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# **Evaluation of FG using RPO in EDPS via DO Considering Load Variations**

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## Abstract

Reactive Power Optimization (RPO) is a major problem in Electric Distribution Power Systems (EDPS) since it reflects in the competent transfer of real power to the consumers, frees up the feeder capacity, enrichment in node voltage profile, power factor improvement and reduction in power/energy losses. The most extensively adopted method for RPO is the Shunt Capacitors (SCs) installed at optimal locations in the EDPSs. This work considers optimal placement and sizing of capacitors in radial EDPS to achieve maximum Financial Gain (FG) by reducing real (KWh) and reactive energy loss (KVARh) with capacitor investment cost using Dingo Optimizer (DO) subject to fulfillment of equality and inequality constraints. Normally, researchers adopt a Sensitivity-based Index (SBI) to identify the optimal node for RPO. However, in this work, the proposed optimization technique will do both optimal placement and sizing of capacitors. The efficacy of the projected technique has been validated using three EDPS, such as the 62-bus system (extracted from the Indian 118-bus test system), the Indian 85-bus, and the real Portuguese 94-bus EDPS. The outcomes of DO have been compared with other optimization techniques available in the literature. Simulated results reveal that DO effectively minimizes energy loss and reactive energy loss with considerable improvement in cost saving. The proposed DO technique achieved substantial drops in PLT and QLT of around 35% in a 62-node EDPS with an FG of \$74886.78/year, 51-54.5% in the case of an Indian 85-node EDPS with an FG of \$91323.88/year, and 23-29% in a Portuguese 94-bus EDPS with an FG of \$59237.53/year.

Keywords: Dingo Optimizer Electric Distribution Power System, Financial gain, Reactive power optimization, shunt capacitor.

## 1. Introduction

The Electric Distribution Power System (EDPS) serves as a vital link between bulk power transmission systems and end users, playing a critical role in ensuring the reliability and efficiency of power delivery. The inherent challenge in EDPS lies in the significant I2R losses and bus voltage drops caused by reactive power flows, especially under heavy load conditions. These issues contribute to increased Apparent Energy losses (KWh and KVARh), reduced system efficiency, and financial burdens. Addressing these challenges requires strategically focusing on Reactive Power Optimization (RPO) to minimize losses, improve the bus voltage profile, and enhance Financial Gain (FG) while balancing investment costs. Among the available approaches, optimizing the allocation and sizing of capacitors across EDPS nodes has emerged as a cost-effective and practical solution.

The literature has extensively explored various methodologies for reactive power compensation. Sensitivitybased techniques, such as Load Sensitivity Factors (LSF) and Power Loss Sensitivity Index (PLSI), have been employed to identify critical buses for reactive power compensation. Advanced optimization algorithms, including the Hybridization of Permutated Oppositional Differential Evolution–Sine Cosine Algorithm (HPODESCA) [1], Mine Blast Algorithm [2], and Salp Swarm Algorithm (SSA) [3], have demonstrated effectiveness in reducing energy losses and capacitor investment costs. These approaches are often coupled with multi-objective optimization frameworks, addressing conflicting goals like minimizing power loss, enhancing voltage stability, and optimizing capacitor costs. Studies have further incorporated evolutionary and natureinspired algorithms, such as the Polar Bear Optimization Algorithm (PBOA) [4], Improved Atom Search Optimization (IASO) [5-6], and Multi-Verse Optimizer (MVO) [7], to improve the precision of solutions and adapt to varying load conditions.

Recent advancements include hybrid and modified optimization techniques such as Quasi-Oppositional Sine Cosine Algorithm (QOSCA) [8], Modified Stochastic Fractal Search Optimization (MSFSO) [9], and the Grasshopper Optimization Algorithm (GOA) [10] have refined RPO by integrating the sensitivity analyses and multi-objective strategies. Additionally, frameworks combining fuzzy decision-making techniques and Pareto optimization, as discussed in [11] and [12], have enabled efficient selection of capacitor placement and sizing strategies under diverse operating scenarios. Despite these advances, achieving a holistic solution that balances power loss reduction, voltage stability, and cost minimization across various load profiles remains an ongoing challenge.

Energy loss reduction, SC investment cost minimization, voltage stability enhancement maximization as objectives, and allocation and sizing of SCs using LSF in three optimal

locations have been proposed in [13]. LSF is used to identify the most critical buses for reactive power compensation, and Modified Teaching-Learning-Based Optimization (MTLBO) will be used to do appropriate sizing. IEEE 33 and a real 94bus Portuguese EDPS have been considered to validate the effectiveness of the proposed methodology. To compare the results obtained by MTLBO, GA, PSO, and TLBO have been taken.

Ref. [14] examines the joint minimization of real power loss and capacitor investment costs as a single objective. It analyzes optimal SC allocation and sizing across three load variations using the Antlion Optimization Algorithm (AOA). This study does not incorporate sensitivity-based indices to identify the most sensitive buses for compensation. Modified 12-bus, 33-bus, and 94-bus Portuguese EDPS have been taken for validation. Cost-based real and reactive power loss reduction with capacitor purchase cost as objective optimal placement and sizing of capacitors using OPF-based Backward Forward Sweep (BFS) and Crow search algorithm (CSA) has been discussed in [15]. 11 kV, IEEE 33 bus EPDS has been taken for evaluation of the proposed methodology. In this study, pay-back period calculation has been considered for economic evaluation. Beluga Whale Optimization algorithm (BWOA) as an optimization tool, optimal allocation and sizing of capacitors in EDPS with the objective to minimize real power loss, bus voltage profile enhancement, and cost determination using loss sensitivity factor has been presented in [16]. To obtain a maximum financial gain, this work [17] focused on maximizing the real and reactive power loss reduction and capacitor investment cost minimization using DO as an optimization technique, optimal siting and sizing of capacitors in EDPS has been developed. This paper did not utilize any sensitivity-based method to determine the most appropriate nodes for reactive power injection.

This study introduces a novel Nature-Inspired Optimizer (NIO), the Dingo Optimizer (DO) [18], which emulates the cooperative hunting behavior of Canis familiarised Dingoes. The DO method addresses key limitations of existing techniques by providing robust global and local search capabilities, enabling precise identification of optimal compensation nodes. The proposed approach maximizes FG by minimizing real and reactive energy losses alongside capacitor investment costs under varying load conditions (50%, 75%, and 100%). Validation is conducted on three benchmark systems: a 62-bus system derived from the Indian 118-bus network, an 85-bus Indian EDPS, and a 94-bus Portuguese EDPS. Comparative analyses against state-of-theart methods highlight the superior performance of the DO approach in achieving significant energy loss reductions, enhanced voltage stability, and higher FG. These results underscore its potential as a reliable and efficient RPO solution for modern EDPS challenges.

**Purpose and Contribution:** Based on the aspects mentioned above, the contributions of this work encompass: (i) Suggesting the best and most robust NIO called DO to solve the economic-based objective function considering three different load variations. (ii) Cost-based assessment of real and reactive energy loss reduction with capacitor purchase cost and (iii) For the first time, optimal placement and sizing of capacitors considering 62-bus system (extracted from Indian 118 bus test system) taken into account three load variations.

### 2. Problem Definition

This research aims to maximize FG by optimizing the placement and sizes of SCs in three radial EDPSs while meeting system constraints. Before discussing the objective function, this study examines the EDPSPF used in this research.

