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Improved Pufferfish Optimization Algorithm for Optimal Allocation of Photovoltaic Fast Charging Stations in Radial Distribution System

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Abstract: Adding fast charging stations (FCSs) and photovoltaic systems (PVs) to modern electrical distribution networks (EDNs) can cause problems like voltage fluctuations and more power loss. One way to solve these issues is to use a levy-flight-based improved Pufferfish optimization algorithm (IPOA), which can find better answers to the PVs and FCSs in EDNs. The modifications enhance the exploration and exploitation phase of the existing algorithm, resulting in faster convergence rates and improved fitness. The algorithm has been tested on standard tension/ compression spring design problem and compared to other classical algorithms, like particle swarm optimization (PSO) or genetic algorithm (GA). The hybrid Levy flight algorithm works best on many test functions, which makes IPOA more useful for engineering global optimization problems. Also, the suggested method reduces actual power losses and improves voltage profiles in a number of different situations when dealing with the PVs and FCSs allocation problem in EDNs. Simulations on an IEEE 33-bus and 69-bus EDN demonstrate the superior performance of the IPOA over other metaheuristics. To highlight, IPOA's numerical results with mean values of 75.11 (33-bus) and 71.32 (69-bus) with exceptionally low variability confirm it as the most reliable and efficient optimization algorithm for minimizing the objective function. The IPOA outperforms other algorithms with superior convergence, stability, and computational efficiency. This work highlights IPOA's potential for addressing multi-objective optimization in complex, constrained energy systems.

Keywords: Photovoltaic systems, Fast charging stations, Radial feeders, Pufferfish optimization algorithm, Levy flight distribution, Multi-objective optimization, Voltage stability.

1. Introduction

The growth of electric vehicles (EVs) and photovoltaic systems (PVs) is transforming electrical distribution networks (EDNs), but it presents challenges like uncoordinated charging patterns and voltage instability. Coordinated allocation of charging stations and PVs is crucial for balanced operation, efficient resource utilization, and minimal grid disruptions, necessitating robust optimization techniques.

In [1], PVs are optimized for real power loss reduction and annual economic loss cost using multi-objective whale optimization (MOWOA). In [2], enhanced pathfinder algorithm is employed for finding the best locations and sizes of PVs and CSs considering different levels of EV penetration. Real power loss, voltage profile and greenhouse gas (GHG) emission are considered while solving the problem. In [3], Chernobyl disaster optimizer (CDO) is proposed for loss reduction, voltage profile improvement, reliability enhancement considering PVs, distribution- static VAr compensator (D-STATCOM) and energy storage system (ESS). In [4], hunter prey optimization (HPO) is proposed for PVs, D-STATCOM and CSs by aiming loss reduction and voltage stability enhancement. In [5], a hybrid BFOA-PSO is formulated with bacterial foraging optimization algorithm (BFOA) and particle swarm optimization (PSO) for optimal placement of CSs in EDNs. The study shows minimal power losses and minor voltage deviation changes by the proposed methodology. In [6], a hybrid technique for locating CSs, combining gray wolf optimization (GWO) and PSO is presented. The approach minimizes active power loss, maximizes net profit, and improves grid reliability. In [7], a joint planning model for optimizing the locations and capacities of CSs and PVs in EDS to reduce energy losses and the optimization problem is solved using genetic algorithm (GA). In [8], a method to optimize real power loss and voltage deviation is presented while integrating fast-charging stations (FCSs) and PVs in EDNs using cuckoo search (CSA), GA, and simulated annealing (SA). In [9], a mathematical model for CS placement, focusing on coverage, losses, and voltage deviations is proposed. It uses a hybrid PSO-DS algorithm formulated by PSO direct search (DS) to optimize the placement of CSs and shunt capacitors (SCBs). In [10], the study proposes two-stage processes for FCSs allocation by charging station owner decision index (CSODI) and the hybrid gray wolf optimization-particle swarm optimization (GWO-PSO) algorithm. The GWO-PSO technique achieves the best possible locations with low power loss, land cost, and EV population. To find the ideal locations for plug-in electric vehicle (PEV) with charge profile, a mixed integer liner programming (MILP) stochastic optimization problem is proposed [11]. Also, kernel density estimator (KDE), a nonparametric approach, is used to model uncertain PEV arrival and departure. The proposed mixed integer liner programming (MILP) approach yielded better results in less time. In [12], a fuzzy classified method is proposed for optimal sizing and placement of CSs, PVs, and D-STATCOMs for 69-bus radial distribution systems using the RAO-3 algorithm. The method aims to reduce real power loss, enhance the substation power factor, improve the voltage profile, and allocate the optimum number of EVs at CSs. In [13], the research aims to minimize network loss by maximizing the placement of CSs and DGs in the power grid using arithmetic optimization algorithm (AOA). In [14], a modified Archimedes optimization algorithm (MAOA) is proposed for optimal placement of CSs, based on power loss, voltage deviation, and voltage stability index. In [15], the research proposes the optimal placement and capacity of battery energy storage systems (BESS) in EDNs integrated with PVs and EVs. The goal is to minimize system costs, including installation, replacement, operation, and maintenance. Three metaheuristic algorithms, PSO, african vultures optimization algorithm (AVOA), and salp swarm algorithm (SSA), are used to solve the problem. In [16], the study uses a hybrid GA-PSO to optimize the placement of CSs and PVs in EDNs. It validates the effectiveness of the GA-PSO, resulting in minimum bus voltage within acceptable margins, low losses and CO_2 emissions. In [17], the study focuses on integrating CSs into EDNs, particularly when PVs are involved. A hybrid GA and simulated annealing (GA-SA) is used to find optimal locations for CSs, aiming to reduce power losses and maintain acceptable voltage levels, enhancing the sustainability and reliability of distribution networks. In [18], PSO is proposed to demonstrating superior optimization effectiveness and computational efficiency, making it a promising technique for CSs and PVs placement in EDNs. Further, the review in [19] discusses the concept, advantages, PVs and CSs allocation methods and algorithms.

