FINANCIAL SAVINGS BASED SELECTION OF OPTIMAL BUSES AND CAPACITY FOR RPIs IN REDS

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The current research article suggests a framework to solve the Reactive Power Injections (RPIs) in Radial Electric Distribution Systems (REDS) using the Dingo Optimization Algorithm (DOA) to maximize Financial Savings (FSs). This article formulates the objective function by considering three significant factors: maximizing the reduction in Real and Reactive Power Losses (RRPL) while minimizing capacitor investment costs with weight factor considerations and adhering to bus voltage profile enhancement. Notably, this work does not employ a Sensitivity Based Index (SBI) to identify critical nodes for Reactive Power Injection (RPI). The emphasis lies on showcasing the Fitness Scores (FSs) achieved by the proposed method through Optimal Capacitor placement and sizing (OCPS) under three scenarios. Simulation results demonstrate the superior solutions in terms of maximum FSs, RRPL reduction, and minimal bus voltage deviations obtained by the proposed method.

Keywords: Dingo Optimization Algorithm, Financial Savings, Radial Electric Distribution System, Reactive Power Injections, Real and Reactive Power Losses

1. Introduction

It is a common practice adopted by the distribution engineers to Integrate Shunt Capacitors (ISC) in Radial Electric Distribution Systems (REDS) to consume negative VARs, which reflects some of the lagging components of inductive VARs at the buses of integration which in turn changes the characteristics of the inductive load. For the last five decades, many researchers focused on ISC with proper capacity along the distribution networks to improve the node voltage enrichment, apparent power loss reduction, reduce lagging component of branch current, free-up the feeder capacity, enhancement in voltage stability, apparent power demand decrease, sub-station transformer power factor enhancement, etc. Thus, more real power output is available for delivery [1]. It is well known from the literature that the REDS share major power losses around

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70% of the total losses which needs special interest in reducing the power losses [2]. Around 15% to 18% of electrical energy generated in India has been wasted as heat loss (I^2R). On the other hand, the power deficit in India is around 18%. It is achievable to reduce the Real and Reactive Power Losses (RRPL) from roughly 18% to below 8% in the electric utility sector, increasing the Financial Savings (FSs). Hence it is mandatory to find suitable nodes and the appropriate reactive power capacities in REDS. ISCs at non-optimal nodes will increase the RRPL reduction and reduction in node voltage deviation. From the literature, it is apparent that optimal ISC is a complex, complicated, non-linear, combinatorial, and mixed integer optimization problem that must be addressed using different optimization techniques and algorithms that have been presented earlier.

In [3], Reactive Power Injection (RPI) has been performed in Radial Electric Distribution Systems (REDSs) using the Artificial Electric Field Algorithm (AEFA) as an optimization tool to reduce energy loss and capacitor investment cost. The paper employs two scenarios: The first scenario involves utilizing the Loss Sensitivity Factor (LSF) for optimal node selection, while AEFA performs optimal sizing. In the second scenario, AEFA is responsible for both Optimal Capacitor placement and sizing (OCPS). The efficacy of the proposed method has been validated using the PG&E 69 bus and Indian 118 bus test systems. Modified Particle Swarm Optimization Algorithm (MPSO) based optimization of RPI in REDS with three objective functions comprising of power/energy loss minimization with capacitor investment cost (fixed and switchable) under three load levels has been performed in [4]. In this work, normalized LSF-based identification of most potential nodes has been adopted. Stochastic Fractal Search Optimization (SFSO) technique as an optimization method, OCPS from single to three optimal locations to minimize power loss has been proposed in [5]. Apart from capacitor allocation and sizing, one PV type DG injecting real power equal to 20% and less than 100% of real power injection considering with and without geographical constraints after reactive power injection has been proposed in this paper. Modified LSF-based selection of most prospective nodes for RPI has been engaged in [6] and optimal capacity of capacitor has been done by Multi-verse Optimizer. The objective function revolves around minimizing both power loss and capacitor investment costs.