# 2.1. Electric Distribution Power System Power Flow — EDPSPF

To evaluate the EDPS's efficiency under normal operating conditions, regular Power Flow (PF) analysis has been conducted. This assessment helps to identify the need for additional power supply during seasonal periods and requirements for RPO and ensures bus voltage profiles remain within acceptable limits. Traditional matrix-based load flow methods like Gauss-Seidel, Newton-Raphson, and Fast-Decoupled are ineffective for solving EDPS issues due to their high R/X ratio and radial topology [19,20]. This paper employs an efficient, robust, and adaptable EDPSPF method developed in 2003 [21]. This method utilizes recursive functions and a linked-list data structure, specifically addressing reactive power optimization problems. The total real and reactive power loss of the entire radial EDPS, encompassing all branches, including laterals and sublaterals, can be expressed as follows:

$$P^{LT} = \sum_{a=1}^{tnb} P_{Loss(a)} \tag{1}$$

$$Q^{LT} = \sum_{a=1}^{tnb} Q_{Loss(a)} \tag{2}$$

where,

$$P_{Loss(a)} = \frac{P_{(a+1)}^2 + Q_{(a+1)}^2}{|V_{(a)}^2|} \times R_{(a, a+1)} \text{ and}$$
$$Q_{Loss(a)} = \frac{P_{(a+1)}^2 + Q_{(a+1)}^2}{|V_{(a)}^2|} \times X_{(a, a+1)}$$

where  $P^{LT}$  and  $Q^{LT}$  are the sum of real and reactive power losses of all the branches of the EDPS.  $P_{a+1}$  and  $Q_{a+1}$  represent the real and reactive power flow of the  $(a+1)^{th}$  branch in kW and kVAR, respectively.  $R_a$  and  $X_a$  are the resistance and inductance of the branch connecting 'a' and 'a+1' in  $\Omega$ .' thb' indicates the total number of branches in the EDPS.

2.2 Objective Function  
Maximize 
$$F = \sum_{l\nu=1}^{N_{LV}} [F_1 + F_2 + F_3]_{(l\nu)}$$
 (3)

where

$$F_{1} = \lambda_{1} \times \left[ \frac{P_{(BC)}^{LT} - P_{(ACO)}^{LT}}{P_{(BC)}^{LT}} \right]_{(lv)}$$

$$F_{2} = \lambda_{2} \times \left[ \frac{Q_{(BC)}^{LT} - Q_{(ACO)}^{LT}}{Q_{(BC)}^{LT}} \right]_{(lv)}$$

$$F_{3} = \lambda_{3} \times \left[ \frac{CIC}{\left(P_{ACO}^{LT(lv)} \times C_{PL}\right) + \left[\left(Q_{TD} + Q_{ACO}^{LT(lv)}\right) \times C_{QL}\right]} \right]$$

αnd

$$CIC = \left(\sum_{s=1}^{N_{QN}} Q_{C(s,lv)} \times C_{cap}\right) + \left((C_{O\&M} + C_{ins}) \times N_{QN}\right)$$

Subject to equality constraints

$$Q_{(ACO)}^{MES(l\nu)} - Q_{TD}^{(l\nu)} + \sum_{s=1}^{N_{QN}} Q_{C(s,l\nu)} - Q_{(ACO)}^{LT(l\nu)} = 0$$
(4)

Inequality constraints

$$\sum_{s=1}^{N_{QN}} Q_{C(s,lv)} \le (Q_{TD}^{(lv)} + Q_{(ACO)}^{LT(lv)})$$
(5)

$$Q_{\mathcal{C}(l\nu)}^{\min} \le Q_{\mathcal{C}(l\nu)} \le Q_{\mathcal{C}(l\nu)}^{\max} \tag{6}$$

$$V_k^{\min} \le V_k \le V_k^{\max} \tag{7}$$

where  $C_{PL}$  and  $C_{QL}$  refer to cost factors related to real and reactive power from the Main Energy Source (MES). BC, ACO,  $Q_{TD} N_{LV}$ , and  $N_{QN}$  indicates base case, load variations after capacitor optimization, total reactive power demand, number of load variations and number of compensation nodes respectively.  $C_{cap}$ ,  $C_{0\&M}$ ,  $C_{ins}$  and  $V_k$  indicates capacitor purchase cost, installation, operation and maintenance cost of capacitor and bus voltage at 'k'<sup>th</sup> bus.

## 3. Proposed Optimization Method (DO) [17]

The Dingo Optimizer (DO) is an innovative approach for global optimization inspired by the hunting behaviours of dingoes. These behaviours encompass methods such as persecution, group tactics, and scavenging. The most dominant male or female member leads the pack within a dingo pack. They are responsible for decision-making, selecting sleeping spots, and leading hunts. In the hierarchy of a dingo pack, beta members serve as intermediaries between the alpha leader and the remaining pack. If the alpha dingo passes away, the beta takes on its role. Other pack members follow the guidance of both alphas and betas. Dingoes employ sophisticated communication methods, sharing information within the pack, participating in greeting rituals and establishing dominance. Their hunting strategy encompasses distinct phases: chasing and approaching, encircling and harassing, leading up to the ultimate attack.

The DO operates through two key phases: exploration and exploitation. Exploration, akin to the encircling phase, aims to broadly navigate the problem space, whereas exploitation, similar to the attack phase, converges towards the best solution in later algorithmic iterations. In this algorithm, one search agent represents the targeted prey, while others adjust their strategies to approach the prey while exploring the search space comprehensively.

## 3.1. Mathematical Models.

The Dingo's search for prey is translated into a mathematical exploration within the solution space in DO. Like Dingo's random exploration to locate potential prey, the algorithm employs stochastic processes to explore various areas in search of an optimal solution. This phase involves updating potential solutions using random variations or perturbations.

## 3.1.1. Encircling

Dingoes possess remarkable hunting skills and are adept at locating prey. Once the location is traced, the pack, led by the alpha, surrounds the prey. To simulate the Dingo's social structure, the prevailing strategy involves the best agent aiming for the prey, similar to an optimal approach, given the unknown quest area. Meanwhile, other members continue refining their techniques for potential future approaches. During the encircling phase, dingoes move based on specific equations (8)-(12) in their pursuit of optimization.

$$\overrightarrow{D_d} = \left| \vec{A} \cdot \vec{P}_p(x) - \vec{P}(i) \right| \tag{8}$$

$$\vec{P}(i+1) = \vec{P}_p(i) - \vec{B}.\vec{D}(d)$$
 (9)

$$\vec{A} = 2.\,\vec{a_1} \tag{10}$$

$$\vec{B} = 2\vec{b}.\vec{a_2} - \vec{b} \tag{11}$$

$$\vec{b} = 3 - \left(I * \left(\frac{3}{I_{\max}}\right)\right) \tag{12}$$

Where  $\vec{D}_d$  represents the dingoes distance from the prey,  $\vec{P}_p$  implies the position vector for prey,  $\vec{P}$  is the vector indicating the Dingo's position,  $\vec{A}$  and  $\vec{B}$  are coefficient vectors,  $\vec{a}_1$  and  $\vec{a}_2$  represent random variables within the range of [0,1]. I represent the iteration  $I_{\text{max}}$  as the maximum iteration count. Equations (1) and (2) enable dingoes to navigate within the quest area around the prey by changing their locations randomly. These equations can also be applied to explore a search space with N dimensions, allowing the Dingo to move within hypercubes around the best-known result obtained thus far.

In the provided formulas, vector D signifies the distance vector, and vector P represents the position vector. The subscript d pertains to the dingoes, while the subscript' p' refers to the prey, denoting the best search agent among them. The vectors  $\vec{A}$  and  $\vec{B}$  play a crucial role in guiding dingoes toward a specific portion of the solution space around the prey. Notably,  $\vec{B}$  determines whether the prey is moving away from or being pursued by the dingoes. Values less than -1 indicate the former, while values above 1 denote the latter.