From the aforementioned literature, integration of PVs and FCSs in EDNs enhances power system efficiency, reliability, and sustainability, addressing challenges like power loss reduction, voltage profile improvement, cost minimization, and greenhouse gas emission reduction [20]. On the other side, as per the no-free-lunch theorem, it is not possible to address all kinds of optimization problems with any single algorithm. Thus, researchers continue to inspire the introduction of new algorithms or the enhancement of existing ones to better adapt to real-time complex optimization problems.

Many metaheuristics have been developed in recent times, including the carpet weaver optimization (CWO) [21], sculptor optimization algorithm (SOA) [22], apiary organizational-based optimization algorithm (AOA) [23], focus and shake algorithm (FSA) [24], swarm bipolar algorithm (SBA) [25], swarm space hopping algorithm (SSHA) [26], migration-crossover algorithm (MCA) [27], addax optimization algorithm (AOA) [28], dollmaker optimization algorithm (DOA) [29], quadratic time optimization (QTO) [30], potter optimization algorithm (POA) [31], and fossa optimization algorithm (FOA) [32]. In this context, the following are the major contributions of thus paper.

1. *Introduction of POA with improvements for PV and FCSs allocation*: The Pufferfish Optimization Algorithm (POA) [33] is designed to tackle multi-objective problems, specifically focusing on the reduction of real power loss and the enhancement of voltage profiles while solving PVs and FCSs allocation.

2. *Enhanced exploration phase*: Levy light distribution method is introduced for initializing the population in the exploration phase of basic POA.

3. *Comparison with other algorithms*: The performance of POA is evaluated in relation to artificial rabbits optimization (ARO) [34] and Osprey optimization algorithm (OOA) [35], showing enhanced effectiveness in addressing the specified problem.

4. *Simulations on IEEE 33-bus and 69-bus system*: Simulations were performed on the IEEE 33-bus test system, demonstrating the effectiveness of the Adaptive POA across various scenarios.

The remainder of the paper is structured as follows: Section 2 addresses the modelling of concepts, including PVs and FCSs; Section 3 presents the problem formulation along with its equality and inequality constraints; Section 4 outlines the solution methodology of the IPOA; Section 5 discusses the simulation results; and Section 6 offers a comprehensive conclusion that emphasizes the principal contributions and findings.

2. Modelling of concepts

This section introduces the modelling of PVs and FCSs, emphasizing their operational characteristics, power demands, and integration challenges within EDNs.

2.1 Photovoltaic distribution generation

Photovoltaic systems (PVs) in EDNs primarily deliver active power using DC-AC converters. Ideally, the working power factor of converters is one, allowing the effect of PV at a bus to be achieved by offsetting the active power load to match the output of the PV. Mathematically,

$$\bar{P}_{d,i} = P_{d,i} - P_{pv,i} \tag{1}$$

2.2 Fast charging station

FCS modelling demonstrates voltage-dependent attributes of EVs using AC-to-DC converter, buck converter, and energy storage battery, representing active and reactive power demands. Mathematically,

$$P_{cs,i} = P_{cs,r} \times (0.93 + 0.07 \times |V_i|^{-3.107}) \tag{2}$$

$$Q_{cs,i} = P_{cs,i} \times \tan\left(cos^{-1}(0.97)\right) \tag{3}$$

The active and reactive power loadings at bus-*i* after CS integration are given by:

$$\bar{P}_{d,i} = P_{d,i} + P_{cs,i} \tag{4}$$

$$\bar{Q}_{d,i} = Q_{d,i} + Q_{cs,i} \tag{5}$$

3. Problem formulation

In this section, the proposed multi-objective optimization problem for loss reduction and voltage profile improvement is explained.

3.1 Objective function

Basically the real power loss is directly proportional to the square of current flow through a branch and its resistance. Thus, the total real power loss of the network is given by,

$$P_{loss} = \sum_{b}^{nbr} I_b^2 r_b \tag{6}$$

Further, the voltage profile across the network needs to be maintained at an adequate level. The average voltage deviation (AVD) is defined:

$$AVD = \frac{1}{nbus}\sqrt{\sum_{i=1}^{nbus}(|V_s| - |V_i|)^2} \tag{7}$$

The proposed multi-objective is formulated for minimizing simultaneously and is given by,

$$OF = min(P_{loss} + AVD) \tag{8}$$

3.2 Constraints

In order to maintain operational requirements and planning constraints, the following are considered in this work.

$$|V_{min}| \le |V_i| \le |V_{max}| \tag{9}$$

$$0 \le P_{pv,i} \le P_D \tag{10}$$

$$\sum_{i=i}^{npv} P_{pv,i} \le P_D \tag{11}$$

$$2 \le \left(l_{pv}, l_{cs}\right) \le nbus \tag{12}$$

$$2 \le l_{cs} \le nbus \tag{13}$$

4. Solution methodology

This section describes the optimization method derived from the Pufferfish Optimization Algorithm (POA), which is inspired by the attacking and defense mechanisms of pufferfish and its improved variant IPOA using Lévy flight distribution.

