

Techno-economic Analysis of Photovoltaic Distributed Generation Units, Capacitor Banks, and Electric Vehicle Charging Stations on Distribution Network. A Case Study of the Ashanti Region, Ghana

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Case Report

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TECHNO-ECONOMIC ANALYSIS OF PHOTOVOLTAIC DISTRIBUTED GENERATION UNITS, CAPACITOR BANKS, AND ELECTRIC VEHICLE CHARGING STATIONS ON DISTRIBUTION NETWORK. A CASE STUDY OF THE ASHANTI REGION, GHANA

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Abstract – Distribution networks in sub-Saharan Africa face severe active power losses and widespread undervoltage, challenges that are intensifying as photovoltaic (PV) generation and electric vehicle (EV) adoption accelerate. This paper presents a unified techno-economic multi-objective framework for the simultaneous optimal siting and sizing of PV distributed generation (PV-DG) units, capacitor banks, and fast EV charging station (EVCS) hubs in radial distribution networks. Three objectives are minimized concurrently: active power loss, voltage deviation index, and total capital investment cost. The framework employs two Pareto-based algorithms, IMOMRFO and MOAVOA, with TOPSIS used to identify best-compromise solutions. A 15-year discounted cash-flow model evaluates net present value, payback period, and return on investment for each solution. The real ECG Ashanti Regional 50-bus 33 kV network was modelled in ETAP, with all optimisation and techno-economic computations implemented in MATLAB. On the Ashanti network, IMOMRFO reduced active power loss by 81%, eliminated all 29 voltage violations, and yielded a 15-year net present profit of approximately 36.69 MUSD against a capital investment of 26.60 MUSD, demonstrating that coordinated multi-asset planning can simultaneously rehabilitate network performance and deliver strong long-term financial returns for sub-Saharan African network.

Keywords: Capacitor banks, electric vehicle charging stations, IMOMRFO, MOAVOA, multi-objective optimisation, photovoltaic distributed generation, techno-economic analysis, TOPSIS

1. Introduction

The global power sector is being reshaped by three main forces: decarbonization of generation, rapid expansion of renewables, and accelerating electrification of transport [1], [2], [3], [4], [5]. Many countries are targeting high renewable penetration by 2050, while EVs are projected to contribute several percent up to more than 20% of future electricity demand in some regions, forcing distribution networks to host high PV-DG penetration, bidirectional flows, and dense fast-charging clusters without violating technical limits or compromising reliability [6] [7], [8], [9], [10], [11], [12]. Ghana reflects these trends. ECG's 33 kV regional networks, particularly the Ashanti network, already exhibit high active and reactive losses, long radial feeders, and widespread undervoltage with minimum bus voltages well below 0.95 p.u. [13]. In this context,

planned PV-DG and EVCS deployment on an already stressed network makes coordinated techno-economic planning essential to avoid aggravating existing technical deficiencies[14], [15], [16], [17]. This context highlights the need for planning frameworks that treat PV-DG units, capacitor banks, and fast EVCSs as coupled techno-economic decision variables on real Ghanaian networks. Technically, any portfolio must reduce losses, improve voltage profiles, and respect branch current limits[18], [19]; economically, it must be evaluated over a realistic project horizon that includes capital expenditure, O&M, inverter replacement, loss-reduction benefits, PV energy value, and EV charging margins so that utilities such as ECG can make robust investment decisions under tight budget constraints [20]. Motivated by this, the present paper develops a comprehensive techno-economic

multi-objective framework for the simultaneous optimal siting and sizing of PV-DG units, capacitor banks, and fast EVCSs in radial distribution networks. It applies it to both the IEEE 33-bus benchmark and the real ECG Ashanti 50-bus 33 kV network. The aim is to show how coordinated planning of these assets can transform a weak, high-loss network into one with markedly improved technical performance and attractive long-term economic returns, providing actionable guidance for planners in Ghana and similar Sub-Saharan African systems [21].

Earlier work on distribution reinforcement has largely focused on optimal DG and capacitor placement for loss minimization and voltage improvement on standard IEEE test feeders, using single-objective or weighted-sum formulations with metaheuristics such as GA, PSO, and ABC, and often achieving 60–80% loss reductions but without full lifecycle economic assessment [13], [20], [22], [23], [24]. More recent studies incorporate EVCSs, PV plants, wind farms, and BESS to mitigate uncoordinated charging impacts while minimizing total lifecycle cost; for example, [20], [25] [25], [26], [27] showed that integrated planning of EVCSs, renewable DG, BESS, and capacitor banks over a 15-year horizon can simultaneously lower lifecycle cost and enhance voltages and branch loading. However, few studies jointly size and site DG units, capacitor banks, and fast EVCS hubs within a unified multi-objective formulation that explicitly disaggregates investment, O&M, grid imports, PV savings, loss-reduction savings, and EV charging margins in an NPV-based techno-economic analysis, and even fewer consider real, heavily loaded African MV networks with severe losses, undervoltage, and capital constraints [13], [22]. In particular, there is a lack of work that combines three-objective optimisation (loss, voltage deviation, and investment cost), full 15-year NPV evaluation, and algorithm benchmarking on a real network such as the ECG Ashanti 33 kV system, with results presented in a form directly usable for utility decision-making through clearly identified best-compromise solutions and explicit reporting of voltage improvements, loss reductions, investment levels, and lifecycle profitability.

The main contributions of this paper are briefly presented as follows:

- Integrated techno-economic model for joint planning of PV-DG, capacitor banks, and fast EVCSs (loss, voltage deviation, investment cost + 15-year NPV).
- Validation on both IEEE 33-bus and real ECG Ashanti 50-bus 33 kV networks under realistic Sub-Saharan African conditions.

- Pareto-based decision support using non-dominated solutions and TOPSIS to select best-compromise plans.
- 15-year lifecycle cash-flow analysis quantifying PV savings, loss-reduction savings, EV margins, CAPEX, O&M, inverter replacement, NPV, and payback.
- Comparative evaluation of MOAVOA and IMOMRFO in terms of loss reduction, voltage improvement, and overall techno-economic performance on both networks.

2. Problem Formulation

This study considers the coordinated integration of PV-DG units, EV charging stations, and capacitor banks into the distribution grid. PV-DG and capacitor banks act as distributed generation resources, while EVCSs are modeled as additional loads during charging. In the adopted scheme, PV-DG supplies part of the total demand; any deficit is covered by the upstream grid, and any surplus PV generation is exported back to the grid so that supply and demand remain balanced at all times.