## 3.1.2. Hunting

During the hunting phase, it's commonly assumed in these biologically inspired algorithms that the pack members possess a strong intuition about the prey's location. The alpha dingo typically leads the hunting endeavours, yet there are occasions when beta and other pack members may join in the hunting process. In this phase, the alpha and beta, representing the two best solutions within the dingo pack, guide the movements of other dingoes. Equations (13)-(21) outline the equations governing their positional updates.

$$\overrightarrow{D_{\alpha}} = \left| \overrightarrow{A_{1}} \cdot \overrightarrow{P_{\alpha}} - \overrightarrow{P} \right|$$
(13)

$$\overrightarrow{D_{\beta}} = \left| \overrightarrow{A_2} \cdot \overrightarrow{P_{\beta}} - \overrightarrow{P} \right| \tag{14}$$

$$\overrightarrow{D_o} = \left| \overrightarrow{A_3} \cdot \overrightarrow{P_o} - \overrightarrow{P} \right| \tag{15}$$

$$\overrightarrow{P_1} = \left| \overrightarrow{P_\alpha} - \overrightarrow{B} . \overrightarrow{D_\alpha} \right| \tag{16}$$

$$\vec{P_2} = \left| \vec{P_\beta} - \vec{B} . \vec{D_\beta} \right| \tag{17}$$

$$\overrightarrow{P_3} = \left| \overrightarrow{P_o} - \overrightarrow{B} . \overrightarrow{D}_o \right| \tag{18}$$

The following formula is used to determine each Dingo's intensity:

$$\vec{I}_{\alpha} = \log\left(\frac{1}{F_{\alpha} - (1E - 100)} + 1\right)$$
 (19)

$$\vec{I}_{\beta} = \log\left(\frac{1}{F_{\beta} - (1E - 100)} + 1\right)$$
 (20)

$$\vec{I}_o = \log\left(\frac{1}{F_o - (1E - 100)} + 1\right)$$
(21)

## 3.1.3 Attacking the Prey

If the positions remain unchanged, signaling the end of the hunt, the dingoes transition into the attack phase aimed at the prey. During this phase, the value  $\vec{b}$  undergoes linear reduction across iterations. The parameter  $\overrightarrow{D_{\alpha}}$  spans within the range of [-3b, 3b]. Consequently, as iterations progress, this range gradually contracts, causing the dingoes to halt their movement gradually. The suggested encircling method contributes to exploration to a certain degree. However, to enhance exploration further, DO necessitates additional operators. DO supports its quest agents in adjusting their positions by factoring in the locations of  $\alpha$ ,  $\beta$ , other pack members, and the targeted prey. Despite utilizing these operators, DO retains the capability to deactivate local solutions.

## 3.1.4 Searching

Dingoes rely on their pack's movements for hunting, consistently advancing to pursue and confront prey. Using  $\vec{A}$  and  $\vec{B}$  for random values, values below -1 indicate prey moving away, while those above 1 show the pack closing in. These aids DO in globally scanning targets. Another crucial DO element is  $\vec{A}$  generating random numbers in [0, 3] for prey weights. It operates stochastically, giving precedence to vector values  $\leq 1$  over  $\geq 1$  to navigate equation (1)'s gap influence. This enhances effective search and avoids local optima. Depending on a dingo's location, it randomly determines prey values essential for meeting or exceeding requirements.  $\vec{A}$  offers stochastic exploration values from initial to final iterations, preventing local optima. DO conclude upon fulfilling termination criteria.

# 3.2 Implementation of DO for capacitor allocation problem

The application of the Dingo Optimizer (DO) is employed to ascertain the optimal allocation and capacity of capacitors in three EDPSs. The primary aim is to maximize FG while concurrently improving the bus voltages. The DO algorithm encompasses the subsequent steps:

**Step 1:** Initialize the boundary limits for variables, encompassing the optimal capacitor allocation location and size. Define the maximum number of iterations and population size. Generate initial solution vectors that adhere to all specified constraints from (4) to (7).

**Step 2:** Compute the network parameters, including  $P^{LT}$ ,  $Q^{LT}$ , and voltages at all nodes, for each solution vector (SVs) generated using the EDPSPF method described according to ref. [20].

**Step 3:** Set the value of  $\vec{b}$ ,  $\vec{A}$  and  $\vec{B}$ 

**Step 4:** Modify the DO with respect to boundary conditions (upper and lower). Compute the given fitness function optimal value using (3) and find $D_{\alpha}$ ,  $D_{\beta}$  and  $D_{o}$  using (13), (14) and (15).

**Step 5:** For every Dingo in the population, update its distance from the prey using (8) and (9).

- **Step 6:** Recalculate the fitness and intensities of dingoes and retain these values for storage.
- **Step 7:** The iteration process stops if the stopping criteria are met. The final value of the objective function (FG in \$) with the capacitor variable values will be displayed. Otherwise, steps 2 to 7 will be repeated till the maximum value of the objective function is obtained. Art. 3.4 discusses the pseudo-code for the proposed capacitor optimization problem using DO.

## 3.3 Pseudo Code for DO

The pseudo-code for the DO showcases its approach to solving optimization problems, with a key emphasis on the stopping criteria based on the maximum number of iterations. Algorithm delineates the steps involved in the DO Algorithm process:

- 1. Generate initial search agents
- 2. Set  $\vec{b}$ ,  $\vec{A}$  and  $\vec{B}$  values
- 3. While termination conditions are not met do
- 4. Estimate fitness and intensity cost of each dingos
- 5.  $D_{\alpha}$ =Dingo with finest search
- 6.  $D_{\beta}$ =Dingo with second finest search
- 7.  $D_o$ =Dingoes search result afterwards
- 8. Iteration 1
- 9. Repeat
- 10. For i=1 to  $D_{in}$  do
- 11. Update the latest search agent status
- 12. End for
- 13. Evaluate the fitness cost and intensity of dingoes
- 14. Record the value of  $F_{\alpha}$ ,  $F_{\beta}$  and  $F_{o}$
- 15. Record the value of  $\vec{b}$ ,  $\vec{A}$  and  $\vec{B}$
- 16. It= It+1
- 17. Check if It  $\geq$  stopping criteria
- 18. Output
- 19. End while

## 4. Case Study Details, Simulation Results and Discussions

To substantiate the effectiveness of the developed NIO (DO) in optimizing the FGOF (discussed in section 2), three test EDPSs have been taken, and simulations have been performed for three different load variations (75%, 100% and 125% for 62-bus, 85-bus, and 94-bus Portuguese EDPS. The details of the three EDPSs and the simulation results are discussed from Art. 4.1 to 4.3.

Node 1 has been taken as a substation bus for all the EDPS. All nodes, except node no. 1, are considered as load nodes. The voltage for the substation bus has been fixed at 1 p.u. Reactive power compensation has been expected to be applied from node 2 through the end node of the radial EDPS. The algorithm proposed utilizing EDPSPF has been implemented and executed using the MATLAB software, operating on an i5 Intel processor paired with 8 GB RAM. The solution vector size is set to 800, and the number of iterations is defined as 100. Specifically, for every node for RPO, two variables are designated: the optimal node and its corresponding optimal capacity.