Reference [7] presents the integration of quasi-opposition-based learning (QOBL) and chaotic local search (CLS) with the original SFS algorithm. This combined approach is implemented in REDS to determine the optimal number of nodes while considering appropriate sizing for both fixed and switchable capacitors under various loading conditions. This paper considers two objective functions. The first one deals with energy loss minimization and capacitor investment cost minimization considering 24 hours and 365 days. In the second objective function, fourteen-hour-based load levels are adopted to evaluate the objective function. PG&E 69 bus, Indian 118 bus, and a Real 152 bus test system have been taken for assessment of the proposed method. The optimal number, optimal allocation, and capacity determination of multiple capacitors in REDS to maximize the overall power loss reduction based on total cost savings using Analytical closed-form expressions have been addressed in [8]. In this work, two analytical closed-form expressions have been proposed under four different cases comprising a total number of compensation nodes, optimal nodes, and the optimal sizing of capacitors.

In [9], a hybridization of Permutated Oppositional Differential Evolution - Sine Cosine Algorithm (HPODESCA) and Sensitivity-Based Decision-Making Technique (SBDMT) is proposed to maximize the Fitness Scores (FSs) in addressing the ISC problem. The Quasi-Oppositional Technique (QOT) is employed at initialization and within the main loop stages to generate the initial population. Additionally, four sensitivity-based approaches are used to identify potential nodes for reactive power compensation, ranked via a multi-criteria decision-making (MCDM) approach based on their similarity to the ideal solution. On the other hand, [10] introduces a Remora Optimization Algorithm (ROA) for minimizing the power loss and capacitor investment cost. It resolves the OCPS problem, with and without the Power Loss of Network Lines Index (PLNLI). The IEEE 33 and PG&E 69 bus test systems are employed to validate the effectiveness of this approach.

Ref. [11] Implements a Mixed-Integer Second-Order Cone Programming model (MI-SOCP) to optimize the OCPS problem in REDS, aiming to minimize power loss. Ref. [12] Utilizes the Hybrid Grey Wolf Optimizer (HGWO) to minimize the power or energy loss and capacitor purchase cost by optimizing OCPS. The study validates the method across various test systems but does not employ sensitivity indices to identify critical compensation nodes.

In [13], the Chu and Beasley Genetic Algorithm (CBGA) coupled with the General Algebraic Modelling System (GAMS) has been employed as an optimization technique. This approach focuses on achieving OCPS in REDS, aiming to minimize operational and investment costs. Ref. [14] focuses on the DG and OCPS problem in REDS with the target to minimize power loss, and maximization of voltage stability index (VSI) using the BAT algorithm. LSF-based identification of the most critical buses for real and reactive power compensation has been adopted in this paper. BAT algorithm will carry out appropriate sizing of DGs / capacitors. Commercial, Residential, Industrial, and Constant power loads are considered in this work and three load variations such as 50%, 100%, and 160% are considered.

Proposed Work: In this study, the utilization of a novel, superior, and robust Nature Inspired Metaheuristics Optimization Algorithm (NIMOA) known as the Dingo Optimization Algorithm (DOA) [15] has been introduced. DOA employs dynamic adjustments to update the alpha, beta, and other member dingoes. It has been employed for the optimal allocation and capacity determination of RPI. DOA has been recognized as a potent NIMOA that can address a wide range / diverse array of optimization challenges and effectively overcome the aforementioned difficulties. The primary aim of this study is to attain the highest possible FSs through the concurrent optimization of RRPL reduction with capacitors and their associated costs. This NIMOA has been tested and validated on two sinusoidal REDSs such as an 18-bus (extended version of the 15-bus system) and a PG&E 69-bus. The performance of the suggested NIMOA has been assessed by concluding simulation results and comparative studies.

2. Statement of Problem

This work aims to maximize the FSs by ISCs optimally in three REDS while satisfying both equality and inequality constraints. Before discussing the objective function, it is better to focus on the REDS Load Flow (REDSLF) adopted in this work.

