, challenging, requires interaction, and blended optimisation problem comprising integer and discrete variables. Thus, the determination of optimal position and capacity of capacitors along with optimal AEDNS plays a significant role in the planning and operation of EDN. Only a few research articles in the literature consider P_{Loss} reduction as an objective or operating cost minimisation using combined optimisation of AEDNS and OCS [11]–[14].

P_{Loss} reduction, bus voltage, and line current violation constraint with environmental benefits as objectives, reactive power optimisation via capacitors with AEDNS in five different scenarios using Improved Binary PSO (IBPSO) were reported in [11]. This paper focusses on reactive power injection at five and seven optimal buses in 16 and standard 33-bus test systems. In [12], four different algorithms (MBBO, MIC, CS, and MBFBO) were used to optimise independent OCS and simultaneous optimisation of AEDNS with OCS to reduce P_{Loss}/energy loss, improve voltage profile, and increase annual cost savings. Using standard 33- and 69-bus test systems, the performance of the above-mentioned algorithms is validated. Only a few papers discussed OCS after optimisation of AEDNS, i.e., optimal capacitor placement and sizing in the reconfigured EDN [13], [14]. In [13], four optimisation techniques (MBBO, BTLBO, and DDE) were used to optimise AEDNS and OCS, followed by AEDNS while considering IEEE 33- and PG&E 69-bus test systems. The objective function was defined as loss reduction with bus voltage and branch current limits. The real coded GA, SA, SSA, and Salp Swarm Algorithm with Genetic Algorithm (SSA-GA) as optimisation methods, three different scenarios such as AEDNS, OCS, and simultaneous optimisation of AEDNS and OCS at seven optimal nodes in the standard 33-bus system were performed in [14]. From [15]–[17], it was proved that combined optimisation of AEDNS, OCS, and Integration of Dispersed Generation (IDG) in EDN yields still better-improved performance than individual/combined optimisation of any two methods subject to the satisfaction of equality and inequality constraints. After combining OCS and AEDNS optimisation, this work considers Distributed Generation (DG) allocation and sizing at three locations in a standard 33-bus test system and five optimal nodes for real Egypt EDN. The ultimate goal is to increase the I^2R loss reduction, thus creating more profit.

The Seagull Optimisation Algorithm (SOA) was developed in 2019 [18], which has been shown to be quick, unique, strong, and computationally efficient, inspired by the migrating and attacking behaviours of a seagull. From [18], it is understood that SOA has many competitive advantages compared to other algorithms, which is why it has been used in various practical engineering problems. In this work, SOA was modified using Levy Flight Mechanism (LFM) to solve the Economical Based Objective Function (EBOF). The effectiveness of the LFM incorporated SOA (LFM-SOA) was recognised in minimising the P_{Loss} and maximising the economic profit in two-stage optimisation using OCS, AEDNS, OCS, and AEDNS one after the other (first stage) and IDG at optimal nodes in reactive power supported optimal EDN (second stage).

This article examines the effectiveness of the suggested method in attaining better P_{Loss} reduction, which indicates an increase in economic benefit, using standard 33-bus test systems and a real 22 KV, 59-bus eight feeder Cairo, Egypt, EDN. Considering the factors mentioned above, this work's contribution consists of the following:

1. Suggesting a futuristic LFM-SOA resolve EBOF,
2. Evaluation of the impact of economic gain against P_{Loss} reduction using AEDNS with and without OCS and IDG in reactive power-supported optimal EDN;
3. Prologue of a real 59-bus system Cairo, Egypt, EDN for OCS and AEDNS optimisation.

The full work is divided into 5 sections. The formulation of the problem consisting of EBOF with necessary constraints and fundamental power flow is discussed in Section II. The proposed methodology (LFM-SOA) and its ability to resolve the EBOF for the suggested optimisation problem are covered in Section III. Section IV includes simulations and discussions of the acquired results, and Section V closes with the obtained results and a list of references.

II. MATHEMATICAL FORMULATIONS FOR THE CHOSEN PROBLEM

The purpose of OCS and AEDNS optimisation in the radial EDN is to maximise the net profit by minimising $P_{Loss,}$ lowering the capacitor investment cost and minimising the DG power purchase cost provided the power balancing and inequality limitations are satisfied. These issues are presented mathematically as stated in (1)–(10).

$$\textbf{Maximize}\ \text{Total Net Profit} = \left(\mathrm{TP}_1 + \mathrm{TP}_2\right), \tag{1}$$

where TP_1 refers to the total profit achieved by optimising AEDNS with and without optimal OCS and TP_2 refers to the total profit achieved by optimising IDG in reactive power-supported optimal EDN:

$$TP_1 = \frac{\left(C_{Cap} \times \sum_{k}^{TCN} Q_{C(k)}\right)}{\left(C_{PL} \times \left(P_{TL}^{BC} - P_{TL}^{ARPO}\right)\right)}, \tag{2}$$

$$TP_2 = \frac{\left(\mathrm{C_{PL}} \times \mathrm{P_{TL(IDG)}}\right)}{(\mathrm{C_{DGP}} \times \sum_{k}^{\mathrm{TDG}} \mathrm{P_{DG(k)}})}. \tag{3}$$