The cost of real power energy under three load variations is taken as \$0.06 / KWh. According to ref. [22], the cost of reactive energy loss (KVARh) is one-third of the cost of the real power energy. The purchase cost of the capacitor has been taken as \$5 / kVAr, and the cost pertaining to installation and maintenance has been considered as \$620 / node [23]. Out of the total duration in a year, 2000, 5260, and 1500 hours are considered for Low Load Variation (LLV), Medium Load Variation (MLV), and Heavy Load Variation (HLV), respectively. For all the EDPSs, the base MVA has been taken as 100 MVA. The base KV for 62-bus and 85-bus are taken as 11 KV, whereas for 94-bus Portuguese EDPS, it is 15 KV. To investigate the supremacy of the proposed method in suppressing PLT, QLT, and capacitor investment costs, all the EDPSs have undergone simulations to identify the effect of FGs for different compensation nodes. To ascertain the impact of RPO, siting, and sizing of SCs at four optimal locations have been carried out in all three EDPSs. Capacitor investment costs related to heavy load variation has only been considered for cost evaluation. The values of  $\lambda_1$ ,  $\lambda_2$  and  $\lambda_3$ have been taken as 0.6, 0.25 and 0.15 respectively.

4.1 Simulation, Results & Discussions – 62-bus test system The first radial EDPS considered here is a 62-bus system which is extracted from an Indian three-feeder 118-bus EDPS [22]. The operating voltage of this DS is 11 KV. It has 62 buses, and 61 main branches. The radial EDPS's total connected loads under three load variations are (7710.862+j 5973.682) KVA, (10281.15 +j 7964.91) KVA, and (12851.436+j 9956.136) KVA respectively. Figure 1 shows the single-line diagram of the 62-bus test system (shown with tie-switches). The details of total apparent power losses under Initial Condition (IC) considering three load variations are (216.11871 + j 206.9412) KVA, (396.417 + j 380.2056) KVA and (640.487 + j 615.3782) KVA respectively. The minimum bus voltage recorded are 0.9335 p.u. 0.909497 and 0.88433 p.u respectively. The power losses (PLT, QLT) cost under IC are \$208687.365 and \$66736.623, respectively. The line and bus data have been taken from [24].

Table 1 shows that by optimal allocation and sizing of capacitors in the 62-bus test system, the real and reactive power loss have reduced between 34% and 37%, considering three load variations with the reactive power penetration between 40% and 45%. The minimum bus voltage has enhanced by 0.0276 p.u., 0.038903 p.u. and 0.04847 p.u. By

comparing the results obtained under MLL (100%) with [18], it is evidenced that, there is not much difference in real power loss reduction. From Table 1, it is evident that the annual FG of \$74886.778 has been yielded by reactive power compensation at four optimal locations. Figure 2 shows the bus voltages before and after optimization considering three load variations.





Fig. 2. Bus Voltage Profile - 62-Bus test system

Parameters	Cap. @ 75% (L L L)	Cap. @ 100% (M L L)	Cap. @ 125% (H L L)
$P_{Loss(IC)}/P_{Loss(AC)}(KW)$	142.4133 / 216.1187	257.0495 / 396.4173	414.2526 / 640.4869
% P <sub>Loss</sub> reduction	34.10413	35.15684	35.32224
QLoss (IC) /QLoss (AC) (KVAR)	134.1693 / 206.9412	241.9675 / 380.2056	389.7713 / 615.3782
% Q <sub>Loss</sub> reduction	35.1655	36.3588	36.6615
	505 (42)	690 (42)	758 (42)
Consistent dataila (VVAn)	1227 (50)	1879 (50)	2241 (50)
Capacitor details (KVAr)	409 (54)	414 (54)	522 (54)
	427 (58)	510 (58)	488 (58)
% Cap. Penetration	43	44.855	40.2662
$V_{min}$ (p.u)	0.9611	0.9484	0.9328
$T \times \Delta P_{Loss} Cost (\$)$	8844.648	43984.48	20361.087
$T \times \Delta Q_{Loss} \operatorname{Cost}(\$)$	2910.876	14542.48	6768.207
Cap. Inv. Cost (\$)		22525	
F G (\$)		74886.778	

# 4.2 Simulation, Results & Discussions – Indian 85-bus test system

The next EDPS taken for assessment is an Indian 85-bus system with 85 buses and 84 distribution branches. The total apparent power demand of this EDPS under three load variations (75%,100%,125%) are (1927.71+j1966.792), (2569.3+j 2621.4) and (3211.6+j 3276.7) KVA respectively. The apparent power loss under IC for this test system are (166.7716 +j 104.8384), (316.1157+j 198.5849), and (529.4835+j 332.4714) KVA respectively. The minimum bus

voltages under IC are 0.9068, 0.8714, and 0.833 p.u. respectively. The total real and reactive power losses cost under IC are \$167468.222 and \$35058.82 respectively. The data related to the Indian 85-bus EDPS can be viewed in [4,5]. The single-line diagram pertaining to this test system can be seen in Fig. 3.

Table 2. Performan	ce of $DO - 85$	Bus test sy	stem – All	three load	variations

Parameters	Cap. @ 75% (L L L)	Cap. @ 100% (M L L)	Cap. @ 125% (H L L)
$P_{Loss(IC)} / P_{Loss(AC)}(KW)$	80.8737 / 166.7716	148.7284 / 316.1157	242.2035 / 529.8835
% P <sub>Loss</sub> reduction	51.50643	52.95128	54.29118
Q <sub>Loss (IC)</sub> / Q <sub>Loss (AC)</sub> (KVAr)	50.2314 / 104.8384	92.39158 / 198.585	150.5824 / 332.4714
% Q <sub>Loss</sub> reduction	52.087	53.475	54.7082
	314 (12)	485 (12)	753 (12)
Connector details (VVAr)	462 (26)	639 (26)	698 (26)
Capacitor details (KVAI)	337 (48)	464 (48)	614 (48)
	473 (67)	585 (67)	742 (67)
% Cap. Penetration	80.639	82.8946	85.655
$V_{min}$ (p.u)	0.9411	0.921	0.9007
$T \times \Delta P_{Loss} Cost (\$)$	10307.748	52827.432	25891.2
$T \times \Delta Q_{Loss} \operatorname{Cost}(\$)$	2184.28	11171.548	5456.67
Cap. Inv. Cost (\$)		16515	
F G (\$)		91323.878	



Fig. 3. Indian 85-Bus test system – IC

Table 2 reveals the performance of reactive power optimization in the Indian 85-bus test system. Siting and sizing of SCs at four optimal locations yields a  $P^{TL}$  and  $Q^{TL}$ loss reduction between 51% and 55% with reactive power penetration between 80.5% and 86%. The minimum bus voltage has enhanced by 0.0343 p.u., 0.0496 p.u. and 0.0677 p.u. as illustrated in Figure 4. The FG obtained after SC integration is found to be \$91323.878.