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4.1 Pufferfish optimization algorithm

Pufferfish, members of the Tetraodontidae family, use a distinctive defense strategy by inflating their elastic stomachs with water, thereby becoming spiky spheres to dissuade predators and its application to classical engineering problem.

4.1.1. Initialization phase

The proposed POA method is an efficient optimization strategy that uses population search within an iterative framework. Each POA member sets decision variables based on its location in the search space, representing potential solutions as vectors. The algorithm's population is represented mathematically as a matrix, with initial positions determined by Eq. (14) and Eq. (15).

$$P = \begin{bmatrix} P_1 \\ \vdots \\ P_N \end{bmatrix}_{N\times m} = \begin{bmatrix} p_{11} & \cdots & p_{1m} \\ \vdots & \ddots & \vdots \\ p_{N1} & \cdots & P_{Nm} \end{bmatrix}_{N\times m} \tag{14}$$

$$p_{id} = lb_d + r \cdot (ub_d - lb_d) \tag{15}$$

where P is the population matrix, P_j is the jth POA member (candidate solution) and p_{id} is its dth dimension in the search space (decision variable), N and m are the number of population members, and number of decision variables, respectively; r is a random number between [0, 1], lb_d and $ub_d$are the lower bound and upper bound of the dth decision variable, respectively.

The objective function of a problem can be evaluated using each POA member as a candidate solution, represented using a vector according to Eq. (16).

$$F = [F_1 \quad \cdots \quad F_i \quad \cdots \quad F_N]^T_{N\times 1} \tag{16}$$

The proposed POA approach updates population members' positions in problem-solving space by simulating natural behaviors between pufferfish and predators, including exploration, exploitation, defense mechanisms, and threat and escape.

4.1.2. Exploration phase (Predator's attack)

The initial phase of POA updates population members' positions based on predator attack strategy, increasing algorithm's global search power,

$$CP_i = \{P_k : F(P_k) < F(P_i), k \neq i\},$$
$$\text{where } i = 1, \ldots, N \text{ and } k \in \{1,2, \ldots N\} \tag{17}$$

The POA design assumes a random selection of a pufferfish from the CP_i set. The chosen pufferfish ($SP_{i,j}$) is then calculated using Eq. (18) and if the objective function value improves, the new position is replaced by the previous position using Eq. (19).

$$p_{i,j}^{P_1} = p_{i,j} + r_{i,j} \cdot \left(SP_{i,j} - I_{i,j} \cdot p_{i,j}\right) \tag{18}$$

$$P_i = \begin{cases} P_{i,j}^{P_1} & if\ F\left(P_{i,j}^{P_1}\right) < F(P_i) \\ P_i & else \end{cases} \tag{19}$$

where $P_{i,j}^{P_1}$ is the new position for jth dimension of predator i, $SP_{i,j}$ is the position of the selected pufferfish, $I_{i,j}$ is a random integer (1 or 2), $r_{i,j}$ is a random number in [0, 1].

4.1.3. Exploitation phase (Pufferfish's defense)

In the second phase of POA, the position of population members is updated based on a pufferfish's defense mechanism against predator attacks. If the predator's position improves the objective function value, it replaces the previous member.

$$p_{i,j}^{P_2} = p_{i,j} + \left(1 - 2 \cdot r_{i,j}\right) \cdot \{(ub_d - lb_d)/t\} \tag{20}$$

$$P_i = \begin{cases} P_{i,j}^{P_2} & if\ F\left(P_{i,j}^{P_2}\right) \leq F(P_i) \\ P_i & else \end{cases} \tag{21}$$

where $P_{i,j}^{P_2}$ is the newly computed location for the ith predator, derived from the second phase of the suggested POA, The variable $p_{i,j}^{P_2}$ represents its jth dimension, $F\left(P_{i,j}^{P_2}\right)$ signifies its objective function value, $r_{i,j}$ are random values within the interval [0, 1], and t serves as the iteration count.

The POA algorithm updates the position of POA members based on exploration and exploitation phases, continuing through iterations using Eq. (30) through Eq. (34) until the last iteration T. The best POA member's position is stored based on evaluated objective function values. A detailed explanation POA can be found in [30].

4.2 Improvement with Lévy flight distribution

The initialization phase of the POA can be improved by incorporating the Lévy flight distribution, which helps enhance solution diversity and improve the global search capability of the

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algorithm. Its representation of the improved initialization phase as follows:

$$p_{id} = lb_d + s \cdot (ub_d - lb_d) \tag{22}$$

Lévy flight is a random walk where the step sizes are drawn from a Lévy distribution. It is defined mathematically as:

$$L(s) \sim |s|^{-\lambda},\ 1 < \lambda \leq 3 \tag{23}$$

where $L(s)$ is step size and λ Lévy distribution parameter (typically set between 1 and 3).

$$s = \frac{\mu}{|v|^{\frac{1}{\gamma}}} \tag{24}$$

where $\mu \sim N(0,1)$ and $v \sim N(0,1)$ are random numbers drawn from a standard normal distribution, respectively. To ensure positions remain within bounds, the following relation is applied.

$$p_{id} = max[lb_d, min(p_{id}, ub_d)] \tag{25}$$

This way, Lévy flight can ensure diversity in initialization by generating a mix of small and large random steps, promoting broader exploration of the search space, which prevents premature convergence and improves the algorithm's overall search ability.

4.3 Computational efficacy of IPOA

To evaluate the performance of the IPOA, one of the real-time engineering problems is solved. The algorithm is then compared against PSO, GA, ARO and OOA, basic POA. For all algorithms, population size and maximum iterations are taken as 30 and 100, respectively.