A. Equality Constraints

The EDN power flow equations can be quantitatively expressed as:

$$Q_{\mathrm{MPS}} - \sum Q_D + \sum_{k}^{TCN} Q_{C(k)} - Q_{TL} = 0, \tag{4}$$

$$P_{MPS} - \sum P_D + \sum_{k}^{TDG} P_{DG(k)} - P_{TL} = 0. \tag{5}$$

B. Inequality Constraints

Real and reactive power injection limit

The maximum amount of real and reactive power that can be injected can be expressed as:

$$\sum_{k}^{TCN} Q_{C(k)} \le \left(\sum Q_D + Q_{TL}^{ARPO}\right), \tag{6}$$

$$\sum_{k}^{TDG} P_{DG(k)} \leq (\alpha)\times\left(\sum P_D + P_{TL}^{AIDG}\right). \tag{7}$$

Real and reactive power constraint limit:

$$Q_{C(k)}^{\min} \leq Q_{C(k)} \leq Q_{C(k)}^{\max}, \tag{8}$$

$$P_{DG(k)}^{\min} \leq P_{DG(k)} \leq P_{DG(k)}^{\max}. \tag{9}$$

Bus voltage limitation can be stated as

$$V_{(k)}^{\min} \leq V_{(k)} \leq V_{(k)}^{\max}. \tag{10}$$

C. Radiality and Isolation Constraints

The EDN must always be maintained in a radial configuration to prevent excessive current flow. It is not recommended to open sectionalising switches that are connected to sources and do not form part of any loops in a mesh network. It is to be ensured that all nodes receive power supply during AEDNS, and that no customer is left unconnected.

D. EDN Power Flow (EDNPF)

This work considers a reliable, quick, adaptable, resilient, and computationally efficient method of EDNPF which is based on the recursive function and a created power flow of the linked list data structure [19] to produce accurate findings. The author effectively uses dynamic data structures to take advantage of the tree-like topology of EDN. The IDG has significantly increased complexity and increased the degree to which the state of the EDN is crucial. In this work, the EDNPF mentioned in [20] was used to resolve the EBOF. Equations (11) and (12) can be used to calculate the total P_{Loss} and Q_{Loss} sustained throughout network:

$$\mathrm{P}_{\mathrm{TL}} = \sum_{\mathrm{k}=1}^{\mathrm{N_{TB}}} \mathrm{P}_{\mathrm{LOSS(k)}}, \tag{11}$$

$$\mathrm{Q}_{\mathrm{TL}} = \sum_{\mathrm{k}=1}^{\mathrm{N_{TB}}} \mathrm{Q}_{\mathrm{LOSS(k)}}, \tag{12}$$

where "k" specifies the branch, P_{TL} and Q_{TL} denote the total real and reactive power loss, respectively, in the EDN, and N_{TB} indicates the number of branches.

III. PROPOSED METHODOLOGY FOR THE CHOSEN WORK [18]

Solving a large number of variables with constraints is very tiresome, complex, and classical numerical techniques cannot guarantee optimum solutions. It is commonly known that swarm-based optimisation algorithms are more straightforward to implement than evolutionary algorithms, since they have fewer parameters. Any optimisation algorithm should consider key factors, such as exploration and exploitation of a search space, and maintain a healthy balance between the two. So, to obtain the nearly ideal answers, these two parameters must be fine-tuned. The motivation behind LFM-SOA and its mathematical modelling have been briefly covered in this section.

The Laridae family of birds, which includes a wide variety of species with various masses and lengths, includes seagulls in its scientific classification. The food that sophisticated seagulls eat includes insects, fish, reptiles, amphibians, earthworms, and more. Most seagulls have white feathers on their bodies. Seagulls use breadcrumbs and make rainy sounds with their feet to lure fish and earthworms. Seagulls often drink fresh and salt water, unlike other animals. Seagulls employ a particular pair of glands over their eyes that were specifically developed to flush the salt by opening the bill.

Seagulls typically live in colonies and use their cunning to locate and catch their prey. The main tasks of seagulls during migration and attack behaviour (seasonal movement from one location to another) are to locate the most plentiful food sources that will provide sufficient energy.

1. The initial positions of seagulls are altered to prevent collisions between them.
2. Seagulls migrate in groups and fly in the general direction of the seagull with the best chance of survival. The fittest seagull can be used to update the initial placements of seagulls.
3. Using their spiral natural shape movement, seagulls frequently attack migrating birds over the water as they fly from one point to another.

The conceptual model of these behaviours is shown in [18]. These behaviours of seagulls can be described as an objective function that needs to be optimised.

A. SOA Mathematical Formulation

The two natural behaviours of the seagull (migration and attack) are formulated as mathematical models, as discussed in this section.

B. Exploration - Migration Behaviour

The algorithm simulation for migration was carried out while considering the three conditions stated below, simulating the migration of a flock of seagulls. Avoiding crashes, travelling in the direction of the best neighbour, and staying near the best search agent are some of these requirements.