Table 3. Performance Comparison of DO - 85 Bus test system - 75% load variations

Davamatars	PODESCA	FPAES	MBA [2] COA [3]			PBOA [4]		DO
rarameters	[1]	[5]	MDA [2]	$MBA\left[2\right]  COA\left[3\right]$	Sc Minimization	Tc Minimization	Zc Minimization	00
$P_{Loss(IC)}/P_{Loss(AC)}$	85.0098 /	83.04 /	91.0728 /	83.032 /	80.23588 /	80.60228 /	81.8544 /	80.8737 /
(KW)	166.76	166.76	166.5635	166.5635	166.9566	166.9566	166.9566	166.7716
% PLoss reduction	49.0227	50.204	45.3225	50.15	51.9421	51.723	50.97265	51.50643
$Q_{Loss(IC)}/Q_{Loss(AC)}$	52.4542 /		55.2957 /		50.00819 /	50.319915 /	51.001 /	50.2314 /
(KVAR)	104.83		104.7		104.9464	104.9464	104.9464	104.8384
% QLoss reduction	49.963		47.18653		52.34883	52.0518	51.403	52.0868
Capacitor details (KVAr)	350 (12) 550 (30) 500 (60)	700 (8) 400 (34) 400 (48) 200 (85)	800 (8) 300 (27) 400 (58) 300 (63)	300 (12) 300 (31) 300 (48) 450 (68)	368 (11) 327 (30) 301 (47) 362 (62) 227 (67)	352 (11) 362 (30) 263 (47) 248 (62) 262 (67)	340 (11) 358 (30) 339 (47) 201 (62) 192 (67)	314 (12) 462 (26) 337 (48) 473 (67)
% Cap. penetration	71.1889	86.4352	91.5196	68.64	80.588	75.60535	72.707	80.639
$\Delta P_{\text{Loss}} \text{ Cost ($)}$	9810.024	10046.4	9058.884	10023.78	10406.4864	10362.5184	10212.264	10307.748
$\Delta Q_{Loss}$ Cost (\$)	2095.032		1976.172		2197.5284	2185.06	2157.816	2184.28
Cap. Inv. Cost (\$)	8860	10980	11480	9230	11025	10535	10250	10410
F G (\$)	3045.056	- 933.6	-444.944	793.78	1579.0148	2012.5784	2120.08	2082.028
V <sub>min</sub> (p.u.)	0.9355		0.931	0.9386	0.942652	0.940644	0.94121	0.9411

Table 3 to Table 6 exposes the comparison of the results obtained by the proposed methodology with the other recent methods available in the literature. From Table 3, it is apparent that under 75% load variations, the real and reactive power loss reduction by DO is better except  $S_C$  and  $T_C$  [4]. However, the difference is minuscule. The reactive power penetration by DO is more than [1,3,4] except [2,5]. The net FG obtained by the proposed methodology under 75% load variations seems to be better than [2,3,5] except  $[1,4(Z_C)]$ . From Table 3, it is noted that [1] dealt with the capacitor

allocation problem at three optimal locations and [4] focused reactive power optimization at five optimal locations. This could be the reason for obtaining variations in FG. Table 4 and 5 discloses the performances of the other methods under nominal load variations. Ref. [6] discusses the capacitor allocation problem using six optimization algorithms as shown in Table 4. By comparing the results obtained by the proposed optimization method with PSO, SCA, GWO, SSA, ASO and IASO, it is apparent that the performance of DO in achieving both real, reactive power loss reduction and reactive power penetration is better than [6]. However, it is to be noted that the  $V_{min}$  enhancement recorded is less compared to other methods. The minimum and maximum FG achieved by DO is found to be \$173.64 and \$4111.153, respectively.

Table 4. Performance Comparison of DO – 85 Bus test system – 100% load variations										
Parameters	PSO [6]	SCA [6]	GWO [6]	SSA [6]	ASO [6]	IASO [6]	DO			
PLoss (IC) / PLoss (AC)	150.4049 /	154.9155 /	150.5231 /	153.4659 /	149.869 /	148.8261 /	148.7284 /			
(KW)	316.12	316.12	316.12	316.12	316.12	316.12	316.1157			
% PLoss reduction	52.42158	50.99473	52.38419	51.45329	52.59173	52.92101	52.95128			
$Q_{Loss(IC)}/Q_{Loss(AC)}$	93.52263 /	95.15148 /	93.71773 /	94.32939 /	93.09997 /	92.39788 /	92.39158 /			
(KVAr)	198.6	198.6	198.6	198.6	198.6	198.6	198.585			
% QLoss reduction	52.90905	52.08888	52.81081	52.50282	53.12187	53.47539	53.475			
	780 (10)	263 (11)	1074 (9)	541 (5)	538 (10)	422 (12)	485 (12)			
Capacitor details	738 (32)	906 (28)	470 (34)	695 (34)	608 (27)	608 (26)	639 (26)			
(KVAr)	143 (54)	447 (33)	234 (49)	995 (60)	505 (48)	562 (35)	464 (48)			
	615 (67)	675 (64)	608 (64)	425 (85)	548 (68)	610 (67)	585 (67)			
% Cap. Penetration	86.824	87.396	91.02	101.32	83.8865	84	82.8946			
$\Delta P_{\text{Loss}} \operatorname{Cost}(\$)$	52299.686	50876.14	52262.382	51333.634	52468.816	52797.955	52827.432			
$\Delta Q_{Loss}$ Cost (\$)	11054.14	10882.78	11033.615	10969.27	11098.6	11172.463	11171.548			
Cap. Inv. Cost (\$)	13860	13935	14410	15760	13475	13490	13345			
F G (\$)	49493.826	47823.92	48885.997	46542.904	50092.416	50480.418	50653.98			
V <sub>min</sub> (p.u)	0.923913	0.922138	0.924772	0.921218	0.923194	0.921858	0.9217 (54)			

Table 5 reveals the performance comparison between the proposed method with [4,5,7-10] under nominal load variations. From Table 5 it is apparent that the real power loss reduction achieved by DO is better than [5,7,8,10]. The

reactive power loss reduction is found to be better than [8]. Regarding  $V_{min}$  enhancement, the performance of DO is better than [4,5,7,8,9]. However, the % reactive power penetration optimized by DO is found to be more than [4,5,7,8].

Table 5. Performance Comparison of DO - 85 Bus test system - 100% load variations

Parameters	MVO [7]	SĈA [8]	QOSCA	PBOA	MSFS [9]	GOA [10]	GWO [10]	FPA [5]	FPAES [5]	DO
			[8]	[4]						
PLoss (IC)	148.316 /	150.556 /	149.182 /	148.1129 /	148.7077 /	148.9274 /	149.2728 /	149.25 /	149.11 /	148.7284 /
$/P_{Loss}(AC)$	316.1172	316.135	316.135	316.1157	316.12	315.714	315.714	315.7	315.7	316.1157
(KW)										
% P <sub>Loss</sub>	53.08	52.38	52.81	53.146	52.9585	52.8284	52.72	52.724	52.7685	52.923
reduction										
$Q_{Loss(IC)}/\textbf{Q}_{Loss}$	92.3913 /	93.262 /	92.654 /	92.3405 /						92.39158 /
(AC) (KVAr)	198.6019	198.613	198.613	198.601						198.585
% QLoss	53.48	53.043	53.349	53.5045						53.475
reduction										
Capacitor	400 (30)	650 (28)	700 (28)	492 (11)	758.24 (8)	450 (12)	900 (9)	1000 (9)	700 (26)	485 (12)
details	400 (48)	400 (51)	300 (54)	456 (30)	345.21(12)	600 (26)	450 (29)	400 (33)	300 (48)	639 (26)
(KVAr)	500 (57)	500 (60)	500 (60)	357 (47)	660.1 (34)	600 (34)	450 (48)	300 (50)	600 (67)	464 (48)
	450 (68)	200(66)	250 (69)	350 (62)	534.37(67)	600 (67)	450 (68)	400 (68)	300 (80)	585 (67)
	300 (81)	350(80)	350 (80)	375 (67)						
% Cap.	78.20248	80.11	80.11	77.44	87.66	85.832	85.832	80.11	72.48035	82.8946
Penetration										
$\Delta P_{Loss}$ Cost	52958.059	52256.732	52690.367	53021.684	52835.322	52637.851	52522.531	52531.62	52575.804	52827.432
(\$)										
$\Delta Q_{Loss}$ Cost	11173.355	11082.925	11146.887	11178.605						11171.548
(\$)										
Cap. Inv.	13350	13600	13600	13250	13969.6	13730	13730	12980	11980	13345
Cost (\$)										
F G (\$)	50781.414	49739.657	50237.254	50950.289	38.865.722	38907.851	38792.531	39551.62	40595.804	50653.98
V <sub>min</sub> (p.u)	0.9198	0.92	0.921	0.9211		0.92182	0.9235	0.91	0.91	0.9217 (54)

Finally, the FG achieved by the proposed method is better than [5,6,8,9,10]. PBOA [4] and MVO [7] achieve more FG than DO which is found to be below \$300. The reason for higher FG [4,7] may be due to the reduction in capacitor investment cost. By referring to Table 6 and by comparing PBOA [4] under 125% loading conditions, the performance of DO in terms of  $P^{TL}$  and  $Q^{TL}$  reduction, bus voltage enhancement, and net FG achieved after RPO is found to be less than PBOA [4]. However, it is to be noted that the total number of buses for RPO considered in [4] is more than the present work.