Tension/ compression spring design problem: The objective function is to minimize the weight of the tension/ compression spring $f(\vec{x})$. The optimal design must satisfy constraints $g_{i(\vec{x})}$, on shear stress, surge frequency, and deflection. This problem contains three constant variables $\vec{x}$, mean coil diameter (D), number of active coils (N) and wide diameter (d). The lower and upper limits are defined in Eq. (31).

$$\text{Min } f(\vec{x}) = x_1^2 x_2 (x_3 + 2),\ \vec{x} = [d, D, N] \tag{26}$$

$$g_{1(\vec{x})} = \left(1 - \frac{x_2^3 x_3}{71785 x_1^4}\right) \leq 0 \tag{27}$$

$$g_{2(\vec{x})} = \left(\frac{4x_2^2 - x_1 x_2}{12566(x_1 x_1^3 - x_1^4)} + \frac{1}{5108 x_1^2} - 1\right) \leq 0 \tag{28}$$

Table 1. Optimized results of selected functions

Method	Optimal variables			Target
	d	***D***	***N***	
PSO	0.0520	0.3640	10.8905	0.0127
GA	0.0512	0.3452	12.0040	0.0127
ARO	0.0517	0.3576	11.2445	0.0127
OOA	0.0517	0.3561	11.3334	0.0127
POA	0.0512	0.3499	12.0764	0.0127
IPOA	0.0520	0.3641	10.8684	**0.0127**

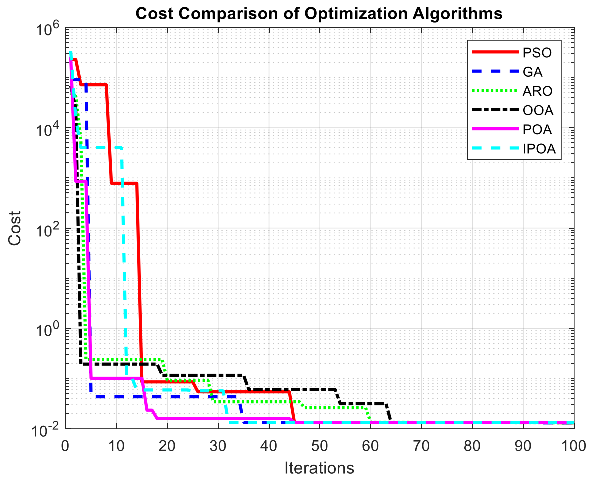

Figure. 1 Convergence characteristics for tension/ compression spring design

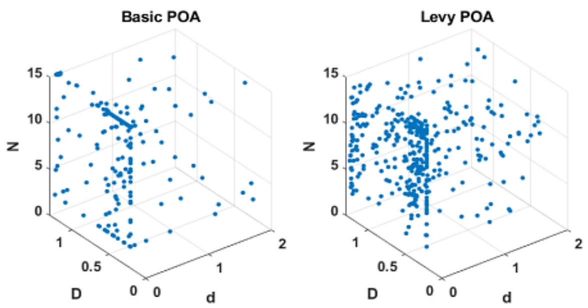

Figure. 2 Comparison of exploration in POA and IPOA

$$g_{3(\vec{x})} = \left(1 - \frac{140.45 x_1}{x_2^2 x_3}\right) \leq 0 \tag{29}$$

$$g_{4(\vec{x})} = \left(\frac{x_1 + x_2}{1.5} - 1\right) \leq 0 \tag{30}$$

$$\vec{x} = \begin{cases} 0.05 \leq x_1(d) \leq 2.00 \\ 0.25 \leq x_2(D) \leq 1.30 \\ 2.00 \leq x_3(N) \leq 15.0 \end{cases} \tag{31}$$

In Table 1, IPOA outperforms other algorithms with least target value, indicating better exploration of search space and resulting in a global solution.

Levy flight, a power-law distribution, enhances the optimization algorithm's exploration capabilities by allowing long-tailed steps and avoiding local optima. This has prevented the algorithm from getting stuck in local minima and allows for a broader exploration of the solution space as shown in Fig. 2, making it more robust and capable of finding better solutions in complex problem landscapes.

5. Results and discussion

The computational efficiency of POA is evaluated by simulating various scenarios on IEEE 33-bus and 69-bus radial EDNs utilizing a PC equipped with an Intel® Core™ i7 8750 CPU @ 2.20 GHz and 16 GB RAM, employing MATLAB programming. A number of similar metaheuristics are compared to the IPOA, and 30 separate simulations are used for statistical analysis.

5.1 Case 1: Base case

In the base case, the 33-bus EDN experiences a load of 3715 kW and 2300 kVAr. The load flow analysis shows that the network lost a total of 210.99 kW and 143.0329 kVAr. At bus-18, the lowest voltage level was recorded at 0.9038 p.u. The Average Voltage Deviation (AVD) is calculated as 0.0104 p.u. Similarly, for the 69-bus EDN, the load is 3801.5 kW and 2694.7 kVAr. Load flow results indicate total network losses of 225.0034 kW and 102.1994 kVAr, with the minimum voltage observed at 0.9092 p.u. at bus-68. The AVD for this system is determined to be 0.0046 p.u.

5.2 Case 2: Integration of PV systems

In this study, three PVs are optimally integrated into the 33-bus and 69-bus EDNs to enhance network performance.