Preventing collisions: To calculate a new search agent position, a new variable "A" was introduced in (13) to account for possible collisions with adjacent neighbours, such as other seagulls [18]:

$$\vec{C}_S = \mathrm{A} \times \vec{P}_S(X), \tag{13}$$

$$\mathrm{A} = f_C - \left(\mathrm{X} \times \left(f_C \div Max_{iteration}\right)\right), \tag{14}$$

where X = 0, 1, 2, … Max. iteration, $\vec{C}_S$ is the role of a search agent (does not collide with another search agent), $\vec{P}_S$ is the location of the search agent right now, X is the most recent iteration, A is the way a search agent moves through a particular search space, f_C is the frequency of the controlling variable A (linear drops from f_C to 0) (f_C is set as 2).

The comprehensive discussion of the sensitivity analysis of f_C can be found in [18]

Moving in the direction of the best neighbour: After avoiding a neighbour-to-neighbour collision, the search agents travel toward the direction of best neighbour

$$\vec{M}_S = \mathrm{B} \times \left(\vec{P}_{bS}(X) - \vec{P}_S(X)\right), \tag{15}$$

where $\vec{M}_S$ represents the positions of the search agent $\vec{P}_S$ in relation to the ideal search agent (i.e., the fittest seagull). The behaviour of "B" is randomised (responsible for ensuring that exploitation and exploration are adequately balanced) and is computed as

$$B = 2 \times A^2 \times rd, \tag{16}$$

where A random number between 0 and 1 is called "rd".

Continue to be near the top searcher: Finally, the search agent changes its position in relation to the optimal search agent [18]

$$\vec{D}_S = \left|\vec{C}_S + \vec{M}_S\right|, \tag{17}$$

where $\vec{D}_S$ denotes the separation between the search agent and the search agent with the best fit (i.e., the seagull with the lowest fitness value).

C. Exploitation - Attacking Behaviour

The operation hopes to highlight the history and expertise of the search procedure. Seagulls may continuously alter their attack angle and speed while migrating. Seagulls keep their airborne position by using their wings and weight. When attacking the victim, the predator moves in a spiral-like pattern in the air [18]. The following describes this behaviour in the planes x, y, and z:

$$x' = r \times \cos(k), \tag{18}$$

$$y' = r \times \sin(k), \tag{19}$$

$$z' = r \times k, \tag{20}$$

$$r = u \times e^{kv}, \tag{21}$$

where k is a random number between 0 and 2 and r is the radius of each spiral turn. The spiral shape is defined by the variables u and v, and the base of the natural logarithm is e. The revised position of the search agent was determined using (18) through (21), is indicated by (22)

$$\vec{P}_S(X) = \left(\vec{D}_S \times x' \times y' \times z'\right) + \vec{P}_{bS}(X), \tag{22}$$

where $P_s(X)$ saves the best solution and updates the position of other search agents.

The main flaws of SOA are the occasional premature convergence, sometimes known as local convergence, and the low convergence performance. To avoid the drawbacks mentioned above, an influential concept named "Levy Flight Mechanism" (LFM) was utilised to update the position of the particles. The introduction of LFM, which changes the position of the searching element to establish the ideal location and capacitance size, as well as the ideal structure of the EDN and IDG, can improve the performance between the exploration and exploitation capabilities of SOA. The LFM-determined jump size improved the capability of exploration to prevent being stuck in local optima. The updated position using LFM is provided in (23)

$$\vec{P}_S(X)_{new} = levy(\alpha, \beta, \gamma, \Delta), \tag{23}$$

where the flat parameter (α), the symmetry parameter (β), the empirical standard deviation (γ), and the location of the Levy distribution (Δ) are all mentioned. The value of "α" was taken from [21].

Starting with a population that is formed at random, the proposed optimisation process works. Regarding the best search agent, search agents can alter their positions during the iteration process. Variable B is responsible for a gradual transition from exploration to exploitation, while variable A drops linearly from f_C to 0. The pseudocode for the suggested optimisation algorithm is shown below.

D. Pseudocode for LFM-SOA

Algorithm 1. Seagull optimization algorithm.

```
Initialise parameters A, B, and IT_Max
Set the values of fc, u, and v as 2,1, and 1, respectively
while (x < IT_Max) do
Using the Compute Fitness (P_S)# function
Calculate the fitness values of each search agent (P_bS)

/*Migration behaviour*/
rd = 0 to 1 (generate the random number)
k = 0 to 2π (generate the random number)

/*Attacking behaviour*/
r = u×e^kv (Generate the spiral behaviour during migration)
Using (17), calculate the distance D_S
Calculate P ← x′ × y′ × z′
(Calculate the value of the x, y, and z planes using (18)-(22))

Levy flight modified for position update:
P_S(x) new = levy(α, β, γ, △)
γ = ((D_S × P) + P_bS)/2
△ = ((D_S × P) - P_bS)/2
where β=rand (∝)
x ← x + 1
end while
return
end procedure

#(Procedure for computating fitness)
Fori = 1 to n
do ("n" represents the dimension (total number of variables) of a given problem)
 FITs[i] ← Fitness Function (Ps(→i,:))
 /*Calculate the fitness of each individual*/
end for
FIT_sbest ← BEST(FITs[])
 /*Calculate the best fitness value using the BEST function*/
return FIT_sbest
end procedure
```

E. Application of LFM-SOA to the Chosen Problem

The stage-wise implementation of LFM-SOA is discussed below.