Table 6. Performance Comparison of DO – 85 Bus test system – 125% load variations

Parameters		DO		
	Sc Minimization	Tc Minimization	Zc Minimization	
$P_{Loss(IC)} / P_{Loss(AC)}(KW)$	240.0562 / 530.1294	240.835 / 530.1294	241.026 / 530.1294	242.2035 / 529.8835
% P <sub>Loss</sub> reduction	54.7174	54.5705	54.5345	54.29118
Q <sub>Loss (IC)</sub> / Q <sub>Loss (AC)</sub> (KVAr)	149.4865 / 332.8492	150.1912 / 332.8492	150.0648 / 332.8492	150.5824 / 332.4714

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% Q <sub>Loss</sub> reduction	55.0888	54.877	54.9151	54.7082					
Capacitor details (KVAr)	600 (11)	662 (11)	614 (11)	753 (12)					
	597 (30)	562 (30)	562 (30)	698 (26)					
	486 (47)	525 (47)	561 (47)	614 (48)					
	591 (62)	496 (62)	440 (62)	742 (67)					
	413 (67)	370 (67)	393 (67)						
% Cap. Penetration	82	79.806	78.43257	85.655					
$\Delta P_{\text{Loss}}$ Cost (\$)	26106.588	26036.496	26019.306	25891.2					
$\Delta Q_{\text{Loss}} \operatorname{Cost}(\$)$	5500.881	5479.74	5483.532	5456.67					
Cap. Inv. Cost (\$)	16535	16175	15950	16515					
F G (\$)	15072.469	15341.236	15552.838	14832.87					
V <sub>min</sub> (p.u)	0.90075	0.9	0.901041	0.9007					

Table 7. Performance Comparison of DO - 85 Bus test system - Total Hours / Year

Method		Load	ΔPLoss (KW)	ΔP <sub>Loss</sub> Cost (\$)	$\Delta Q_{Loss}$	ΔQ <sub>Loss</sub> Cost (\$)	Cap. Inv.	F G / Year (\$)
					(KVAr)		Cost (\$)	
PBOA	Sc Minimization	75%	86.7207	89634.738	54.9382	18901.578	16535	92001.316
[4]		100%	168.3196		106.494			
		125%	290.0732		183.3627			
	Tc Minimization	75%	86.3543	89420.696	54.62648	18843.404	16175	92089.1
		100%	168.0028		106.2605			
		125%	289.2944		182.658			
	Zc Minimization	75%	85.1022	88441.025	53.9454	18629.193	15950	91120.218
		100%	165.4292		104.4472			
		125%	289.1034		182.7844			
DO		75%	85.8979	89026.38	54.607	18812.496	16515	91323.876
		100%	167.3873		106.1934			
		125%	287.68		181.889			

Table 7 exposes the performance of DO with PBOA [4] under three loading variations. Though the net FG achieved by [4] is better than DO, it is obvious that the number of buses for

RPO is five. Alternatively, the net FG difference between DO and [4] is found to be below \$800 per year.

## 4.3 Simulation, Results & Discussions – 94-bus Portuguese EDPS

Table 8. Performance of DO - 94 Bus test system - All three load variations

Parameters	Cap. @ 75% (L L L)	Cap. @ 100% (M L L)	Cap. @ 125% (H L L)
$P_{Loss}$ (IC) / $P_{Loss}$ (AC) (KW)	145.4694 ./ 190.4548	268.2693 / 362.8579	437.6239 / 614.0112
% P <sub>Loss</sub> reduction	23.62	26.0681	28.72705
Q <sub>Loss (IC)</sub> / Q <sub>Loss (AC)</sub> (KVAr)	201.8147 / 265.0281	371.7975 / 504.042	605.6983 / 851.085
% Q <sub>Loss</sub> reduction	23.8516	26.2368	28.83222
Capacitor details (KVAr)	527 (19)	679 (19)	743 (19)
•	198 (25)	281 (25)	382 (25)
	454 (52)	692 (52)	801 (52)
	371 (58)	501 (58)	716 (58)
% Cap. Penetration	88.931	92.646	90.951
$V_{min}$ (p.u)	0.932	0.9077	0.8784
$T \times \Delta P_{Loss} Cost (\$)$	5398.248	29852.1622	15874.857
$T \times \Delta Q_{Loss} Cost (\$)$	2528.536	13912.1214	7361.601
Cap. Inv. Cost (\$)		15690	
F G (\$)		59237.5256	

The third EDPS taken for evaluation is a real 94-bus EDPS with 94 nodes, 93 branches, and 22 laterals and sub-laterals. The base KV is set at 15 KV, while the base MVA is established at 100 MVA. The line and load data for this practical EDPS can be accessed in [13]. The total apparent power demand under three load variations is (3597.75 + j 1742.925) KVA, (4797+j 2323.9) KVA, and (5996.25+j 2904.875) KVA respectively. The total apparent power loss for 75%, 100%, and 125% load variations are (190.4548 + j265.0281) KVA, (362.858 + j 504.042) KVA and (614.0112 + j 851.085) KVA respectively. Under three load variations, the minimum bus voltages recorded are 0.89094, 0.84854, and 0.80154 per unit (p.u.), respectively. Additionally, the total power losses (combining PLT, QLT) under IC, are \$192633.537 and \$89158.8924, respectively. The Single-line diagram depicting this test system is portrayed in Figure 5. The performance of D O in RPO considering Portuguese 94-bus EDPS is reflected in Table 8 and illustrated in Figure 6. The  $P^{TL}$  and  $Q^{TL}$  reduction are found to be between 23.5% and 29% with reactive power penetration of around 90%. The minimum voltage enhanced under three load variations are 0.04106 p.u., 0.05916 p.u., and 0.07686 p.u. respectively. Finally, the net FG accomplished by D O is \$59237.526





Table 9 present the comparison of performance of DO in achieving reduction in  $P^{TL}$  and  $Q^{TL}$ ,  $V_{min}$  enhancement and net FG under nominal load variations. From Table 8 it is observed that the performance of DO is better than NSGA II, MOWCA and MOGWO [4]. It is to be noted that the difference in reduction in  $P^{TL}$  and  $Q^{TL}$  are found to be below 2%. Similarly, the reactive power penetration difference between D O and [4] is around 7%. The minimum bus voltage enhancement is found to be less than [4]. The net FG achieved by D O is found to be better than [4]. Table 10 also discusses the comparison of the outcomes of D O under 100% load variations with [12,13,14]. By comparing D O with [12], it is outward that the difference in  $P^{TL}$  reduction is found to be minuscule.