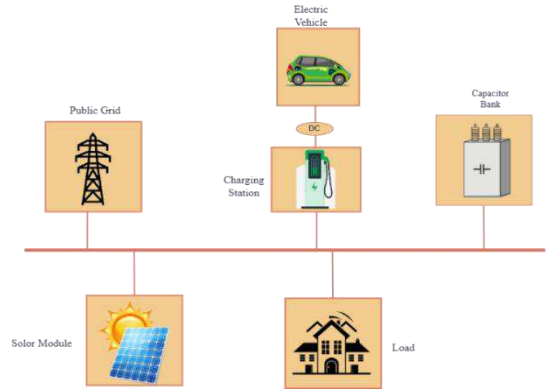


Fig 1: The electric network model with grid-connected distribution units.

Two test systems are used in this study: the real ECG Ashanti Regional 50-bus 33 kV network, as shown in Fig 2, and the IEEE 33-bus 12.66 kV network. The Ashanti network has 50 buses and 49 branches, with Bus 1 as the slack and Buses 2–50 as load buses supplied by eight radial feeders terminating at Buses 2, 8, 15, 26, 30, 37, 41, and 44.

At peak demand, the Ashanti system carries 374,328 kW and 137,357 kVAr, with branch parameters represented by series resistances and reactances. In the base case without PV-DG, capacitor banks, or EVCSs, it suffers 14,530.08 kW of active loss, 66,650.18 kVAr of reactive loss, and a minimum voltage of 0.817 p.u. at Bus 35, with 29 buses below 0.95 p.u., clearly indicating a weak, high-loss operating condition. The network data were assembled from substation records and modeled as a single-line diagram in ETAP.

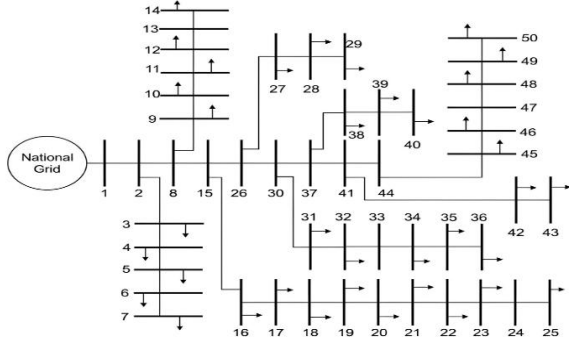


Fig 2: The line diagram of ECG 33 kV distribution Network in the Ashanti region

The IEEE 33-bus network, used for benchmarking, consists of 33 buses and 32 branches at 12.66 kV, with Bus 1 as the slack and buses 2–33 as load buses, as shown in Fig 3. It carries total loads of 3,715 kW and 2,300 kVAr, with a base-case active loss of 201.8925 kW, a minimum voltage of 0.913374 p.u. at Bus 18, and 21 buses violating the 0.95 p.u. lower limit, making it a standard reference for validating optimisation methods and comparing with existing studies.

2.1 Objective Functions

Three objective functions are formulated to capture the key technical and economic performance aspects of the distribution networks under different PV-DG, CAP BANK, and EVCS allocation plans. The first objective aims to minimize the total active and reactive power loss in the distribution network. For a given operating point, the total power loss is calculated as the sum of resistive losses over all branches, as shown in (1):

$$F_1 = P_{\text{loss}} = \sum_{k=1}^{N_{br}} |I_k|^2 R_k \text{ (kW)} \quad (1)$$

where N_{br} is the number of branches, I_k is the complex current flowing through the branch k , and R_k is the branch resistance in ohms. Minimizing F_1 reduces feeder loading and directly decreases the energy purchased from the upstream grid over the project horizon. In the implementation, P_{loss} is obtained from

the backward–forward sweep (BFS) load-flow solution and reported in kilowatts for both the IEEE 33-bus and ECG Ashanti 50-bus networks.

The second objective minimizes the voltage deviation index (VDI), which measures the cumulative deviation of all bus voltages from the nominal value of 1.0 p.u as expressed in (2).

$$F_2 = \text{VDI} = \sum_{i=1}^{N_b} (1 - V_i)^2 \times 100 \text{ (\%)} \quad (2)$$

The third objective minimizes the total capital investment cost associated with installing PV-DG units, EVCS hubs, and capacitor banks as expressed in (3), (4), (5), and (6).

$$F_3 = C_{\text{inv}} = \frac{C_{PV} + C_{EV} + C_{CB}}{1000} \text{ (kUSD)} \quad (3)$$

where C_{PV} , C_{EV} and C_{CB} are the capital costs of PV-DG, EVCSs, and capacitor banks, respectively, in USD. These components are given by

$$C_{PV} = \text{Pr}_{\text{cap}}^{\text{PV}} \sum_{d=1}^{N_{DG}} P_d^{\text{DG}} \quad (4)$$

$$C_{EV} = N_{EV} \text{Pr}_{\text{cap}}^{\text{EV}} \quad (5)$$

$$C_{CB} = \text{Pr}_{\text{cap}}^{\text{CB}} \sum_{c=1}^{N_{CB}} Q_c^{\text{CB}} + N_{CB} C_{\text{place}}^{\text{CB}} \quad (6)$$

where $\text{Pr}_{\text{cap}}^{\text{PV}}$ is the unit capital cost of PV-DG per kW, P_d^{DG} is the rated active power of the PV-DG unit d , N_{EV} is the number of EVCS hubs, $\text{Pr}_{\text{cap}}^{\text{EV}}$ is the cost per EVCS hub, $\text{Pr}_{\text{cap}}^{\text{CB}}$ is the cost per kVAr of capacitor capacity, Q_c^{CB} is the reactive rating of the capacitor bank c , and $C_{\text{place}}^{\text{CB}}$ is the fixed installation cost per capacitor site.

Minimizing F_3 prevents the optimisation from pursuing purely technical improvements at impractically high investment levels. The combined objective vector used for Pareto-based optimisation is represented as (7)

$$\mathbf{F} = [F_1, F_2, F_3] = [P_{\text{loss}}, \text{VDI}, C_{\text{inv}}]. \quad (7)$$

2.2 System Constraints

The optimisation problem is subject to technical and practical constraints that ensure all candidate solutions are physically feasible and consistent with planning requirements.

Voltage limits.

Bus-voltage magnitudes must remain within prescribed bounds to ensure acceptable power quality. In this study, the allowable range follows IEC 60038, with $0.95 \leq$

$V_i \leq 1.05$ p.u. for all buses in both networks. Any candidate solution whose BFS load-flow violates these limits is treated as infeasible.