33-Bus Network: The optimal PV locations are identified as buses 13, 24, and 30, with corresponding sizes of 801.7 kW, 1091.33 kW, and 1053.64 kW. This integration reduces losses to 72.79 kW and 50.65 kVAr, respectively. The minimum voltage improves to 0.9687 p.u. at bus-33, and the AVD decreases significantly to 0.0037 p.u. Compared to MOWOA [1], the IPOA results are highly competitive, as presented in Table 2.

69-Bus Network: The best place for the PVs cuts power losses to 69.4262 kW and 34.968 kVAr, respectively. The minimum voltage increases to 0.979 p.u. at bus-65, further improving network performance. The IPOA results in this case are also very competitive with EPFA [2], as detailed in Table 2.

Table 2. Comparison of PV allocation with literature

EDN	Reference	PVs in kW / Bus #	P_{loss} (kW)
33-bus	MOWOA [1]	801.84/13 1091.46/24 1046.58/30	72.848
	Proposed IPOA	801.7/13 1091.33/24 1053.64 /30	72.79
69-bus	EPFA [2]	381.45/17 1718.84/61 525.56/11	69.43
	Proposed IPOA	380.43/18 1718.97/61 526.75/11	69.4262

Table 3. Comparison of CSs allocation

EDN	CSs in kW / Bus #	P_{loss} (kW)	AVD (p.u.)
33-bus	400 (2) 250 (19) 100 (26)	223.2506	0.0114
69-bus	800 (2) 500 (28) 200 (47)	225.1038	0.0046

5.3 Case 3: Integration of CS

This case explores the optimal integration of three FCSs in the network. The power ratings of FCSs range from 50 kW (one CHAdeMO/CCS connector) to 400 kW (eight connectors). For this study, capacities of 400 kW, 250 kW, and 100 kW are selected for the 33-bus network, and 800 kW, 500 kW, and 200 kW for the 69-bus network. Table 3 summarizes the results.

33-Bus Network: Buses 2, 19, and 26 are the ideal locations for the FCSs. Due to the additional CS load, the active and reactive power losses increase to 223.25 kW and 150.409 kVAr, respectively. The Average Voltage Deviation (AVD) slightly increases to 0.0114 p.u., and the minimum voltage magnitude remains stable. Compared to Case 1, real power losses rise by 5.81%.

69-Bus Network: The search space for the FCS locations includes bus ranges [2, 27], [28, 46], and [47, 69]. The best locations are identified as buses 2, 19, and 26. The additional CS load results in active and reactive power losses of 225.1038 kW and 102.4322 kVAr, respectively. At bus-65, we observe a minimum voltage of 0.9092 p.u. and an AVD of 0.0046 p.u. In comparison to Case 1, the increase in real power losses (0.046%) is negligible, indicating minimal impact on network efficiency.

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Table 4. Comparison of Case Studies

EDN	PVs Size (bus)	EVs	P_{loss} (kW)	AVD (p.u.)
33-bus	819.54 (13) 1133.88 (24) 1098.73 (30)	400 (2) 250 (19) 100 (26)	75.0853	0.0038
69-bus	465.51 (17) 548.77 (53) 1683.67 (61)	800 (2) 500 (28) 200 (47)	70.2224	0.0011

5.4 Case 4: Integration of both PV and CS

In this case, simultaneous allocation of PVs and CSs are planned. Results are given in Table 4. Notably in the both test systems, the CS locations are still remains same as in Case 3. However, the locations are sizes are differing due to increased EV loading in the networks.

33-Bus Network: The best PV locations are 14, 24 and 30. The best PV sizes are 370.28 kW, 525.38 kW, and 932.67 kW, respectively. Thus, the power losses are reduced to 80.02 kW and 55.57 kVAr, respectively. On the other side, the minimum voltage magnitude is noticed as 0.9684 p.u. at bus-18. Further, the AVD is significantly reduced to 0.0036 p.u.

69-Bus Network: The best PV locations are 14, 24 and 30. The best PV sizes are 370.28 kW, 525.38 kW, and 932.67 kW, respectively. Thus, the power losses are reduced to 70.2224 kW and 35.3522 kVAr, respectively. On the other side, the minimum voltage is noticed as 0.979 p.u. at bus-65. Further, the AVD is significantly reduced to 0.0011 p.u.

5.5 Comparative study of IPOA and Others

The results in Table 5 show how well six optimization algorithms-PSO, GA, ARO, OOA, POA, and IPOA—work on two test systems, 33-bus and 69-bus, to find the smallest value of an objective function.

33-Bus Network: IPOA has outstanding performance, attaining the lowest mean (75.11) and unmatched consistency (SD: 0.05), establishing it as the most efficient algorithm. POA yields balanced outcomes with a comparatively low mean (81.98) and reasonable stability (SD: 3.40). PSO demonstrates constant performance (SD: 1.92), although it exhibits a larger mean (87.78), rendering it less effective for reduction. ARO and OOA demonstrate modest variability (SD: 5.29 and 4.81, respectively) and outperform PSO somewhat; however, they are less effective than IPOA or POA.