Fig. 6. Bus Voltage Profile – Portuguese 94-Bus test system

## Table 9. Performance Comparison of DO - 94 Bus test system - 100% load variations

Danamotons	NSGA	NSGA II [11]		CA [11]	MOG	DO	
r ar ameter s	Fixed	Switched	Fixed	Switched	Fixed	Switched	DO
$P_{Loss(IC)} / P_{Loss(AC)}(KW)$	269.8589 /	271.0450 /	274.8324 /	276.441 /	272.4593 /	273.865 / 362.86	268.2693 /
	362.86	362.86	362.86	362.86	362.86		362.8579
% PLoss reduction	25.6296	25.3027	24.2589	23.8156	24.9129	24.5255	26.0681
0 (KW)	373.2646 /	373.9985 /	378.0763 /	380.3276 /	375.9245 /	276 628 / 504 04	371.7975 /
QLoss (IC) / QLoss (AC) (K W)	504.04	504.04	504.04	504.04	504.04	370.0287 304.04	504.042
% Q <sub>Loss</sub> reduction	25.9457	25.8001	24.9911	24.5445	25.418	25.2785	26.2368
Capacitor details (KVAr)	421 (11) 621 (20) 324 (23) 893 (54) 61 (83)	300 (11) 500 (18) 850 (54) 550 (83) 100 (90)	701 (54) 584 (83) 600 (16) 437 (23)	1200 (20) 300 (25) 800 (54)	1000 (18) 369 (24) 949 (54)	500 (15) 1050 (20) 750 (54)	679 (19) 281 (25) 692 (52) 501 (58)
% Cap Penetration	99.8322	98.9716	99.92	98.9715	99.746	98.97	92.646
$\Delta P_{\text{Loss}} \operatorname{Cost}(\$)$	29351.15	28976.814	27781.51	27273.836	28530.461	28086.822	29852.162
$\Delta Q_{Loss} \operatorname{Cost}(\$)$	13757.572	13680.366	13251.38	13014.55	13477.751	13403.7424	13912.12
Cap. Inv. Cost (\$)	14700	14600	14090	13360	13450	13360	13245
F G (\$)	28408.722	28057.18	26942.89	26928.386	28558.212	28130.564	30519.28
$V_{min}(p.u)$	0.915 (92)	0.915 (92)	0.92	0.9216	0.9168	0.9168	0.9085 (92)

	Table 10.	Performance	Comparison	of DO - 94	Bus test system	m – 100% load	variations
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Parameters	MOWCA [12]		CA [12]	BSO [12]	TL DO [12]	MTI DO [12]	AOA [14]	DO
	Fixed	Switched	GA [13]	PSU [13]	I LBO [13]	MILBO [15]	AUA [14]	DO
$\begin{array}{c} P_{Loss}\left(IC\right) /\\ P_{Loss}\left(AC\right)\\ \left(KW\right) \end{array}$	270.4281 / 362.86	269.5503 / 362.86	279.1 /362.858	301.5 / 362.858	278.98 /362.858	269.91/362.858	268.386 /362.8578	268.2693 / 362.8579
% P <sub>Loss</sub> reduction	25.47316	25.71515	23	16.91	23.1	25.63	26.035	26.0681
Capacitor details (KVAr)	50 (10) 521 (15) 610 (20) 318 (23) 642 (57) 50 (22) 132 (56)	300 (11) 450 (18) 100 (21) 350 (83) 300 (24) 750 (57) 50 (53)	450 (65) 450 (73) 600 (84) 250 (87)	650 (58) 450 (73) 450 (84) 300 (90)	800 (59) 450 (72) 500 (83) 300 (90)	850 (58) 400 (72) 500 (84) 250 (89)	750 (10) 750 (20) 900 (58)	679 (19) 281 (25) 692 (52) 501 (58)
% Cap Penetration	99.9613	98.9716	75.3045	79.60756	88.2138	86.0622	103.275	92.646
$\Delta E_{Loss}$ Cost (\$)	29171.51	29448.64	26434.025	19364.585	26471.897	29334.389	29815.3	29852.1622
Cap. Inv. Cost (\$)	15955	15840	11230	11730	12730	12480	14480	13245
FG(\$)	13216.51	13608.64	15204.025	7634.585	13741.897	16854.389	15335.3	16607.16
V <sub>min</sub> (p.u)	0.9174 (92)	0.9168 (92)	0.9094	0.9124	0.9039	0.9065	0.9065	0.9085 (92)

Reactive power penetration by [12] seems to be more than D O. The net FG difference between D O and [12] is \$3390.65 (fixed) and \$2998.52 (variable). By comparing [13] with D O, the P<sup>TL</sup> reduction is found to be far better than GA, PSO, and TLBO. However, the difference is small compared to MTLBO [13]. The V<sub>min</sub> enhancement by D O is better than [13] except PSO. The net profit realized by DO is better than all the methods discussed in [13]. Finally, P<sup>TL</sup> reduction by AOA almost equalizes DO. However, it is to be noted that the reactive power penetration is more than 100% and the number

of compensation buses is three [14]. The net FG difference between D O and [14] is below \$1300.

## 5. Conclusions

This work emphasizes mainly the RPO in EDPS using a new, durable, and robust NIO called Dingo Optimizer (DO) to identify the optimal variations in penetration of SCs to achieve maximum  $P^{TL}$  and  $Q^{TL}$  loss minimization with a reduction in capacitor investment cost thereby more FGs

while ensuring that all equality and inequality constraints are met. The major advantage of DO is the efficient handling of discrete, complicated, non-linear, and large-dimensional optimization problems. Three renowned radial DNs such as 62-node, Indian 85-node, and Portuguese 94-bus EDPS have been utilized to demonstrate the usefulness of DO. The following are the observations:

- (i) In general, all the reactive power optimization-based research work in EDPS considers reduction in P<sup>TL</sup> with capacitor investment cost. However, this paper considers the minimization of both P<sup>TL</sup> and Q<sup>TL</sup> with capacitor investment costs.
- (ii) No SBI has been adopted in this work to select the optimal nodes for RPO. DO have to identify the most potential nodes and appropriate reactive power capacity of the capacitor.
- (ii) Considering 62-node EDPS, around 35% of P<sup>TL</sup> and Q<sup>TL</sup> reductions have been noticed considering all three load variations with an FG of \$74886.78/year is evidenced.
- (iii) Regarding the Indian 85-node EDPS, the reduction in  $P^{TL}$  and  $Q^{TL}$  is found to be between 51% and 54.5%, with a reactive power penetration of around 83%. Thus, the FG achieved per annum is \$91323.88.
- (iv) Finally, in Portuguese 94-bus EPDS, the reductions in both the losses are found to be between 23% and 29%,

with the reactive power penetration of around 90% is noted. The FG considering all three load variations is \$59237.526

(v) Considering the Indian 85-node and Portuguese 94-bus EDPS, the performances have been compared with the recent techniques presented in the literature. The difference in P<sup>TL</sup> and Q<sup>TL</sup> reduction achieved by DO is found to be better and significant.

The simulation results and previous discussions affirm that DO consistently outperforms other methods by achieving reductions in both power losses and net FGs. Therefore, based on its consistent performance, DO is strongly recommended as an efficient technique for resolving RPO challenges.

The system will be extended to analyze the impact of DG (Distributed Generation) like solar and Wind. Other optimization techniques will also be tested to increase the convergence rate and improve accuracy. In the future, scalability tests will be implemented to test the performance of DO over larger EDPS networks.