Current and thermal limits.

Branch currents must not exceed their thermal ratings. Let $I_k^{\max}$ denote the maximum admissible current in the branch k , determined by the conductor and equipment capabilities. Any allocation that causes $|I_k| > I_k^{\max}$. The BFS solution is rejected as infeasible during optimisation [28].

Generation and penetration limits

To avoid unrealistic penetration levels, each PV-DG active power and capacitor-bank reactive power are constrained within predefined bounds, $P_d^{DG, \min} \leq P_d^{DG} \leq P_d^{DG, \max}$ and $Q_{CB, \min} \leq Q_c^{CB} \leq Q_{CB, \max}$. These bounds are implemented via the VarMin and VarMax vectors, and enforced by clipping decision variables inside the constraint-handling routine [29]

Connected-bus limits and zoning constraints.

Device placements are constrained for technical and geographical realism. The decision vector is

$$X = [P_1^{DG}, \dots, P_{N_{DG}}^{DG}, b_1^{DG}, \dots, b_{N_{DG}}^{DG}, b_1^{EV}, \dots, b_{N_{EV}}^{EV}, Q_1^{CB}, \dots, Q_{N_{CB}}^{CB}, b_1^{CB}, \dots, b_{N_{CB}}^{CB}] \quad (8)$$

where b^{DG} , b^{EV} , and b^{CB} are the bus indices of PV-DG units, EVCS hubs, and capacitor banks, respectively [9].

The following constraints apply:

- **Slack-bus exclusion:** Bus 1 is the slack/source bus and cannot host PV-DG, EVCS, or capacitor-bank devices, $b_d^{DG} \neq 1$, i.e.
- **EVCS zoning (Ashanti network):** EVCS buses are restricted to three geographical zones, **Zone 1:** $b^{EV} \in \{2, \dots, 17\}$, **Zone 2:** $b^{EV} \in \{18, \dots, 34\}$, **Zone 3:** $b^{EV} \in \{35, \dots, 50\}$, with each station n assigned cyclically to the zone $z = \text{mod}(n - 1, 3) + 1$.
- **No bus overlap:** PV-DG buses must not coincide with EVCS buses, and capacitor-bank buses must not coincide with either PV-DG or EVCS buses: $b_d^{DG} \neq b_e^{EV}$,
- **Uniqueness:** PV-DG bus indices and capacitor-bank bus indices are kept unique, preventing multiple identical devices at the same bus.

These rules are enforced algorithmically by rounding

and clamping bus indices to their allowed ranges and, when conflicts occur, reassigning devices to the nearest permissible buses within their respective sets [30]

2.3 EVCS Load Model

Each fast EVCS hub is modelled as a constant-power load. [13], [31] Let P_{rated}^{EV} denote the rated power of an EVCS hub and η_{EV} Its capacity factor. The effective average active demand per hub is shown in (9)

$$P_{eff}^{EV} = P_{rated}^{EV} \eta_{EV} \quad (9)$$

In this study, each EVCS hub is rated at $P_{rated}^{EV} = 975$ kW with capacity factor $\eta_{EV} = 0.20$, giving as $P_{eff}^{EV} = 195$.

If EVCS hub e is connected to the bus b_e^{EV} , The net active load at that bus becomes (10)

$$P_i^{\text{net}} = P_i^{\text{load}} + P_{eff}^{EV}, i = b_e^{EV} \quad (10)$$

where P_i^{load} Is, the original bus active load. The associated reactive demand is represented by an assumed power factor or an equivalent kVAR contribution, consistent with the network model.

2.4 PV-DG Generation Model

PV-DG units are modelled as constant active-power injections operating at unity power factor [32], so their reactive power output is set to zero in this study, and the reactive load at each PV-DG bus remains equal to the original demand. If PV-DG unit d with rated power P_d^{DG} is connected to the bus, the G. b_d^{DG} , The net active load at that bus is expressed as (11).

$$P_i^{\text{net}} = P_i^{\text{load}} - P_d^{DG} + \sum_{e: b_e^{EV}=i} P_{eff}^{EV}, i = b_d^{DG}, \quad (11)$$

while the reactive load at that bus remains equal to the original reactive demand.

In the per-unit BFS formulation, the net active and reactive powers at the bus i are converted as shown in (12)

$$\begin{cases} P_i^{pu} = \frac{P_i^{\text{net}}}{1000 S_{base}} \\ Q_i^{pu} = \frac{Q_i^{\text{load}}}{1000 S_{base}} \end{cases} \quad (12)$$

with base power $S_{base} = 100$ MVA. The annual electrical energy generated by the installed PV-DG units is obtained using (13).

$$E_{PV,ann} = \left(\sum_{d=1}^{N_{DG}} P_d^{DG} \right) CF_{PV} h_y \quad (13)$$

where CF_{PV} is the PV capacity factor (26.25% in this study) and $h_y = 8760$ hours/year. This annual energy is used in the techno-economic analysis to quantify the present value of PV energy savings over the 15-year project horizon.

3. Techno-Economic Model

This section describes the 15-year techno-economic framework used to evaluate each candidate's allocation of PV-DG units, EVCS hubs, and capacitor banks on the IEEE 33-bus and ECG Ashanti networks. The model quantifies all major cost and revenue streams in discounted terms and derives standard investment indicators.

3.1 Year Net Present Value Framework

All cash flows are evaluated over a project horizon of $N_y = 15$ years [20] using a constant real discount rate r (20% in this study, consistent with the typical utility cost of capital in Ghana). The discount factor in the year y is expressed in (14)

$$DF_y = \frac{1}{(1+r)^y}, y = 1, \dots, 15 \quad (14)$$

For any annual cash flow C_y (positive for benefit, negative for cost), Its present value (PV) is expressed in (15)

$$PV(C) = \sum_{y=1}^{N_y} C_y DF_y \quad (15)$$

This framework is applied to investment, O&M, replacement, PV energy savings, loss-reduction savings, and EV charging revenues to obtain a consistent 15-year net present value. In all cases, the discount summation is evaluated from $y=1$ to $y=15$, with year 0 representing the initial investment and excluded from the discounted series.