Table 5. Comparison of Case 4

33-Bus					
Method	**Min**	**Max**	**Mean**	**Median**	**SD**
PSO	86.72	93.94	87.78	86.73	1.92
GA	81.71	105.07	84.72	81.74	5.72
ARO	79.61	97.88	83.65	81.06	5.29
OOA	79.59	108.46	81.38	79.59	4.81
POA	80.04	93.42	81.98	80.06	3.40
IPOA	75.09	75.28	75.11	75.09	0.05
69-bus					
Method	**Min**	**Max**	**Mean**	**Median**	**SD**
PSO	69.48	99.93	70.99	69.49	4.42
GA	70.26	86.31	72.03	70.88	2.75
ARO	69.74	86.89	72.25	70.18	4.66
OOA	71.64	82.04	77.01	78.67	4.58
POA	70.19	97.27	73.58	70.84	7.43
IPOA	70.22	75.65	71.32	70.53	1.67

GA exhibits the greatest variability (SD: 5.72) and mean (84.72), rendering it less trustworthy and efficient.

69-Bus Network: In this system, IPOA demonstrates superior performance with a low mean (71.32) and high consistency (SD: 1.67). PSO attains the second-lowest mean (70.99) with moderate stability (SD: 4.42), rendering it a competitive option. GA demonstrates commendable stability (SD: 2.75) but exhibits a little elevated mean (72.03). ARO and OOA are less useful because their averages are high (72.25 and 77.01, respectively) and their variability is moderate. POA, despite exhibiting the greatest variability (SD: 7.43), attains a mean of 73.58, signifying sporadic peaks but erratic performance.

6. Conclusion

This study identifies critical gaps in optimizing PVs and FCSs integration, including managing real power losses and voltage instability. By leveraging the Improved Pufferfish Optimization Algorithm (IPOA), the study successfully addresses these challenges. The methodology demonstrates substantial improvements in power loss reduction and voltage profile enhancement. This study examines how combining PVs and EVs affects power losses in 33-bus and 69-bus distribution networks. In the base case, with EVs, and with both EVs and PVs, PV power loss reduction is used to evaluate network performance. Base case power losses in the 33-bus network are 210 kW. When optimally integrated, PVs cut losses to 72.79 kW, a 65.34% loss reduction, proving their usefulness in network efficiency. Adding EVs as a load increases network losses to 223.25 kW owing to charging station demand. However, adding PVs to EVs cuts losses to 75 kW. PVs reduce loss by 66.41% in this situation, demonstrating their capacity to mitigate EV loads and preserve network performance. Base case losses for the 69-bus network are 225 kW. PV integration cuts losses by 69.15% to 69.42 kW, demonstrating PVs' impressive power loss reduction. Due to EV charging, network losses rise to 225.11 kW. With simultaneous PV integration, losses drop to 70 kW, a 68.90% reduction. This shows that PVs can reduce EV integration losses and maintain network efficiency. The analysis shows that PV integration is critical to minimizing power losses in both networks. The results show that PVs can counteract increasing losses even with EV loads, highlighting their usefulness in future energy systems that mix renewable energy generation and electric mobility. Synergistic PV-EV integration improves network performance and reduces energy waste sustainably.

Notation List

$P_{d,i}$ & $Q_{d,i}$	Base case active and reactive power loadings of bus-*i*,
$\bar{P}_{d,i}$ & $\bar{Q}_{d,i}$	Active and reactive power loadings of bus-*i* after PV/ CS integration
$P_{cs,i}$ & $Q_{cs,i}$	Active and reactive power demands of CS,
$\|V_i\|$ & $\|V_s\|$	Voltage magnitudes of bus-*i* and sub-station bus
$P_{cs,r}$	Rated power capacity of CS at nominal voltage
r_b & I_b	Resistance of the branch-*b* and current flow through it
$\|V_s\|$	sub-station bus voltage magnitude
$nbus$ & nbr	Number of buses and number of branches in EDN
P_{loss}	Total distribution losses
AVD	Average voltage deviation
OF	objective function
l_{pv} & l_{cs}	Locations of PV and CS
npv	Number of PV locations
$\|V_{min}\|$	Minimum limit for voltage
$\|V_{max}\|$	Maximum limit for voltage
P_D	Total real power demand of the EDN

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization: Nagaraja Kumari Ch and Sarala P; Methodology: Nagaraja Kumari Ch; Software: Manidhar Thula; Validation: Nagaraja Kumari Ch, Jayasri Ch, and Venkata Mahesh P; Formal Analysis: Nagaraja Kumari Ch; Investigation: Nagaraja Kumari Ch; Resources: Sarala P; Data Curation: Manidhar Thula; Writing—Original Draft Preparation: Nagaraja Kumari Ch; Writing—Review and Editing: Jayasri Ch; Visualization: Venkata Mahesh P; Supervision: Nagaraja Kumari Ch; Project Administration: Sarala P; Funding Acquisition: Sarala P.

References

[1] K. Subbaramaiah, P. Sujatha, "Optimal DG unit placement in distribution networks by multi-objective whale optimization algorithm & its techno-economic analysis", *Electric Power Systems Research*, Vol. 214, e108869, 2023, doi: 10.1016/j.epsr.2022.108869.

[2] T. K. Pandraju, V. Janamala, "Enhanced pathfinder algorithm for optimal integration of solar photovoltaics and rapid charging stations in low-voltage radial feeders", *Journal of Solar Energy Research*, Vol. 8, No. 4, pp. 1680-1690, 2023, doi: 10.22059/jser.2023.359041.1300.

[3] S. R. Penubarthi, R. R. Korrapati, V. Janamala, C. Nimmagadda, A. S. Veerendra, S. Ravindrakumar, "Chernobyl disaster optimizer-based optimal integration of hybrid photovoltaic systems and network reconfiguration for reliable and quality power supply to nuclear research reactors", *Modelling*, Vol. 5, No. 3, pp. 1268-1285, 2024, doi: 10.3390/modelling5030065.