Step 1: Reset f_C, u, v, k, the number of iterations, the dimension of the variables, and the seagull population pop.

Create the initial seagull populations by considering (6) through (11).

Step 2: For the generation of each population, calculate the system variables such as P_{Loss} and bus voltage profiles using the EDNPF discussed in [19], [20]. Compare the fitness values of TP_1/TP_2 ((2) and (3)) between individuals and find the optimal global values for the current population.

Step 3: With the EDNPF mentioned in [19], [20], determine the system factors for the production of each population, such as P_{Loss}/E_{Loss} and bus voltage profiles. Find the global optimal values for the current population by comparing the fitness values of (4) or (5) between different individuals.

Step 4: Compare the fitness values of the individuals in the current seagull population to determine the overall ideal value.

Step 5: When the maximum number of execution iterations has been completed, stop the optimisation process and display the final value of EOF in relation to the ideal EDN structure and the ideal OCS/IDG values (ideal nodes and sizes) or repeat steps 2 through 5 to maintain the position updated.

The conditions in (6) to (10) should be met at the beginning of each iteration. Ten particles exist for AEDNS alone in the standard 33-bus system, six for OCS alone, sixteen for optimising both AEDNS and OCS (one after the other), and six variables for IDG integration. Hence, there are twenty-two variables in total. The variables for the 59-bus system Cairo, Egypt, EDN are twelve for AEDNS optimisation alone, ten for OCS optimisation alone, twenty-two for AEDNS and OCS optimisation (one after the other), and ten variables for IDG integration. Thus, the total variables are 32.

IV. CASE STUDY DETAILS, SIMULATION, AND DISCUSSIONS

An established standard 33-bus test system is considered the first evaluation system, as depicted in Fig. 1. It has 32 branches, 37 edges, and 5 looping branches. This network receives a total apparent power supply of (3926 + j 2443.135) KVA (losses included). The apparent power loss, minimum node voltage, and economic loss under BC are (211 + j 143.135) KVA, 0.9038 p.u., and \$35448, respectively. For this test system, three optimal nodes are considered for OCS.

The next test system considered here is a new real 22 KV, 59-Bus eight feeder Cairo, Egypt, EDN whose structure under BC is as shown in Fig. 2. Parameter details, such as line and bus data, are available in [22]. The test system includes 6 looping branches and 58 switches. Under BC, this network has a total apparent power supply of (50.348 + j 21.448) MVA. The combined real and reactive power losses are (218.9053766 + j 130.8428482) KVA [22], [23]. The reported minimum node voltage is 0.98646 p.u. [22], [23]. For this test system for OCS and IDG, five optimal nodes are considered for compensation. The estimated economic loss under BC is \$36776.0904.

All other nodes, except node number 1, are regarded as load nodes. After adjustment, the allowable range of node voltages was set between 0.95 p.u. and 1.05 p.u. The effectiveness of the LFM-SOA in maximising profit (\$) by minimising P_{Loss} and capacitor investment costs was evaluated in four different scenarios. The annual cost of the capacitor (\$/KVAR) was taken from [8]. The real power cost of MPS (K_{MPS}) was taken as \$168/KW, and the DG power purchase price (KDGP) was assumed to be \$150/KW. The value of "α" is taken as 0.6. Distribution power utilities purchase power from independent power producing companies through a power purchase agreement.

Scenario 1: AEDNS optimisation was employed in the initial condition of the EDN (BC) - Fig. 1 and Fig. 2 to expose the net profit after P_{Loss} reduction.

Scenario 2: OCS optimisation at three/five optimal nodes in the initial condition (Fig. 1 and Fig. 2) of the EDN (BC) was executed to reveal the result of reactive power compensation in achieving P_{Loss} reduction, capacitor investment costs, and net profit.

Scenario 3: AEDNS optimisation after OCS was performed at three/five optimal nodes to identify the effect of AEDNS on P_{Loss} reduction and net profit beyond scenario 2.

Scenario 4: To study the role of OCS in obtaining net profit beyond scenario 1, reactive power compensation was carried out at three/five optimal nodes in the optimal EDN.

Scenarios 5 and 6: To estimate further P_{Loss} reduction and net profit (\$), IDG was carried out at three/five ideal nodes beyond scenarios 3 and 4.

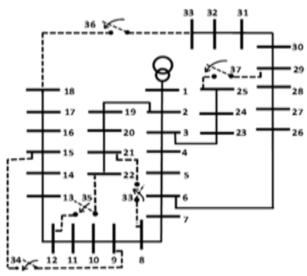

Fig. 1. IEEE 33-bus test system - BC.

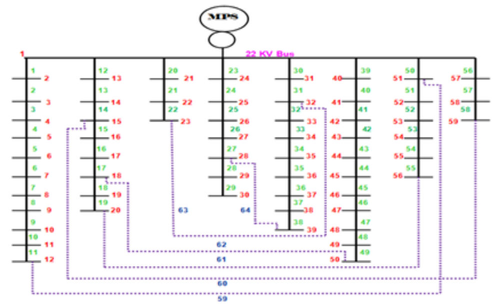

Fig. 2. Real 59-bus system Cairo, Egypt, EDN - BC.