3.2 Investment Costs

The total capital investment is the sum of PV-DG, EVCS, and capacitor-bank capital costs. This is expressed in (16)

$$C_{inv} = C_{PV} + C_{EV} + C_{CB} \quad (16)$$

PV-DG Capital Cost

PV-DG capital cost is modelled as proportional to installed capacity as in (17):

$$C_{PV} = Pr_{cap}^{PV} \sum_{d=1}^{N_{DG}} P_d^{DG} \quad (17)$$

where Pr_{cap}^{PV} is the PV-DG unit capital cost (USD/kW) and P_d^{DG} is the rated power of the PV-DG unit d (kW) [33]

EVCS Capital Cost

Each EVCS hub is assumed to have a fixed installation cost independent of its utilization level, as $C_{EV} = N_{EV} Pr_{cap}^{EV}$: where N_{EV} is the number of EVCS hubs and Pr_{cap}^{EV} is the capital cost per hub (USD/station).

Capacitor Bank Capital Cost

Capacitor-bank capital cost is a function of reactive rating plus a fixed placement cost as expressed in (18);

$$C_{CB} = Pr_{cap}^{CB} \sum_{c=1}^{N_{CB}} Q_c^{CB} + N_{CB} C_{place}^{CB} \quad (18)$$

where Pr_{cap}^{CB} is the unit cost per kVar, Q_c^{CB} Is the rating of the bank c (kVar), and C_{place}^{CB} It is a fixed installation cost per capacitor site

3.3 Operation and Maintenance Costs

Annual O&M costs are modelled separately for PV-DG and EVCS assets, while capacitor-bank O&M is negligible and ignored.

PV O&M and Inverter Replacement

PV-DG O&M is approximated as a fixed percentage α_{PV} of initial PV capital cost per year as expressed in (19):

$$C_{PV,O\&M,ann} = \alpha_{PV} C_{PV} \quad (19).$$

The present value of PV-DG O&M over 15 years is given in (20)

$$NPV_{PV,O\&M} = \sum_{y=1}^{N_y} C_{PV,O\&M,ann} DF_y \quad (20)$$

PV inverters are assumed to be replaced once a year. $y_{rep} = 10$ at unit cost Pr_{inv} (USD/kW) as shown in (21) and (22).

$$C_{rep} = Pr_{inv} \sum_{d=1}^{N_{DG}} P_d^{DG} \quad (21)$$

$$NPV_{rep} = \frac{C_{rep}}{(1+r)^{y_{rep}}} \quad (22)$$

EVCS O&M Cost

EVCS O&M is modelled as a fixed annual cost per hub as $C_{EV,O\&M,ann} = N_{EV} C_{O\&M,unit}^{EV}$ where $C_{O\&M,unit}^{EV}$ is the annual O&M per EVCS station (USD/year). The present value over 15 years is given in (23)

$$NPV_{EV,O\&M} = \sum_{y=1}^{N_y} C_{EV,O\&M,ann} DF_y \quad (23)$$

3.4 Revenue Streams

Three main benefit streams are considered: PV energy savings, loss-reduction savings, and EV charging margin.

PV Energy Savings

The annual electrical energy generated by all PV-DG units is expressed in (24)

$$E_{PV,ann} = \left(\sum_{d=1}^{N_{DG}} P_d^{DG} \right) CF_{PV} h_y \quad (24)$$

where CF_{PV} is the PV capacity factor (26.25% in this study) and $h_y = 8760$ h/year. If T_{grid} is the grid energy tariff (USD/kWh), the annual monetary saving from PV generation is $S_{PV,ann} = E_{PV,ann} T_{grid}$, and its present value is $NPV_{PV} = \sum_{y=1}^{N_y} S_{PV,ann} DF_y$.

Loss Reduction Savings

Let P_{loss}^{base} and P_{loss}^{opt} denote base-case and optimised active power loss (kW), respectively. The annual energy-loss saving is expressed in (25)

$$E_{loss,ann} = (P_{loss}^{base} - P_{loss}^{opt}) h_y \quad (25)$$

and the corresponding annual monetary saving is shown in (26)

$$S_{loss,ann} = E_{loss,ann} T_{grid} \quad (26)$$

The present value of loss-reduction savings is given as (27)

$$NPV_{loss} = \sum_{y=1}^{N_y} S_{loss,ann} DF_y \quad (27)$$

EV Charging Margin Revenue

Each EVCS hub is rated at P_{rated}^{EV} with capacity factor η_{EV} , giving an effective average power as expressed by (28)

$$P_{eff}^{EV} = P_{rated}^{EV} \eta_{EV} \quad (28)$$

The annual energy sold by all EVCSs is given as (29)

$$E_{EV,ann} = N_{EV} P_{rated}^{EV} \eta_{EV} h_y \quad (29)$$

Let T_{EV} be the EV charging tariff (USD/kWh). The annual EV charging revenue is expressed as (30)

$$R_{EV,ann} = E_{EV,ann} T_{EV} \quad (30)$$

while the corresponding grid energy cost to supply this demand is given in (31)

$$C_{EV,energy,ann} = E_{EV,ann} T_{grid} \quad (31)$$

The annual margin generated by EVCS operation is expressed as (32)

$$M_{EV,ann} = E_{EV,ann} (T_{EV} - T_{grid}) \quad (32)$$

with present value is shown in (33).

$$NPV_{EV} = \sum_{y=1}^{N_y} M_{EV,ann} DF_y \quad (33)$$

This annual loss factor formulation avoids overestimating loss-reduction benefits by not assuming peak losses for all 8,760 hours per year. Instead, an annual loss factor (ALF) is used to scale the loss-reduction energy, with a load factor of $LF = 0.60$ and $ALF = LF^2 = 0.36$, as expressed in equation (34).

$$E_{loss,ann} = (P_{loss,base} - P_{loss,opt}) h_y ALF \quad (34)$$

where $P_{loss,base}$ and $P_{loss,opt}$ are the base-case and optimized active-loss levels, respectively, and h_y is the number of hours in a year. The corresponding annual monetary saving is obtained by multiplying the subscript $E_{loss,ann}$ by the grid electricity tariff. In this study, the grid tariff is fixed at $T_{grid} = 0.15$ USD/kWh, and all discounted cash-flow calculations are performed over a 15-year planning horizon using a real discount rate of 20%,

ensuring a realistic NPV of loss-reduction savings under practical operating conditions.