2.1 Radial Electric Distribution System Load Flow (REDSLF)

To assess the REDS's performance, Load Flow (LF) analysis is regularly conducted to ensure power supply sufficiency, reactive power support, and voltage profile enrichment. Traditional LF methods like Gauss-Seidel, Newton-Raphson, and Fast-Decoupled are inadequate for radial DN due to high R/X ratios and radial topology by nature. Instead, a swift and robust REDSLF method developed in 2003 [16], based on recursive functions and a linked-list data structure, has been employed to optimize the reactive power injection. This approach has been identified as an efficient one in handling power losses across the entire DS, including laterals and sub-laterals.

$$P_{Loss(T)} = \sum_{g=1}^{NB} P_{Loss(g)} \tag{1}$$

$$Q_{Loss(T)} = \sum_{g=1}^{NB} Q_{Loss(g)} \tag{2}$$

Where

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

where $P_{Loss(g)}$ and $Q_{Loss(g)}$ are the total real and reactive power losses of the REDS. P_g, Q_g, R_g, and X_g are the real power, reactive power demand at node 'g', and resistance and reactance of the branch 'g' (g to g+1) in kW, kVAR, and in Ω respectively. NB indicates the total number of branches.

2.2 Objective Function

A single objective function comprising total RRPL reduction (OF_1 and OF_2) in REDS and capacitor investment cost reduction (OF_3) using weighing factors has been presented in this work.

$$\text{Maximize } OF = [OF_1 + OF_2 + OF_3] \tag{3}$$

Where $OF_1 = \beta_1 \times \left[\frac{P_{Loss(T)}^{ACI}}{P_{Loss(T)}^{IC}} \right]$

$$OF_2 = \beta_2 \times \left[\frac{Q_{Loss(T)}^{ACI}}{Q_{Loss(T)}^{IC}} \right]$$

$$OF_3 = \beta_3 \times \left[\left\{ \gamma \times \left(\left(C_{cap}^{inv} \times \sum_{m=1}^{N_{CN}} Q_{C(m)} \right) + \left(C_{cap}^{ins} \times N_{CN} \right) \right) \right\} + (C_{cap}^{OM} \times N_{CN}) \right]$$

Subject to Equality constraint

$$Q_{MPS}^{ACI} - Q_{DT} + \sum_{m=1}^{N_{CN}} Q_{C(m)} - Q_{Loss(T)}^{ACI} = 0 \tag{4}$$

Subject to an Inequality constraint

$$Q_C^{\min} \le Q_C \le Q_C^{\max} \tag{5}$$

$$\sum_{m=1}^{N_{CN}} Q_{C(m)} \le (Q_{DT} + Q_{Loss(T)}^{ACI}) \tag{6}$$

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

where C_{cap}^{inv}, C_{cap}^{ins} and C_{cap}^{OM} are the buying cost of the capacitor (discrete capacity in steps of 50 KVAR), installation cost, and Operation and maintenance cost of capacitors in \$/kVAR and \$/node respectively. IC, ACI, N_{CN}, MPS, and Q_{DT} refer to the initial condition of the DS, After Capacitor Installation Optimization, total number of capacitor nodes, main power supply, and total reactive power demand in kVAR respectively. QC(m) indicates the capacity of the capacitor in kVAR. β1, β2 and β3 indicate the weighing factor given to the individual objective functions.

3. Overview of Dingo Optimization Algorithm (DOA):

The Dingo Optimization Algorithm (DOA) is an innovative approach for global optimization inspired by the hunting behaviors of dingoes. The DOA operates through two key phases: exploration and exploitation. Exploration, akin to the encircling phase, aims to broadly navigate the problem space, whereas exploitation, like 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 Optimization Algorithm (DOA) strategically models the hunting actions of dingoes searching, encircling, and attacking prey through mathematical representations to conduct optimization which is discussed below.

3.1.1 Chasing and approaching:

In DO, the dingo's search for prey is translated into a mathematical exploration within the solution space. Like the 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.