A. Results and Discussions - IEEE 33-Bus Test System

The specifications of the standard 33-bus system were already covered. By closing all five tie-switches in scenario 1 (i.e., by AEDNS under BC condition), the P_{Loss} decreases from 211 KW to 125.759 KW, which is 40.3814 %, compared to BC value by opening 7, 14, 10, 32, and 28. The difference between the bus voltage after scenario 1 and BC is 0.0398 p.u. The overall gain after scenario 1 is found to be \$14320.5. The results obtained by LFM-SOA are found to be better than MSSOE [3], PSO, GWO, and MRFOA [4], COA, ICOA, SFO, and PSO [5], and SOS/MSOS [6].

Table I reveals the performance of LFM-SOA pertaining to scenario 2. Taking into account scenario 2, after OCS at three optimal nodes, the P_{Loss} reduction achieved is 34.4 %, with reactive power penetration of around 81 %. The minimum bus voltage has risen by 0.0271 p.u. From Table I, it is also observed that the overall profit obtained in scenario 2 is \$11727.012, which is 33.085 % compared to BC. The results achieved by LFM-SOA were compared with other methods in the literature and found that the performance of the proposed method is better compared to other methods discussed in [7]–[10], [15].

It should be noted that the reduction in P_{Loss} achieved by LFM-SOA equals DVSA, CBGA, and MI-SOCP [8]–[10], and the minimum node voltage after optimisation is low compared to [7]–[10] as mentioned in Table I.

Optimisation of AEDNS in reactive power compensated EDN yields around 25.6 % extra P_{Loss} reduction beyond scenario 2 and around 60 % of the P_{Loss} reduction compared to BC by closing four out of five tie-switches against the opening of respective sectionalising switches. The minimum bus voltage was enhanced by 0.02482 p.u. The profit gained by AEDNS after scenario 2 is found to be $9363.708. From Table II and comparing scenario 3 with the existing methods, the proposed method achieves more P_{Loss} reduction and net profit compared to other methods discussed in [11], [12].

Table III discloses the performance of LFM-SOA in scenario 4, i.e., OCS at three optimal nodes after scenario 1. Scenario 4 yields an extra P_{Loss} reduction of around 19.7288 %. On the contrary, the P_{Loss} reduction difference between scenarios 3 and 4 is around 0.6 % only. It is evident that the bus voltage improvement is better than scenario 3.

TABLE I. PERFORMANCE OF LFM-SOA WITH COMPARISON - IEEE 33-BUS SYSTEM - SCENARIO 2.

Ref.	P_{Loss} (KW)	Optimal size (KVAR)/(Bus)	V_{min} (p.u.)	% P_{Loss} reduction	ΔP_{Loss} cost - ACP ($)	Capacitor cost ($)	% Net Profit
WCA [7]	134/ 202.66	750 (5) 300 (12) 750 (29)	0.9382 (18)	33.88	11534.88	519	32.355
GWO [7]	133.94/ 202.66	750 (5) 300 (13) 750 (29)	0.9397 (18)	33.91	11544.96	519	32.384
DVSA [8]	138.416/ 210.987	450(12) 450(24) 1050(30)	------	34.39596	12191.93	467.1	33.0782
CBGA [9]	138.416/ 211	450 (12) 450 (24) 1050 (30)	0.93 (18)	34.4	12194.112	467.10	33.08523
MI-SOCP [10]	138.416/ 210.987	450 (12) 450 (24) 1050 (30)	------	34.39596	12191.928	467.10	33.0761
AGPSO [15]	138.44/ 211	450 (12) 600 (24) 1050 (30)	0.94 (18)	34.388	12190.08	485.25	33.02
LFM-SOA	138.416/ 211	450 (12) 450 (24) 1050 (30)	0.9309 (18)	34.4	12194.112	467.10	33.08523

TABLE II. PERFORMANCE OF LFM-SOA WITH COMPARISON - IEEE 33-BUS SYSTEM - SCENARIO 3.

Parameters	IBPSO [11]	CS [12]	MIC [12]	MBFBO [12]	MBBO [12]	LFM-SOA
P_{Loss} (KW)	95.91/ 202.68	95.6628/ 202.677	97.6377/ 202.677	97.3076/ 202.677	83.469/ 202.677	85.46/ 211
% P_{Loss} reduction	52.6791	52.8003	51.826	51.9888	58.8167	59.49763
Switch details	7 – 10 – 34 – 36 – 37	8 – 5 – 37 – 30 – 12	9 – 25 – 14 – 33 – 37	8 – 14 – 7 – 36 – 37	7 – 11 – 34 – 36 – 28	6 – 12 – 9 – 32 – 37
Optimal size (KVAR)/(Bus)	900 (1) 300 (3, 14, 22, and 24) 600 (30, 31)	300 (8) 750 (30) 600 (23)	750 (27) 150 (2) 750 (24)	900 (5) 600 (27) 750 (2)	750 (27) 450 (30) 600 (24)	450 (12) 450 (24) 1050 (30)
V_{min} [p.u.]	0.95572	0.9704	0.95	0.95	0.9559	0.95572
ΔP_{Loss} cost - ACP	$17937.36	$17978.39	$17646.6	$17702.06	$20026.944	$21090.72
Capacitor cost ($)	848.7	444	489	503.7	452.85	467.1
% Net Profit	50.1866	51.4964	50.39	50.5095	57.4868	58.18

TABLE III. PERFORMANCE OF LFM-SOA WITH COMPARISON - IEEE 33-BUS SYSTEM - SCENARIO 4.