Table 1: Techno-economic and operational parameters used in the 15-year planning and cash-flow analysis

Parameter	Symbol	Value	Unit
Project horizon	N_y	15	years
Discount rate	r	0.20	–
Grid energy tariff	T_{grid}	0.15	USD/kWh
EV charging tariff	T_{EV}	0.25	USD/kWh
PV capacity factor	CF_{PV}	0.2625	–
EVCS capacity factor	CF_{EV}	0.20	–
EVCS rated power per hub	$P_{\text{rated, EV}}$	975	kW
PV capital cost	$P_{\text{PV}}^{\text{cap}}$	1,000	USD/kW
PV OM rate	$p_{\text{PV, OM}}$	0.015	fraction of capex/year
PV inverter replacement cost	P_{inv}	120	USD/kW
PV inverter replacement year	y_{rep}	10	year
EVCS capital cost per hub	$P_{\text{EV}}^{\text{cap}}$	80,000	USD/station
EVCS OM per hub	$C_{\text{EV}}^{\text{OM}}$	5,000	USD/year
Capacitor bank capital cost	$P_{\text{Cap Bank}}^{\text{cap}}$	20	USD/kVAr
Capacitor placement fixed cost	$C_{\text{place, Cap Bank}}$	800	USD/site
System load factor	LF	0.60	–
Annual loss factor	ALF	0.36	–

3.5 Economic Performance Metrics

Net Present Value (NPV)

The overall net present value of the project is defined as (35)

$$\begin{aligned} \text{NPV}_{\text{net}} = & \text{NPV}_{\text{PV}} + \text{NPV}_{\text{loss}} + \text{NPV}_{\text{EV}} - C_{\text{inv}} \\ & - \text{NPV}_{\text{PV, O\&M}} - \text{NPV}_{\text{EV, O\&M}} \\ & - \text{NPV}_{\text{rep}} \end{aligned} \quad (35)$$

A positive NPV_{net} indicates that the discounted benefits exceed the discounted capital, O&M, and replacement costs over the 15-year horizon.

Simple Payback Period

The payback period is the year in which the cumulative net cash inflow first equals or exceeds the initial capital investment. Let ΔC_y denote the net cash flow in the year y (benefits minus O&M costs, excluding initial investment). The cumulative cash flow is expressed in (36).

$$\text{CUM}_y = \sum_{k=1}^y \Delta C_k \quad (36)$$

The payback year is the smallest, y such that $\text{CUM}_y \geq C_{\text{inv}}$. A shorter payback period indicates faster recovery of the initial investment.

Return on Investment (ROI)

The return on investment over the 15-year horizon is defined in (37)

$$\text{ROI} = \frac{\text{Total undiscounted net profit over 15 years}}{C_{\text{inv}}} \times 100\% \quad (37)$$

Equivalently, using the NPV as a more conservative measure, a discounted ROI can be expressed as (38)

$$\text{ROI}_{\text{NPV}} = \frac{\text{NPV}_{\text{net}}}{C_{\text{inv}}} \times 100\% \quad (38)$$

These indicators, together with NPV_{net} and payback period, provide a clear economic summary for utility planners when comparing alternative PV-DG + Cap Bank + EVCS deployment strategies.

4. Optimisation Algorithms

4.1 Improved Multi-Objective Manta Ray Foraging Optimisation (IMOMRFO)

IMOMRFO is a swarm-based multi-objective algorithm built on the original Manta Ray Foraging Optimisation (MRFO) [34] adapted here to minimize active power loss (1), voltage deviation (2), and capital investment cost (3) simultaneously

Standard MRFO behaviour

MRFO updates each solution X_i using three foraging modes:

Chain foraging (move toward the current best): $X_i^{t+1} = X_i^t + r_1(X_{\text{best}}^t - X_i^t)$, where X_{best}^t is the best solution at iteration, t and $r_1 \in [0,1]$. **Cyclone (spiral) foraging:**

$X_i^{t+1} = X_{best}^t + r_2(X_i^t - X_{best}^t)e^{bl}\cos(2\pi l)$, with $r_2 \in [0,1]$, spiral parameter b , and random $l \in [0,1]$.

Somersault foraging: $X_i^{t+1} = X_i^t + S(r_3X_{best}^t - r_4X_i^t)$, where S is the somersault factor and $r_3, r_4 \in [0,1]$. These three moves are combined in each iteration to explore the search space and then exploit promising regions.

Improvements in IMOMRFO

To increase convergence speed and diversity for the PV-DG+Cap Bank +EVCS problem, IMOMRFO adds:

- **Chaotic initialization** using a Tent map is expressed as (39)

$$z_{k+1} = \begin{cases} \frac{z_k}{\mu}, & 0 \leq z_k < \mu, \\ \frac{1 - z_k}{1 - \mu}, & \mu \leq z_k \leq 1, \end{cases} \quad (39)$$

with z_k mapped into each decision variable's bounds. This gives a well-spread initial population.

- **Adaptive inertia weight** in the update is expressed as (40) and (41)

$$\omega(t) = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{T_{\max}} t \quad (40)$$

$$X_i^{t+1} = \omega(t)X_i^t + r_1(X_{best}^t - X_i^t) \quad (41)$$

favoring exploration early (ω large) and exploitation later (ω small).

- **Lévy-flight mutation** for occasional large jumps is expressed as (42)

$$X_i^{t+1} = X_i^{t+1} + \alpha \text{Lévy}(\beta) \quad (42)$$

where α is a small step factor and $\text{Lévy}(\beta)$ is a heavy-tailed Lévy distribution (typically $\beta \approx 1.5$).