3.1.2 Encircling:

Dingoes possess remarkable hunting skills, 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, like an optimal approach, given the unknown quest area. Meanwhile, other members continue refining their strategies for potential future approaches. During the encircling phase, dingoes move based on specific equations (8)-(12) in their pursuit of optimization.

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

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

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

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

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

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] and I represents the iteration with $I_{\max}$ 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, $\vec{D}$ 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, 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.

3.1.3 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 endeavors, yet there are occasions where beta and other members of the pack may also 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.

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{A_1}.\vec{P}_\alpha - \vec{P}\right| \tag{13}$$

$$\overrightarrow{D_\beta} = \left|\overrightarrow{A_2}.\vec{P}_\beta - \vec{P}\right| \tag{14}$$

$$\overrightarrow{D_o} = \left|\overrightarrow{A_3}.\vec{P}_o - \vec{P}\right| \tag{15}$$

$$\overrightarrow{P_1} = \left|\vec{P}_\alpha - \vec{B}.\vec{D}_\alpha\right| \tag{16}$$

$$\overrightarrow{P_2} = \left|\vec{P}_\beta - \vec{B}.\vec{D}_\beta\right| \tag{17}$$

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

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

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

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

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

3.1.4 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 of 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 gradually halt their movement. The suggested encircling method contributes to exploration to a certain degree. However, to enhance exploration further, DOA needs additional operators. DOA supports its quest agents in adjusting their positions by factoring in the locations of α, β, other pack members, and the targeted prey. Despite utilizing these operators, DOA retains the capability to deactivate local solutions.

3.1.5. Searching:

Dingoes rely on their pack's movements for hunting, consistently advancing to pursue and confront prey. Using $\vec{B}$ and $\vec{A}$ for random values, values below -1 indicate prey moving away, while those above 1 show the pack closing in. These aid DOA in global scanning targets. Another crucial DOA element is generating random numbers in [0, 3] for prey weights. It operates stochastically, giving precedence to vector values ≤1 over ≥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 requirements or exceeding them. offers stochastic exploration values from initial to final iterations, preventing local optima. DOA concludes upon fulfilling termination criteria. Fig. 1 reveals the pseudo-code for the proposed algorithm

```
1. Generate initial search agents
2. Set b⃗, A⃗ and B⃗ values
3. While termination conditions are not met do
4. Estimate the fitness and intensity cost of each dingo
5. D_α =Dingo with finest search
6. D_β =Dingo with the second-finest search
7. D_o =Dingoes search results afterward
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_α , F_β and F_o .
15. Record the value of b⃗ , A⃗ and B⃗ .
16. It= It+1
17. Check if It ≥ stopping criteria
18. Output
19. End while
```

Fig. 1 Pseudocode for the proposed optimization algorithm – DOA

4. Case Study Details, Simulation Results and Discussions:

To substantiate the effectiveness of the DOA in optimizing the objective function (discussed in section 2), two sinusoidal test REDSs have been taken, and simulations have been carried out for RPI considering single to three locations for PG&E 69-bus system and two to four locations for the 18-bus sinusoidal test system. The details of the two sinusoidal REDSs and the simulation results are discussed under Art. 4.1 and 4.2.

Node number 1 has been taken as a substation/slack bus for all the sinusoidal REDS. All nodes, except bus no. 1, are considered as load nodes. The voltage for bus number 1 has been fixed as 1 p.u. RPI has been expected to be applied from node 2 through the end node of the REDS. The proposed algorithm using REDSLF has been developed and executed in MATLAB software, running on an i5 Intel processor with 8 GB RAM. The solution vector size and the number of iterations has been set to 800 and 100, respectively. For each node of the RPI, two variables are assigned (optimal node and optimal sizing).