Parameters	IBPSO [11]	MBBO [13]	DDE [13]	BTLBO [13]	SSA-GA [14]	LFM-SOA
P_{Loss} (KW)	94.26/ 202.68	110.616/ 202.677	111.8599/ 202.677	115.668/ 202.677	90.05/ 202.7	84.1675/ 210.97
% P_{Loss} reduction	53.4932	45.4225	44.8088	42.9297	55.5747	60.1102
Switch details	7 – 14 – 9 – 32 – 37	33 – 14 – 11 – 25 – 37	7 – 13 – 8 – 36 – 28	7 – 13 – 8 – 36 – 28	7 – 14 – 9 – 32 – 37	7 – 14 – 10 – 32 – 28
Optimal size (KVAR)/(Bus)	1200 (4,9) 900 (7) 1800 (8), 300 (16)	300 (12) 300 (25) 300 (20)	300 (33) 600 (30) 900 (3)	150 (13) 300 (29) 900 (30)	450 (7) 600 (21) 900 (30)	600 (7) 450 (21) 1050 (30)
V_{min} [p.u.]	0.9612	0.95	0.96114	0.9554	0.961	0.9612
ΔP_{Loss} cost - ACP ($)	18214.56	15466.25	15257.256	14617.512	18925.2	21307.86
Capacitor cost ($)	1014.3	315	401.7	344.7	410.55	485.25
% Net Profit	50.5144	44.4974	43.6291	41.9174	54.3691	58.7413

Comparing Table II and Table III, it is apparent that the difference in economic gain between scenario 3 and scenario 4 is around \$200 only. Thus, the proposed methodology yields more P_{Loss} reduction, bus voltage enhancement, and economic gain compared to IBPSO [11], MBBO, DDE, BTLBO [13], and SSA-GA [14]. The minimum and maximum profit difference achieved is 4.3722 % [14] and 16.8239 % [BTLBO [13]].

The performance of LFM-SOA in achieving extra P_{Loss} reduction considering type I DGs is revealed in Table IV. As mentioned in (7), the DG penetration limit was restricted to 60 % for scenarios 5 and 6. Similarly, the extra P_{Loss} reduction gained under scenarios 5 and 6 is found to be around 67 KW which is between 78 % compared to scenario 3 and 80 % compared to scenario 4. Thus, the total P_{Loss} reduction has risen to around 92 %. Significant improvement in bus voltages was noticed after scenarios 5 and 6.

The profit obtained under scenarios 5 and 6 is tabulated in Table IV. The profit difference between scenarios 5 and 6 is \$1000 only. Finally, by screening Table V, it is evident that LFM-SOA performs better compared to BA and CSO [18], and the difference is minuscule compared to *LSHADE-EpSin* [19]. On the other hand, the performance of IGA, IPSO, and ITLBO [18] is better than that of LFM-SOA. This may be due to the simultaneous application of real and reactive power injection with AEDNS. Figure 3 shows the node voltage profile considering scenarios from BC to 6.

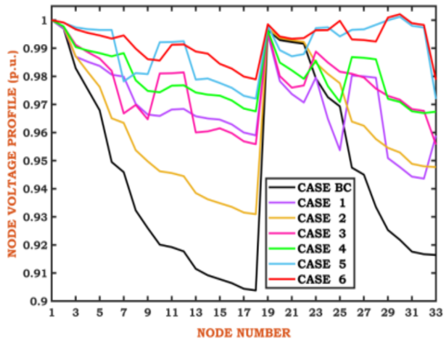

Fig. 3. Bus voltage profile - Scenario BC to 6 - IEEE 33-bus system.

The graph shows that the node voltage profile under scenario 6 is better than other scenarios.

TABLE IV. PERFORMANCE OF LFM-SOA - IEEE 33-BUS SYSTEM - SCENARIOS 5 AND 6.

Parameters	Scenario5	Scenario6
P_{Loss} (KW)	18.896	16.622
Q_{Loss} (KVAr)	23.057	24.698
DG Size (KW)/(Bus)	706 (14), 662 (24) 820 (30)	735 (12), 750 (25) 739 (30)
% DG penetration	57.572	58.539
V_{min} (p.u)	0.97194	0.97881
Extra P_{Loss} reduction (KW)	66.564	67.5455
% Additional P_{Loss} reduction	77.889	80.2513
% Total P_{Loss} reduction	91.0447	92.12241
Profit due to reduction in additional P_{Loss} (\$)	11182.752	11347.644
Profit due to power purchase (\$)	39384	40032
Profit due to scenarios C and D (\$)	20623.62	20822.61
Total Net Profit (\$)	71190.372	72202.254

TABLE V. COMPARISON OF SCENARIO 6 - IEEE 33-BUS SYSTEM.