[4] S. L. Pappu, V. Janamala, A. S. Veerendra, "Hunter–prey optimization algorithm for optimal allocation of PV, DSTATCOM, and EVCS in radial distribution systems", *Advanced Control for Applications: Engineering and Industrial Systems*, e231, 2024, doi: 10.1002/adc2.231.

[5] W. S. Fokui, M. J. Saulo, and L. Ngoo, "Optimal placement of electric vehicle charging stations in a distribution network with randomly distributed rooftop photovoltaic systems", *IEEE Access*, Vol. 9, pp. 132397-132411, 2021, doi: 10.1109/ACCESS.2021.3112847.

[6] M. Bilal and M. Rizwan, "Integration of electric vehicle charging stations and capacitors in distribution systems with vehicle-to-grid facility", *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, pp. 1-30, 2021, doi: 10.1080/15567036.2021.1923870.

[7] X. Zhang, Y. Xu, S. Lu, C. Lu, and Y. Guo, "Joint planning of distributed PV stations and

EV charging stations in the distribution systems based on chance-constrained programming", *IEEE Access*, Vol. 9, pp. 6756-6768, 2021, doi: 10.1109/ACCESS.2021.3049568.

[8] K. Yenchamchalit, Y. Kongjeen, P. Prabpal, and K. Bhumkittipich, "Optimal placement of distributed photovoltaic systems and electric vehicle charging stations using metaheuristic optimization techniques", *Symmetry*, Vol. 13, No. 12, pp. 2378, 2021, doi: /10.3390/sym13122378.

[9] S. Muthukannan and D. Karthikaikannan, "Multiobjective planning strategy for the placement of electric-vehicle charging stations using hybrid optimization algorithm", *IEEE Access*, Vol. 10, pp. 48088-48101, 2022, doi: 10.1109/ACCESS.2022.3168830.

[10] F. Ahmad, A. Iqbal, I. Ashraf, M. Marzband, and I. Khan, "Placement of electric vehicle fast charging stations in distribution network considering power loss, land cost, and electric vehicle population", *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, Vol. 44, No. 1, pp. 1693-1709, 2022, doi: 10.1080/15567036.2022.2055233.

[11] M. Mohammadi-Landi, M. Rastegar, M. Mohammadi, and S. Afrasiabi, "Stochastic optimal sizing of plug-in electric vehicle parking lots in reconfigurable power distribution systems", *IEEE Transactions on Intelligent Transportation Systems*, Vol. 23, No. 10, pp. 17003-17014, 2022, doi: 10.1109/TITS.2022.3166781.

[12] A. K. Mohanty, P. S. Babu, and S. R. Salkuti, "Fuzzy-based simultaneous optimal placement of electric vehicle charging stations, distributed generators, and DSTATCOM in a distribution system", *Energies*, Vol. 15, No. 22, pp. 8702, 2022, doi: 10.3390/en15228702.

[13] K. Kathiravan and P. N. Rajnarayanan, "Application of AOA algorithm for optimal placement of electric vehicle charging station to minimize line losses", *Electric Power Systems Research*, Vol. 214, pp. 108868, 2023, doi: 10.1016/j.epsr.2022.108868.

[14] M. Nurmuhammed, O. Akdağ, and T. Karadağ, "A novel modified Archimedes optimization algorithm for optimal placement of electric vehicle charging stations in distribution networks", *Alexandria Engineering Journal*, Vol. 84, pp. 81-92, 2023, doi: 10.1016/j.aej.2023.10.055.

[15] N. Pompern, S. Premrudeepreechacharn, A. Siritaratiwat, and S. Khunkitti, "Optimal placement and capacity of battery energy storage system in distribution networks integrated with PV and EVs using metaheuristic algorithms", *IEEE Access*, 2023, doi: 10.1109/ACCESS.2023.3291590.

[16] E. A. Rene, W. S. Fokui, and P. K. Kouonchie, "Optimal allocation of plug-in electric vehicle charging stations in the distribution network with distributed generation", *Green Energy and Intelligent Transportation*, Vol. 2, No. 3, pp. 100094, 2023, doi: 10.1016/j.geits.2023.100094.

[17] B. A. Kumar, B. Jyothi, A. R. Singh, M. Bajaj, R. S. Rathore, and M. B. Tuka, "Hybrid genetic algorithm-simulated annealing based electric vehicle charging station placement for optimizing distribution network resilience", *Scientific Reports*, Vol. 14, No. 1, pp. 7637, 2024, doi: 10.1038/s41598-024-58024-8.

[18] M. Altaf, M. Yousif, H. Ijaz, M. Rashid, N. Abbas, M. A. Khan, M. Waseem, and A. M. Saleh, "PSO-based optimal placement of electric vehicle charging stations in a distribution network in smart grid environment incorporating backward forward sweep method", *IET Renewable Power Generation*, Vol. 18, No. 15, pp. 3173-3187, 2024, doi: 10.1049/rpg2.12916.

[19] M. Yao, D. Da, X. Lu, and Y. Wang, "A review of capacity allocation and control strategies for electric vehicle charging stations with integrated photovoltaic and energy storage systems", *World Electric Vehicle Journal*, Vol. 15, No. 3, pp. 101, 2024, doi: 10.3390/wevj15030101.

[20] A. Akter, E. I. Zafir, N. H. Dana, R. Joysoyal, S. K. Sarker, L. Li, S. M. Muyeen, S.K. Das, and I. Kamwa, "A review on microgrid optimization with meta-heuristic techniques: Scopes, trends and recommendation", *Energy Strategy Reviews*, Vol. 51, 101298, 2024, doi: 10.1016/j.esr.2024.101298.