The cost of real power is taken as $120 / kW [17]. According to ref. [18], the cost of reactive energy loss (kVARh) is one-third of the cost of real power. The purchase cost of the capacitor is $2.5 / kVAr and the cost of installation and maintenance has been considered as $460 / node [19]. For all the REDSs, the base MVA has been taken as 100 MVA. The base kV for PG&E 69-bus and 18-bus REDS are taken as 12.66 kV and 11 kV respectively. To ascertain the impact of RPIs on two sinusoidal REDSs, ISCs as mentioned in scenarios 1 to 3 have been carried out. Capacitor investment cost related to heavy load variation has only been considered for cost evaluation.

Scenario 1: Effect of RPIs at two optimal locations for 18-bus system / Single optimal location for PG&E 69-bus system.

Scenario 2: Effect of RPIs at three optimal locations for 18-bus system / Two optimal locations for PG&E 69-bus system

Scenario 3: Effect of RPIs at four optimal locations for 18-bus system / Three optimal locations for PG&E 69-bus

4.1 18-bus test system – Results and discussions:

The first sinusoidal test system taken for evaluation is the 18-bus REDS which is the extension of renowned 15-bus sinusoidal REDS. It has 18 buses, and 17 branches with a total apparent power demand of (1506.4+j 1536.8) kVA. The apparent power loss under the Initial Condition (IC) for this test system is (105.2268+j 98.0618) kVA. The minimum bus voltage under IC is 0.9171p.u. The data about 18-Bus REDS can be viewed in [20]. The single line diagram for the 18-bus test system is shown in Fig. 2. The total RRPL cost under IC is $12627.216 and $3922.47 per annum respectively.

From Table 1 it is evidenced that RPIs under scenarios 1 to 3 yield RRPL reductions between 44% and 52% respectively with reactive power penetration between 81% and 91%. The difference in minimum bus voltage recorded after RPI (i.e.) After Optimization (AO) is 0.0359 p.u. 0.038 p.u. and 0.0383 p.u. respectively considering scenarios 1 to 3. From Table 1, it is also apparent that the net FSs yielded by DOA under scenario 2 have been recorded as the highest compared to scenario 1. However, scenario 3 reduces the net FS by $320.816 compared to scenario 2 because of the increased capacitor investment cost. Fig. 3 shows the performance of DOA in bus voltage enhancement under three scenarios.

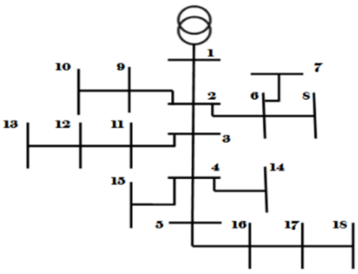

Fig. 2 – One line diagram of 18-bus REDS [32]

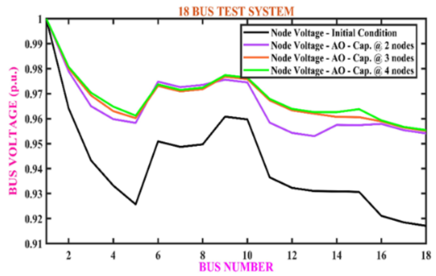

Fig. 3- Bus Voltage profile (IC / AO) – 18-bus system – Scenarios 1 to 3

Table 1

Performance of DOA – 18-bus system – Scenario 1 to 3.

Parameters	**Cap. @ two nodes**	**Cap. @ three nodes**	**Cap. @ four nodes**
P_{Loss} (AO) / P_{Loss} (IC) (kW)	58.2304 / 105.2268	52.3359 / 105.2268	50.5913 / 105.2268
% P_{Loss} reduction	44.662	50.26372	51.9217
Q_{Loss} (AO) /Q_{Loss} (IC) (kVAR)	52.7143 / 98.0618	48.064 / 98.0618	46.6932 / 98.0618
% Q_{Loss} reduction	46.2438	50.986	52.384
Capacitor details (kVAR)	600 (6) 650 (16)	400 (6) 450 (11) 500 (16)	400 (6) 400 (11) 200 (15) 400 (16)
% Cap. Penetration	81.338	87.845	91.098
Δ P_{Loss} Cost ($)	5639.568	6346.908	6556.26
Δ Q_{Loss} Cost ($)	1813.9	1999.912	2054.744
Cap. Cost ($)	4045	4755	5340
Net F Ss ($)	**3408.47**	**3591.82**	**3271.004**
V_{min} (p.u)	0.953	0.9551	0.9554