Ref.	Position of switch	Details of DG rating (KW)	Details of capacitor rating (KVAR)	V_{min} (p.u)	P_{Loss} (KW)/ (P_{Loss} - BC)	% P_{Loss} reduction
IGA [18]	7 – 9 – 17 – 35 – 37	748 (14) 1079 (24) 1043 (30)	300 (15) 300 (25) 1100 (30)	0.9918	11.59/ 202.67	94.2813
IPSO [18]	7 – 9 – 17 – 25 – 35	748 (14) 1003 (24) 1057 (30)	300 (14) 500 (24) 1000 (30)	0.9916	11.12/ 202.67	94.51325
ITLBO [18]	7 – 9 – 17 – 35 – 37	744 (14) 1070 (24) 1048 (30)	300 (15) 500 (24) 1000 (30)	0.9915	11.21/ 202.67	94.4688
BA [18]	14 – 24 – 33 – 35 – 36	1670 (6) 410 (9) 490 (32)	300 (11) 300 (26) 900 (30)	0.9797	22.96/ 202.67	88.6712
CSO [18]	11 – 20 – 24 – 35 – 36	1690 (6) 630 (14) 710 (31)	1200 (7) 600 (3) 600 (33)	0.9860	21.82/ 202.67	89.234
LSHADE-EpSin [19]	7 – 11 – 12 – 17 – 26	557 (15) 813 (25) 630 (32)	703 (3) 399 (9) 1198 (30)	0.9891	15.63/ 210.97	92.5914
LFM-SOA	7 – 14 – 10 – 32 – 28	735 (12) 750 (25) 739 (30)	600 (7) 450 (21) 1050 (30)	0.97881	16.622/ 211	**92.12241**

B. *Results and Discussions - Cairo, Egypt EDN*

Details of this real EDN were conferred previously. Tables VI and VII discuss the effect of LFM-SOA in optimising scenarios from 1 to 6. Considering scenario 1 and from Table VI, it is obvious that by opening three sectionalising switches 7, 18, and 46, the P_{Loss} reduction and profit gained is 36.63592 % with the bus voltage enhancement of 0.0078059 p.u.

In scenario 2, i.e., optimal OCS at five nodes in the BC condition, the P_{Loss} has reduced to 13.2835 % with a reactive power penetration of 51.753 %. The improvement in V_{min} after scenario 2 is acknowledged as 0.0027509 p.u. From Table VI, the net profit is around $2000.

Next, the discussion is based on scenarios 3 and 4 (AEDNS after OCS and OCS after AEDNS). Scenario 3 yields an extra P_{Loss} reduction and net profit of 29.7877 % compared to scenario 2 by closing 3 out of 6 switches. An improvement in bus voltage of 0.0061388 p.u. is noticed beyond scenario 2. The net profit difference between scenarios 2 and 3 is found to be around 30 %. Thus, the total P_{Loss} reduction has reached around 43 %.

TABLE VI. PERFORMANCE OF LFM-SOA - SCENARIO 1 TO 4 - 59-BUS SYSTEM CAIRO, EGYPT, EDN.

Parameters	Scenario 1	Scenario 2	Scenario 3	Scenario 4
P_{Loss} (KW)	138.70737	189.82705	124.62	122.99
% P_{Loss} reduction	36.63592	13.2835	43.0713	43.8159
Switch details	07 – 60 – 18 – 46 – 63 – 64	59 – 60 – 61 – 62 – 63 – 64	07 – 60 – 19 – 46 – 63 – 64	07 – 60 – 18 – 46 – 63 – 64
Optimal size (KVAR)/(Bus)	------	3300 (7) 2100 (29) 1650 (35) 1650 (43) 2400 (49)	3300 (7) 2100 (29) 1650 (35) 1650 (43) 2400 (49)	2400 (7) 2100 (29) 2100 (34) 1200 (45) 2400 (50)
V_{min} (p.u.)	0.9942659	0.9892109	0.9953497	0.9953497
ΔP_{Loss} cost - ACP	$13473.264	$4885.1577	$15839.942	$16113.782
Capacitor cost ($)	------	1988.7	1988.7	1759.2
% Net Profit	36.63592	7.876	37.6637	39.0323

TABLE VII. PERFORMANCE OF LFM-SOA - SCENARIOS 5 AND 6 - 59-BUS SYSTEM, CAIRO, EGYPT, EDN.

Parameters	Scenario 5	Scenario 6
P_{Loss} (KW)	37.5076	37.33136
Q_{Loss} (KVAR)	22.4185	22.3132
DG bus and size (KW)	4901 (7) 6446 (28) 4535 (35) 6575 (43) 7771 (50)	5147 (7) 6115 (28) 4650 (34) 6539 (43) 7777 (50)
% DG penetration	59.8946	59.8966
V_{min} (p.u)	0.996709182	0.996483553
Additional P_{Loss} reduction (KW)	87.1123	85.6588
% Additional P_{Loss} reduction	69.9024	69.647
% Total P_{Loss} reduction	82.8658	82.94637
Profit due to DGP ($)	5,44,104	5,44,104
Profit due to power loss reduction - after IDG	$14,466.8664	$14,482.74
Profit due to AEDNS with OCS (Scenarios 3 and 4)	$13,851.254	$14,354.562
Total Net Profit after optimisation (Scenarios 1 to 6)	**$5,72,422.12**	**$5,72,941.302**