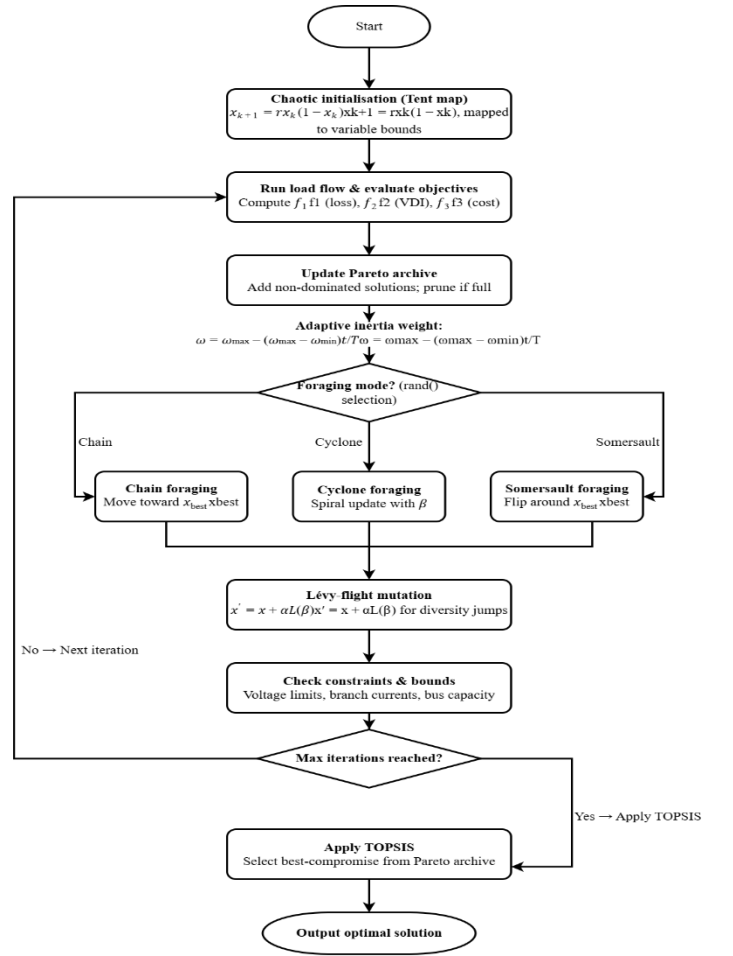


Fig 3: Flowchart for Improved Multi-Objective Manta Ray Foraging Optimisation

Table 2: Parameters for Improved Multi-Objective Manta Ray Foraging Optimisation

IMOMRFO parameter	Numerical definition
Population size	100
Max. number of iterations	200
Somersault factor (S_max)	2
Somersault factor (S_min)	0.5
Levy exponent (β)	1.5
Loss weight (w_PL)	20
Cost weight (w_ECON)	1
TOPSIS weight for loss	0.25
TOPSIS weight for VDI	0.25
TOPSIS weight for cost	0.50

4.2 Multi-Objective Artificial Vulture Optimisation Algorithm (MOAVOA)

Standard MOAVOA also operates with a population of candidate solutions and three main positions, update behaviour that balances exploration and exploitation across multiple objectives, which is expressed as (43), (45), and (45). [35]

- **Leader-guided exploitation (move toward the archive leader):**

$$X_i^{t+1} = X_i^t + a_1(L^t - X_i^t) \quad (43)$$

where L^t is a leader solution selected from the Pareto archive at iteration t , and a_1 is a coefficient controlling the strength of attraction.

- **Social exploration (use a random companion vulture):**

$$X_i^{t+1} = X_i^t + a_2(X_r^t - X_i^t) \quad (44)$$

where X_r^t is a randomly chosen vulture (or archive solution), and a_2 controls exploratory movement.

- **Combined leader-companion update:**

$$X_i^{t+1} = L^t + b_1(L^t - X_i^t) + b_2(X_r^t - X_i^t) \quad (45)$$

where b_1 and b_2 are behaviour factors that tune the mix of exploitation (towards L^t) and exploration (towards X_r^t).

At each iteration, these moves are applied to all vultures, and the new solutions are evaluated across multiple objectives, updating the Pareto archive of non-dominated solutions, ensuring MOAVOA searches widely at first and then concentrates around the best trade-off regions.

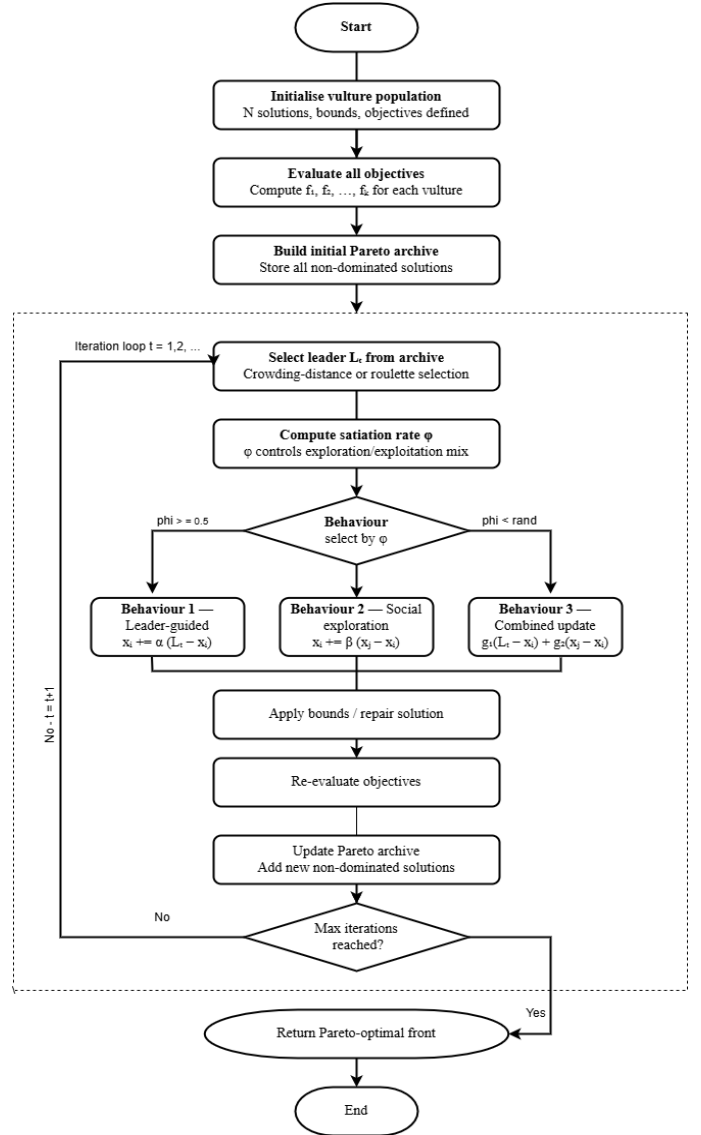


Fig 4: Flowchart for Multi-Objective Artificial Vulture Optimisation Algorithm

Table 3: Multi-Objective Artificial Vulture Optimisation Algorithm

MOAVOA parameter	Numerical definition
Population size	100
Max. number of iterations	200
Probability of following Best1 p_1	0.6
Probability of rotational flight p_2	0.4
Lévy flight exponent β	1.5

Loss weight w_{PL}	20
Voltage deviation weight w_{VD}	2000
Cost weight w_{ECON}	1
TOPSIS weight for loss	0.25
TOPSIS weight for VDI	0.25
TOPSIS weight for cost	0.50

5. RESULTS AND DISCUSSION

Two radial distribution networks were analyzed: The IEEE 33-bus 12.66 kV feeder for benchmark validation and the real ECG Ashanti 50-bus 33 kV network to demonstrate practical performance under Sub-Saharan African conditions. For each network, the MOAVOA and IMOMRFO multi-objective Algorithms were run independently to enable direct comparison. In all cases, three PV-DG units, three capacitor banks, and three EVCS hubs were jointly sited and sized, with Ashanti EVCS hubs constrained to three geographical zones. Each algorithm used a population of 100 and 200 iterations, with 30 independent runs per algorithm–network pair. Load flow was solved using the Backward–Forward Sweep method, and TOPSIS was used to select the best-compromise solution from the Pareto set, and the chosen plan was evaluated over a 15-year horizon at a 20% discount rate.