4.2. PG&E 69-bus test system – Results and discussions:

The next test system considered here is the PG&E 69-bus sinusoidal REDS which has 69 buses 68 sectionalizing switches and five tie-switches. The total real and reactive power demand under nominal load is 4903.0477 kVA at 0.821365 power factor lagging. The RRPL and minimum bus voltage under IC are (225 + j102.14) kVA and 0.90919 p.u. respectively. The RRPL costs under IC are $27000 and $4085.6 per year respectively. Figure 4 shows the single-line diagram of the PG&E 69-bus test system.

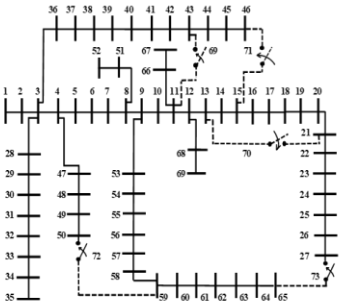

Fig. 4. One-line diagram of PG&E 69-bus REDS

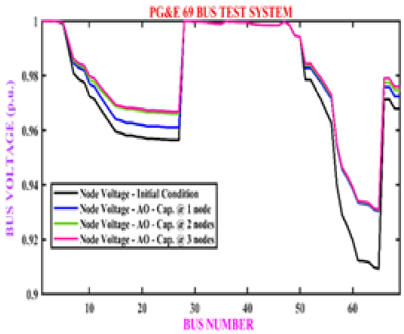

Fig. 5. Bus Voltage profile (IC/AO) – PG&E 69-bus REDS- Scenarios 1 to 3

Table 2 reveals the performances of the PG&E 69-bus test system under three scenarios mentioned previously. From Table 2 it is clear that the RRPL reduction is found to be between 31% to 35.5% with reactive power penetration between 50% and 67%. The differences in minimum bus voltage recorded are 0.02111 p.u., 0.02161 p.u., and 0.02191 p.u. respectively considering scenarios 1 to 3. By calculating the net FSs after scenarios 1 to 3, it is noticeable that the difference between scenarios 2 and 3 and scenarios 1 to 3 are $902.84 and $1215.4 respectively. From Table 2, it is understandable that the net FSs after scenario 1 are better than scenarios 2 and 3. Figure 5 reveals the performance of bus voltages under IC and AO for all the three scenarios.

Table 2

Performance of DOA – PG&E69-bus system – Scenario 1 to 3

Parameters	**Cap. @ single node**	**Cap. @ two nodes**	**Cap. @ three nodes**
P_{Loss} (AO) /P_{Loss} (IC) (kW)	150.9 / 225	146.41 / 225	145.09 / 225
% P_{Loss} reduction	32.93333	34.93	35.51555
Q_{Loss} (AO) / Q_{Loss} (IC) (kVAR)	69.961 / 102.1155	67.245 / 102.14	66.651 / 102.1155
% Q_{Loss} reduction	31.488	34.1481	34.7298
Capacitor details (kVAr)	1350 (61)	300 (18) 1200 (61)	350 (11) 250 (20) 1200 (61)
% Cap. Penetration	50.1188	57.544	66.825
Δ P_{Loss} Cost ($)	8892	9430.8	9589.2
Δ Q_{Loss} Cost ($)	1286.18	1395.8	1418.58

Cap. Cost ($)	3835	4670	5880
Net FSs ($)	**6343.18**	**6156.6**	**5127.78**
V_{min} (p.u)	0.9303	0.9309	0.9317

Tables 3 to 5 expose the comparison of the performance of other optimization techniques with DOA considering three scenarios. From Table 3, it is witnessed that the performance of DOA under scenario 1 yields a better performance (RRPL reduction, bus voltage enhancement, and net FS) than [3,4,5]. Though the real power loss reduction achieved by DOA is better than [8], it is to be noted that due to the lower capacitor value optimized by [8], the net FS is better than DOA.