Taking into account scenario 4 and Table VI, it is apparent that an extra reduction in P_{Loss} of 7.18 % is evidenced by reactive power compensation at five optimal nodes after scenario 1 with reactive power penetration of 47.557 %. The difference between scenarios 3 and 4 in achieving the total P_{Loss} reduction is around 0.75 % only, and the minimum bus voltage is found to be the same for scenarios 3 and 4. The change in P_{Loss} cost and the difference in capacitor investment cost are calculated as $273 and $230, respectively. Thus, scenario 4 is more beneficial both in achieving P_{Loss} reduction, as well as net profit compared to scenario 3.

The performance of LFM-SOA under scenarios 3 and 4 yields net profit of around 37 %. Similarly, to the standard 33-bus system, this real EDN also underwent real power injections at five optimal nodes after scenarios 3 and 4 to get a further improvement in efficacy, as well as profit. Table VII reveals the performance of LFM-SOA after scenarios 5 and 6. It should be noted that DG penetration is restricted to 60 % of the total real power demand. Similarly, the further P_{Loss} gained under scenarios 5 and 6 is found to be around 86 %. Thus, the total P_{Loss} reduction has risen to around 83 %. Significant improvement in node voltages is noted after scenarios 5 and 6. It should be noted that the difference between scenarios 5 and 6 in achieving the total reduction in P_{Loss} and Q_{Loss}, the % extra reduction in P_{Loss}, the % penetration of DG, and the V_{min} are minuscule. From Table VII, it is obvious that the difference between the profit obtained under scenarios 5 and 6 due to the reduction of the P_{Loss} and the total net profit are around $15 and $520, respectively. From [23], it is evident that the performance of LFM-SOA is better than that of GWO, SDO, JFS, PSO, CSO, and WOA. However, AEO achieves 3.5965 KW more P_{Loss}

reduction than LFM-SOA. Figure 4 shows the bus voltage profiles from BC to scenario 6.

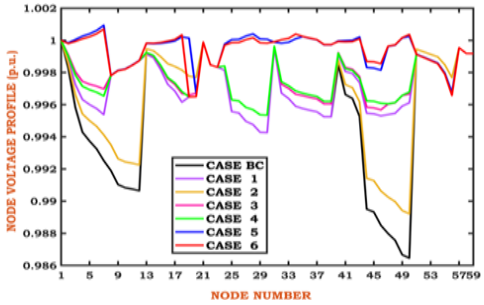

Fig. 4. Bus voltage profile - Scenario BC to 6 - 59-bus system, Cairo, Egypt, EDN.

V. CONCLUSIONS

This work proposes a prominent evolutionary algorithm called "LFM-SOA", which was used for the combined optimisation of EDNSA and OCS with the goal of achieving maximum profit by minimising the P_{Loss}, which was taken as the first step of the optimisation process. To achieve more P_{Loss} reduction and profit, the integration of type I DGs was performed at three/five optimal nodes after AEDNS and OCS. To estimate the proficiency of the LFM-SOA, this work adopts standard 33-bus system and a real 59-bus system, Cairo, Egypt, EDN. The main observations are listed below, which are quite interesting.

1. The best nodes for OCS/IDGs were not determined in this work using any sensitivity indices. LFM-SOA must look for the best buses and the right size.
2. Maximum P_{Loss} reduction of around 60 % and profit of more than $20000 were achieved by optimising OCS and AEDNS one after the other for the standard 33-bus system. For the 59-bus system, Cairo, Egypt, EDN, the maximum P_{Loss} reduction and profit are around 43 % and $14000, respectively.
3. Regarding IDG units, the additional P_{Loss} reduction is found to be around 80 % for the standard 33-bus system and around 70 % for the 59-bus system, Cairo, Egypt EDN beyond OCS and AEDNS optimisation by penetrating 60 % of total real power demand.
4. From the results, it is understood that the differences in total net profit between scenarios 5 and 6 are minuscule, which are estimated to be around $1000 for the IEEE 33-Bus system and around $500 for the Cairo, Egypt EDN.

The above results indicated that LFM-SOA effectively minimises P_{Loss}, thereby increasing the net profits. The performance of LFM-SOA was also compared with other optimisation algorithms in terms of P_{Loss}, bus voltage profile, and net profit. Thus, the proposed methodology is a more suitable and efficient algorithm for solving radial EDN planning and operation problems.

NOMENCLATURE

ΔP_{Loss} - Change in real power loss
P_{TL}, Q_{TL} - Total real and reactive power loss
C_{DGP} - Cost of DG power
Q_C - Capacitor size (KVAR)
C_{PL} - Cost of real power loss
A_{IDG} - After the installation of DG
C_{cap} - Capacitor cost
V_k - The voltage at k^{th} bus
T_{DG} - Total nodes for IDG
P_{DG} - Real power generated by DG
T_{CN} - Total Capacitor Nodes
ARPO - After Reactive Power Optimisation
P_D, Q_D - Real and reactive power demand.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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