[21] S. Alomari, K. Kaabneh, I. AbuFalahah, S. Gochhait, I. Leonova, Z. Montazeri, M. Dehghani and K. Eguchi, "Carpet weaver optimization: A novel simple and effective human-inspired metaheuristic algorithm", *International Journal of Intelligent Engineering and Systems*, Vol.17, No.4, pp. 230-242, 2024, doi: 10.22266/ijies2024.0831.18.

[22] T. Hamadneh, K. Kaabneh, O. AlSayed, G. Bektemyssova, Z. Montazeri, M. Dehghani and K. Eguchi, "Sculptor optimization algorithm: A new human-inspired metaheuristic algorithm for solving optimization problems", *International Journal of Intelligent Engineering*

and Systems, Vol.17, No.4, pp. 564-575, 2024, doi: 10.22266/ijies2024.0831.43.

[23] M. A. Al-Sharqi, A. T. Al-Obaidi and S. O. Al-mamory, "Apiary Organizational-Based Optimization Algorithm: A New Nature-Inspired Metaheuristic Algorithm", *International Journal of Intelligent Engineering and Systems*, Vol.17, No.3, pp. 783-801, 2024, doi: 10.22266/ijies2024.0630.61.

[24] P. D. Kusuma, "Focus and shake algorithm: A new stochastic optimization employing strict and randomized dimension mappings", *International Journal of Intelligent Engineering and Systems*, Vol.17, No.3, pp. 551-562, 2024, doi: 10.22266/ijies2024.0630.43.

[25] P. D. Kusuma and A. Dinimaharawati, "Swarm bipolar algorithm: A metaheuristic based on polarization of two equal size sub swarms", *International Journal of Intelligent Engineering and Systems*, Vol.17, No.2, pp. 377-381, 2024, doi: 10.22266/ijies2024.0430.31.

[26] P. D. Kusuma, M. Kallista, "Swarm space hopping algorithm: A swarm-based stochastic optimizer enriched with half space hopping search", *International Journal of Intelligent Engineering and Systems*, Vol.17, No.2, pp. 670-682, 2024, doi: 10.22266/ijies2024.0430.54.

[27] P. D. Kusuma, M. Kallista, "Migration-crossover algorithm: a swarm-based metaheuristic enriched with crossover technique and unbalanced neighbourhood search", *International Journal of Intelligent Engineering and Systems*, Vol.17, No.1, pp. 698-710, 2024, doi: 10.22266/ijies2024.0229.59.

[28] T. Hamadneh, K. Kaabneh, O. Alssayed, K. Eguchi, S. Gochhait, I. Leonova and M. Dehghani, "Addax optimization algorithm: A novel nature-inspired optimizer for solving engineering applications", *International Journal of Intelligent Engineering and Systems*, Vol.17, No.3, pp. 732-743, 2024, doi: 10.22266/ijies2024.0630.57.

[29] K. Kaabneh, I. AbuFalahah, K. Eguchi, S. Gochhait, I. Leonova, Z. Montazeri and M. Dehghani, "Dollmaker optimization algorithm: A novel human-inspired optimizer for solving optimization problems", *International Journal of Intelligent Engineering and Systems*, Vol.17, No.3, pp. 816-828, 2024, doi: 10.22266/ijies2024.0630.63.

[30] P. D. Kusuma and T. W. Purboyo, "A novel metaheuristic named as quadratic time optimization and its application to handle economic dispatch with spinning reserve and valve point effect", *International Journal of Intelligent Engineering and Systems*, Vol.17, No.5, pp. 920-933, 2024, doi: 10.22266/ijies2024.1031.69.

[31] T. Hamadneh, B. Batiha, O. Alsayyed, G. Bektemyssova, Z. Montazeri, M. Dehghani and K. Eguchi, "On the application of potter optimization algorithm for solving supply chain management application", *International Journal of Intelligent Engineering and Systems*, Vol.17, No.5, pp. 88-99, 2024, doi: 10.22266/ijies2024.1031.09.

[32] T. Hamadneh, B. Batiha, F. Werner, Z. Montazeri, M. Dehghani, G. Bektemyssova and K. Eguchi, "Fossa optimization algorithm: A new bio-inspired metaheuristic algorithm for engineering applications", *International Journal of Intelligent Engineering and Systems*, Vol.17, No.5, pp. 1038-1045, 2024, doi: 10.22266/ijies2024.1031.78.

[33] O. Al-Baik, S. Alomari, O. Alssayed, S. Gochhait, I. Leonova, U. Dutta, O. P. Malik, Z. Montazeri, and M. Dehghani, "Pufferfish Optimization Algorithm: A New Bio-Inspired Metaheuristic Algorithm for Solving Optimization Problems", *Biomimetics*, Vol. 9, No. 2, 65, 2024. doi: 10.1038/s41598-023-35863-5.

[34] L. Wang, Q. Cao, Z. Zhang, S. Mirjalili, and W. Zhao, "Artificial rabbits optimization: A new bio-inspired meta-heuristic algorithm for solving engineering optimization problems", *Engineering Applications of Artificial Intelligence*, Vol. 114, 105082, 2022. doi: 10.1016/j.engappai.2022.105082.

[35] M. Dehghani and P. Trojovský, "Osprey optimization algorithm: A new bio-inspired metaheuristic algorithm for solving engineering optimization problem", *Frontiers in Mechanical Engineering*, 1126450, 2023. doi: 10.3389/fmech.2022.1126450.