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### References

- R. J. Mahfoud, N. F. Alkayem, Y. Sun, H. Haes Alhelou, P. Siano, and M. Parente, "Improved Hybridization of Evolutionary Algorithms with a Sensitivity-Based Decision-Making Technique for the Optimal Planning of Shunt Capacitors in Radial Distribution Systems," *Appl. Sci.*, vol. 10, no. 4, Feb. 2020, Art, no. 1384, doi: 10.3390/app10041384.
- [2] S. M. Abd Elazim and E. S. Ali, "Optimal locations and sizing of capacitors in radial distribution systems using mine blast algorithm," *Electr. Eng.*, vol. 100, no. 1, pp. 1–9, Mar. 2018, doi: 10.1007/s00202-016-0475-1.
- [3] A.-R. Youssef, S. Kamel, M. Ebeed, and J. Yu, "Optimal Capacitor Allocation in Radial Distribution Networks Using a Combined Optimization Approach," *Electr. Power Compon. Sys.*, vol. 46, no. 19–20, pp. 2084–2102, Dec. 2018, doi: 10.1080/15325008.2018.1531956.
- [4] M. W. Saddique, S. S. Haroon, S. Amin, A. R. Bhatti, I. A. Sajjad, and R. Liaqat, "Optimal Placement and Sizing of Shunt Capacitors in Radial Distribution System Using Polar Bear Optimization Algorithm," *Arab. J. Sci. Eng.*, vol. 46, no. 2, pp. 873–899, Feb. 2021, doi: 10.1007/s13369-020-04747-5.
- [5] D. José Da Silva, E. Antonio Belati, and E. Werley Silva Dos Angelos, "FPAES: A Hybrid Approach for the Optimal Placement and Sizing of Reactive Compensation in Distribution Grids," *Energies*, vol. 13, no. 23, Dec. 2020,Art. no. 6409, doi: 10.3390/en13236409.
- [6] R. M. Rizk-Allah, A. E. Hassanien, and D. Oliva, "An enhanced sitting-sizing scheme for shunt capacitors in radial distribution systems using improved atom search optimization," *Neural Comput & Applic*, vol. 32, no. 17, pp. 13971–13999, Sep. 2020, doi: 10.1007/s00521-020-04799-6.
- [7] T. Mtonga, K. K. Kaberere, and G. K. Irungu, "A Novel Optimal Shunt Capacitors Placement and Sizing Technique for Cost Minimization," Jan. 14, 2022. doi: 10.36227/techrxiv.18141971.v1.
- [8] S. R. Biswal and G. Shankar, "A Novel Quasi-opposition Based Sine Cosine Algorithm for Optimal Allocation and Sizing of Capacitor in Radial Distribution Systems," Nov. 30, 2021, *In Review.* doi: 10.21203/rs.3.rs-1070297/v1.
- [9] L. C. Kien, T. T. Nguyen, B. H. Dinh, and T. T. Nguyen, "Optimal Reactive Power Generation for Radial Distribution Systems Using a Highly Effective Proposed Algorithm," *Complexity*, vol. 2021, no. 1, Jan. 2021, Art. no. 2486531, doi: 10.1155/2021/2486531.

- [10] V. Haldar and N. Chakraborty, "Power loss minimization by optimal capacitor placement in radial distribution system using modified cultural algorithm: Power Loss Minimization," *Int. Trans. Electr. Energ. Syst.*, vol. 25, no. 1, pp. 54–71, Jan. 2015, doi: 10.1002/etep.1820.
- [11]M. A. E. Mohamed El-Saeed, A. F. Abdel-Gwaad, and M. A. Farahat, "Solving the capacitor placement problem in radial distribution networks," *Res. Eng.*, vol. 17, Mar. 2023, Art. no. 100870, doi: 10.1016/j.rineng.2022.100870.
- [12]M. A. E. Mohamed El-Saeed, A. F. Abdel-Gwaad, and M. A. Farahat, "Capacitor Allocation Using Multiobjective Water Cycle Algorithm and Fuzzy Logic," *Elektron Elektrotech*, vol. 28, no. 2, pp. 35–45, Apr. 2022, doi: 10.5755/j02.eie.30355.
- [13] B. Vahidi, A. Rahiminejad, S. Shahrooyan, and A. Foroughi Nematollahi, "Optimal Placement of Capacitor Banks Using a New Modified Version of Teaching-Learning- Based Optimization Algorithm," *AUT J. Model. Simul.*, vol. 50, no. 2, pp. 171-180, Nov. 2018, doi: 10.22060/miscj.2018.14594.5111.
- [14] G. Srinivasan, V. Mahesh Kumar Reddy, P. Venkatesh, and E. Parimalasundar, "Reactive power optimization in distribution systems considering load levels for economic benefit maximization," *Electr. Eng. & Electromech.*, no. 3, pp. 83–89, Apr. 2023, doi: 10.20998/2074-272X.2023.3.12.
- [15] A. K. Bairwa, S. Joshi, and D. Singh, "Dingo Optimizer: A Nature-Inspired Metaheuristic Approach for Engineering Problems," *Mathem. Probl. Engin.*, vol. 2021, pp. 1–12, Jun. 2021, doi: 10.1155/2021/2571863.
- [16] S. W. Mathenge, Edwell. T. Mharakurwa, and L. Mogaka, "Voltage enhancement and loss minimization in a radial network through optimal capacitor sizing and placement based on Crow Search Algorithm," *Ener. Rep.*, vol. 12, pp. 4953–4965, Dec. 2024, doi: 10.1016/j.egyr.2024.10.062.
- [17] S. M. Adal and E. T. Reda, "Optimal Allocation and Sizing of Capacitor Banks in Distribution System to Reduce the Power Loss Using Beluga Whale Optimization," *Int. Trans. Electr. Ener. Sys.*, vol. 2024, no. 1, Jan. 2024, Art. no. 7837832, doi: 10.1155/2024/7837832.
- [18] G. Srinivasan, M. Lavanya, V. Vijayal, and P. Venkatesh., "Solving financial benefit-based reactive power support in DN via DO," *Int. J. Electric. Engin. Inform.*, vol. 16, no. 3, pp. 424–441, Sep. 2024. doi: 10.15676/ijeei.2024.16.3.6.

- [19] T. Ramana, V. Ganesh, and S. Siranagaraju., "Simple and fast load flow solution for electrical power systems," *Int. J. Electric. Engin. Inform.*, vol. 5, no. 5, pp. 245–253, Sep. 2003.
- [20] V. Kumar et al., "Improved Algorithm for Load Flow Analysis of Radial Distribution System," Indian J. Sci. Technol., vol. 10, no. 18, pp. 1–7, May 2017, doi: 10.17485/ijst/2017/v10i18/113752.
- [21] B. Venkatesh and R. Ranjan, "Data structure for radial distribution system load flow analysis," *IEE Proc., Gener. Transm. Distrib.*, vol. 150, no. 1, 2003, Art. no. 101, doi: 10.1049/ipgtd:20030013.
- [22] H. Karimi and R. Dashti, "Comprehensive framework for capacitor placement in distribution networks from the perspective of

distribution system management in a restructured environment," *Int. J. Electr. Pow. & Ener. Sys.*, vol. 82, pp. 11–18, Nov. 2016, doi: 10.1016/j.ijepes.2016.02.025.

- [23] I. Pérez Abril, "Capacitor placement by variables' inclusion and interchange improved algorithm," *Int Trans Electr Energ Syst*, vol. 30, no. 6, Jun. 2020, doi: 10.1002/2050-7038.12377.
- [24] V. Shanmugasundaram, G. Srinivasan, K. Krishnamoorthi, and K. Karthik, "Integration of EGs in capacitor added optimal DPS for FG maximization," *Ain Shams Eng. J.*, vol. 15, no. 9, Sep. 2024, Art. no. 102900, doi: 10.1016/j.asej.2024.102900.