The performance of DOA under scenario 2 has been compared with [4 – 10]. It is visible from Table 4 that the real power loss reduction achieved by DOA is better than [5 – 10]. The capacitor penetration optimized by DOA is better than [4–6, 10]. The minimum bus voltage enhanced by DOA is better than [4 – 9] and equals [10]. The net FSs achieved by DOA are better than [4,5,6,8,10]. Though the real power loss reduction realized by MPSO [4] is more than DOA, the net FS by [4] is $363.2 less than DOA. On the other hand, it is apparent from Table 4 that the real power loss reduction attained by [7,9] is less than DOA. While calculating net FS, [7,9] yields a better FS than DOA because of the less cap. investment cost.

Table 3

Comparison of performance of DOA – PG&E69-bus system – Scenario 1

Parameters	AEFA [3] (Strategy 1)	AEFA [3] (Strategy 2)	MPSO [4]	SFSOA [5]	ACE [8]	DOA
P_{Loss} (AO) / P_{Loss} (IC) kW	175.92 / 224.96	152.02 / 224.96	150.9 / 225	152.04 / 225	152.4 / 225	151.12 / 225
% P_{Loss} reduction	21.8	32.42354	32.93333	32.42666	32.2666	32.835555
Q_{Loss} (AO) / Q_{Loss} (IC) kVAR	79.86 / 102.15	70.48 / 102.15	---------	---------	---------	69.961 / 102.14
% Q_{Loss} reduction	21.82	31.01	---------	---------	---------	31.488
Capacitor details (kVAr)	1100 (57)	1350 (61)	1400 (61)	1330 (61)	1239 (61)	1350 (61)
ΔP_{Loss} Cost ($)	5884.8	8752.8	8892	8755.2	8712	8865.6
ΔQ_{Loss} Cost ($)	891.6	1266.8	---------	---------	---------	1287.16
Cap. Inv. Cost ($)	3210	3835	3960	3785	3557.5	3835
Net Profit ($) – considering only P_{Loss} cost	**2674.8**	**4917.8**	**4932**	**4970.2**	**5154.5**	**5030.6**
Net Profit ($) – considering both cost	**3566.4**	**6184.6**	--------	--------	--------	**6317.76**
V_{min} (p.u)	0.921 (65)	0.931 (65)	0.9291	0.93	--------	0.931

Table 5 compares the effect of RPIs at three optimal locations with [4,8,10 – 14]. The real power loss reduction attained by the proposed method is better than [8,10 – 13]. It is to be noted that the capacitor penetration achieved by DOA is better than [10,14] and equals [11,12,13]. However, the capacitor penetration by [4,8] is less than DOA which is found to be minuscule [4]. The minimum bus voltage enhancement achieved by DOA is better than [4,8,10–13]. Finally, the FSs accomplished by DOA are better than [10–14]. The FS difference between DOA and [4,8] seems to be $161 and $430.8 respectively.

Table 4

Comparison of performance of DOA – PG&E69-bus system – Scenario 2

Parameters	MPSO [4]	SFSOA [5]	MVO [6]	SFS / ISFS [7]	ACE [8]	PODESCA [9]	ROA [10]	DOA
P_{Loss} (AO) / P_{Loss} (IC) (kW)	145.27 / 225	146.44 / 225	146.6294 / 224.895	147.762 / 225.0006	146.9 / 225	147.78 / 225.02	146.43 / 224.97	146.41 / 225
% P_{Loss} reduction	35.44	34.91555	34.801	34.33	34.7111	34.3	34.91	34.93
Capacitor details (kVAr)	300 (18) 1400 (61)	361 (17) 1275 (61)	600 (18) 1200 (61)	250 (20) 1150 (61)	299 (18) 1193 (61)	250 (20) 1150 (61)	350 (17) 1262 (61)	300 (18) 1200 (61)
ΔP_{Loss} Cost ($)	9567.6	9427.2	9391.86	9268.62	9372	9268.8	9424.8	9430.8
Cap. Inv. Cost	$5170	$5010	$5420	$4420	$4650	$4420	$4950	$4670
Net Profit ($)	**4397.6**	**4417.2**	**3971.86**	**4848.62**	**4722**	**4848.8**	**4474.8**	**4760.8**
V_{min} (p.u)	0.93	0.9303	0.9308	0.9289	-----	0.9302	0.9309	0.9309