5.1 Technical Performance Analysis IEEE 33-bus network

For the IEEE 33-bus network, the base-case peak-load flow gives a total active power loss of 201.89 kW using (1), with a minimum bus voltage of 0.9134 p.u. at Bus 18, below the 0.95 p.u. limit; in total, 21 of the 33 load buses violate this constraint, and the corresponding VDI is 11.64 %, confirming that the feeder is heavily stressed as reported in Table 4. The loss distribution is heavily skewed toward the main trunk: Branch 2 (2–3) alone contributes 51.57 kW (25.5 % of total loss), Branch 5 (5–6) adds 38.03 kW (18.8 %), Branch 1 (1–2) contributes 12.19 kW (6.0 %), and Branches 6–9 together account for a further ~14.6 kW, whereas the lightly loaded laterals (Branches 18–24 and 25–29) exhibit much smaller losses. Both MOAVOA and IMOMRFO are applied to this feeder using the same three-objective formulation (F1: active power loss, F2: voltage deviation index, F3: capital investment) defined in (7), and a TOPSIS-based best-compromise solution (BCS) is selected from each Pareto front; the main performance metrics for these BCSs are summarized in Table 4.

Table 4: IEEE 33-Bus Validation Results: MOAVOA and IMOMRFO Best Compromise Solutions

Parameter	Base Case	MOAVOA	IMOMRFO
PV-DG Placement (buses)	-	8, 14, 24	28, 13, 27
PV-DG Sizes (kW)	-	400, 320, 320	160, 698, 119
Total PV-DG (kW)	-	1,040	977
EVCS Hub Buses	-	5, 17, 30	3, 20, 24
Cap Bank Buses	-	18, 31, 32	8, 32, 12
Cap Bank Sizes (kVAr)	-	500, 590, 590	724, 619, 724
Active Power Loss (kW)	201.89	76.72	22.25
Active Loss Reduction (%)	-	62.0%	88.98%
Reactive Power Loss (kVAr)	135.00	34.43	11.48
Reactive Loss Reduction (%)	-	74.5%	91.5%
VDI (%)	11.64	3.44	1.41
VDI Improvement (%)	-	75.43%	87.89%
Min. Bus Voltage (p.u.)	0.9134	0.9699	0.9699
Buses below 0.95 p.u.	21	0	0
Capital Investment (k\$)	-	1,316	1,260.74
TOPSIS CC Score	-	0.8034	0.94
15-yr Net Profit (k\$)	-	4,822.16	4,918.88

Both algorithms eliminate all 21 voltage violations and reduce the VDI by 75.43% and 87.89%, from 11.64% to 3.44% and 1.41%, respectively, as computed using the VDI definition in (2), confirming that the three-asset planning framework is highly effective in voltage restoration even on a stressed 12.66 kV network. However, IMOMRFO achieves markedly superior active-power-loss reduction (88.98% compared to MOAVOA’s 62.0%) based on the total loss expression in (1) and the annual loss-reduction formulation in (25)–(27) and (34). and reduces reactive losses by 91.5% versus 74.5%. IMOMRFO also attains these technical gains with slightly lower capital investment (1,261.34 k\$ versus 1,316.6 k\$), consistent with the investment objective F_3 in (3)–(7) and the total capital definition in (16)–(18), yielding a higher 15-year net profit (4,918.88 k\$ versus 4,822.16 k\$) in line with the NPV framework in (14), (15), and (35). These results affirm IMOMRFO’s superiority in solution quality on the IEEE 33-bus benchmark and demonstrate the

effectiveness of the proposed three-objective formulation in (7) in delivering simultaneous technical and economic performance.

Benchmark comparison of the IEEE 33-bus results with representative published studies

Table 5 compares the IEEE 33-bus power-loss performance of the proposed MOAVOA and IMOMRFO best-compromise plans with several representative published optimisation studies that also use the IEEE 33-bus benchmark system. The standard base case corresponds to the classical IEEE 33-bus formulation, for which the load-flow in this study yields a total active power loss of 201.89 kW and a minimum bus voltage of 0.9134 p.u.

Table 5: IEEE 33-bus power-loss benchmark comparison for representative studies

Method/study	Optimal solution (brief description)	Power loss reduction (%) (kW))
Base case (Baran–Wu benchmark)	No DG, no CAP BANK, no reconfiguration	0% (201.9–202.4 kW)
Network reconfiguration – [36]	Radial reconfiguration of switches on the IEEE 33-bus system	55.5% (89.9 kW reduction from 202.4 kW base)
DG + capacitor placement – [37]	Multiple DG and shunt capacitor units optimally sited on the IEEE 33-bus	72.9% (54.90 kW remaining loss)
This work – MOAVOA best-compromise	Simultaneous PV-DG, CAP BANK, and EVCS planning	62.0% (76.72 kW remaining loss)
This work – IMOMRFO best-compromise	Simultaneous PV-DG, CAP BANK, and EVCS planning	88.98% (22.25 kW remaining loss)

These base-case results are consistent with published IEEE 33-bus benchmarks, confirming the correctness of the implemented load-flow model and the starting operating point for subsequent optimisation. [36] Apply optimal network reconfiguration to the same IEEE 33-bus test system and report that the total real-power loss decreases from about 202.4 kW in the base case to 112.5 kW after reconfiguration, corresponding to a reduction of approximately 89.9 kW, or 55.5% relative to the original operating point. [37] report that coordinated placement of DG and capacitor units reduces losses to 54.90 kW, corresponding to a 72.91% reduction relative to the 201.9 kW base case. Against this background, the MOAVOA best-compromise solution in the present work achieves a 62.0% reduction in active loss (76.72 kW remaining). It raises the minimum voltage to 0.9699 p.u., placing it within the performance band of recent DG/capacitor

and reconfiguration studies. The IMOMRFO best-compromise solution performs even better, reducing the IEEE 33-bus active loss to 22.25 kW, which corresponds to an 88.98% reduction relative to the same base case, while also maintaining a minimum voltage of 0.9699 p.u. These results indicate that the proposed planning framework delivers technical performance on the IEEE 33-bus benchmark system that is consistent with, and in terms of residual active loss stronger than, representative recent optimisation methods reported in the literature.