Table 5

Comparison of performance of DOA – PG&E69-bus system – Scenario 3

Parameters	P_{Loss} (AO) / P_{Loss} (IC) (kW)	% P_{Loss} reduction	Capacitor details (kVAr)	ΔP_{Loss} Cost ($)	Cap. Inv. Cost ($)	Net Profit ($)	V_{min} (p.u)
MPSO [4]	144.79 / 225	35.63	320 (21) 1200 (61) 230 (64)	9625.2	5755	**3870.2**	0.9311
ACE [8]	146 / 225	35.1111	201 (12) 207 (21) 1176(61)	9480	5340	**4140**	--------
ROA [10]	145.08 / 224.97	35.51	244 (62) 373 (11) 230 (21) 980 (61)	9586.8	5947.5	**3639.3**	0.93125
MI-SOCP [11]	145.397 / 225.072	35.39978	300 (11) 300 (18) 1200 (61)	9561	5880	**3681**	---------
HGWO [12]	145.22 / 225	35.457777	300 (11) 300 (17) 1200 (61)	9573.6	5880	**3693.6**	0.9308
GAMS [13]	145.58 / 224.9352	35.27914	450 (12) 150 (22) 1200 (61)	9524.784	5880	**3644.784**	---------
CBGA [13]	145.37 / 224.9532	35.37767	450 (12) 150 (22) 1200 (61)	9549.984	5880	**3669.984**	---------

BOA [14]	144.96 / 225	35.57	400 (12) 230 (19) 1237 (61)	9604.8	6047.5	**3557.3**	0.9327
DOA	145.09 / 225	35.51555	350 (11) 250 (20) 1200 (61)	9589.2	5880	**3709.2**	0.9317

5. Conclusion

This work emphasizes mainly the RPIs in sinusoidal REDS using a new, durable, and robust NIMOA called Dingo Optimization Algorithm (DOA) to identify the optimal variations in penetration of SCs to achieve maximum RRPL reduction with a reduction in capacitor investment cost thereby more FSs while ensuring that all equality and inequality constraints are met. The major advantage of DOA is the efficient handling of discrete, complicated, non-linear, and large-dimensional optimization problems. Two renowned sinusoidal REDSs such as 18-bus and PG&E 69-bus have been utilized to demonstrate the usefulness of DOA. The following are the observations:

(i) In general, all the reactive power optimization-based research work in REDS considers reduction in real power loss reduction with capacitor investment cost. However, this work focuses on the minimization of both RRPL reduction with capacitor investment costs.

(ii) No SBIs have been adopted in this work to select the most appropriate nodes for RPI. Instead, DOA has to identify the most possible nodes and the proper reactive power capacity of the capacitor.

(ii) Considering 18-node REDS, the RRPL reduction has been identified between 45% and 53% considering all three scenarios with FSs between \$3.2K to \$3.4K /year is evidenced.

(iii) Regarding PG&E 69-bus REDS, the reductions in RRPL are found to be between 31% and 36%, with the reactive power penetration between 50% and 67% is noticed. The FSs considering all three scenarios vary between \$5.1K and 6.35K. The performances have been compared with the recent NIMOAs presented in the literature. The difference in RRPL reduction achieved by DOA is found to be better and significant.

Based on the simulation results and the preceding discussions, it is evident that DOA consistently outperforms other methods in achieving a reduction in RRPL net FSs. Hence, DOA has been recommended to be another strong and efficient technique for solving optimal RPI.

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