Ashanti Regional 33 kV Network

For the ECG Ashanti Regional 50-bus 33 kV network shown in Figure 2, both MOAVOA and IMOMRFO are applied under the same three-objective formulation (F_1 = active power loss, F_2 = VDI, F_3 = capital investment) as defined in (1)–(3) and aggregated in (7), and the TOPSIS-selected best-compromise solutions are summarized in Table 6.

Table 6: TOPSIS best-compromise solutions on the ECG Ashanti Regional 50-bus 33 kV network

Parameter	MOAVOA	IMOMRFO
PV-DG Placement (buses)	12, 21, 35	13, 21, 34
PV-DG Sizes (kW)	270, 7,950, 5,180	11,480, 9,000, 5,600
Total PV-DG (kW)	13,400	26,080
EVCS Hub Buses	2, 34, 49	3, 22, 48
CAP BANK Buses	3, 4, 6	6, 20, 35
CAP BANK Sizes (kVAr)	450, 3,260, 2,350	4,860, 5,000, 4,140
Total CAP BANK Rating (kVAr)	6,060	14,000
Capital Investment (k\$)	13,763.6	26,602.4
TOPSIS CC Score	0.86	0.93

In both cases, three PV-DG units, three EVCS hubs, and three shunt capacitor banks are deployed as structured by the decision vector in (8), but the algorithms make markedly different techno-economic trade-offs. MOAVOA installs a total of 13,400 kW of PV-DG and 6,060 kVAr of capacitors at a capital cost of 13,764.2 k\$, consistent with the investment expressions in (3)–(6) and (16)–(18), attaining a TOPSIS closeness coefficient of 0.86, whereas IMOMRFO doubles the PV-DG capacity to 26,080 kW and more than doubles

the capacitor capacity to 14,000 kVAR with a higher capital cost of 26,603.0 k\$, achieving a superior TOPSIS score of 0.93. Both algorithms consistently identify Bus 21 as a major PV-DG node, reflecting its high sensitivity to loss reduction in the Ashanti network.

Overall, MOAVOA's best-compromise solution favours lower investment. At the same time, IMOMRFO's configuration prioritizes greater technical improvements in loss reduction and voltage-profile enhancement, leading to a more favourable overall trade-off as reflected in its higher TOPSIS coefficient and net-present-value performance under the 15-year framework of (14), (15), and (35).

Active Power Loss Reduction

Table 7 presents the total and branch-level active power loss results for the Ashanti network.

IMOMRFO achieves an active power loss reduction of 81.0%, cutting the system total loss from 14,530.08 kW to 2,760.70 kW, a saving of 11,769.38 kW, as computed from the loss expression in (1), corresponding to a saving of 11,769.38 kW in the base-optimized loss difference used in (25) and (34).

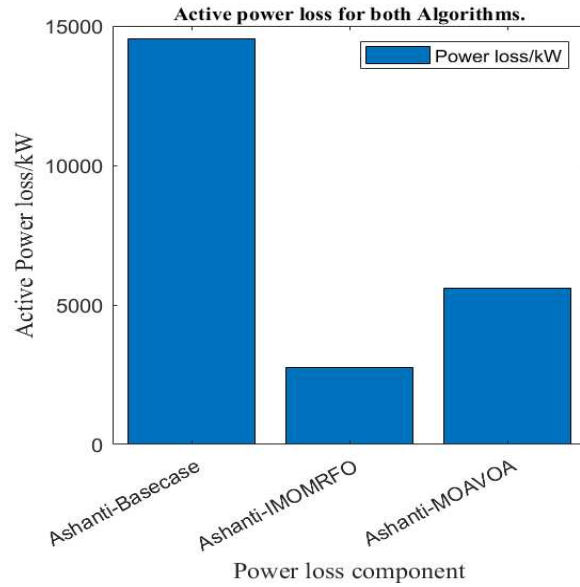


Fig 5: Ashanti Regional 33 kV Active Power Loss

Table 7: Total active power loss and percentage reduction on the Ashanti 50-bus 33 kV network

Scenario	Total Active Loss (kW)	Reduction (%)
Base Case	14,530.08	—
MOAVOA	5,594.05	61.50%
IMOMRFO	2,760.70	81.00%

MOAVOA achieves a still-substantial 61.5% reduction to 5,594.05 kW. The primary drivers of loss reduction differ between the two algorithms: IMOMRFO's 26,080 kW of installed PV-DG nearly halves feeder currents on the heaviest branches, while MOAVOA relies on a more balanced combination of 13,400 kW PV-DG and targeted reactive compensation, both evaluated using the same branch-loss model in (1) and the net-load formulation in (10)–(12). At the branch level, the most absolute improvements occur on Branch 17 (15-18, the Bus 18 feeder), which drops from 2,521.4 kW to 479.1 kW (IMOMRFO), representing a saving of 2,042.3 kW on that single branch alone. Branch 8 (8-9) falls from 1,653.2 kW to 314.1 kW (IMOMRFO), and Branch 2 (2-3) from 1,212.7 kW to 230.4 kW, again all obtained from the branchwise application of (1).

Reactive Power Loss Reduction

Reactive power loss reduction is presented in Table 8 and graphically presented in Fig 6. The combination of shunt capacitor banks and reduced branch currents from PV-DG active-power injection delivers a substantial reduction in reactive losses for both algorithms.

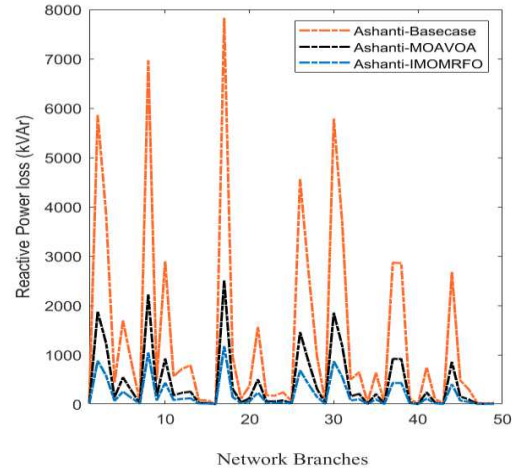


Fig 6: Reactive Power Loss Reduction profile for Ashanti Regional 33kV network

Table 8: Ashanti 50-Bus Reactive Power Loss Summary

Scenario	Total Reactive Loss (kVAr)	Reduction (%)
Base Case	66,650.18	—
MOAVOA	21,328.06	68.0%
IMOMRFO	9,997.53	85.0%

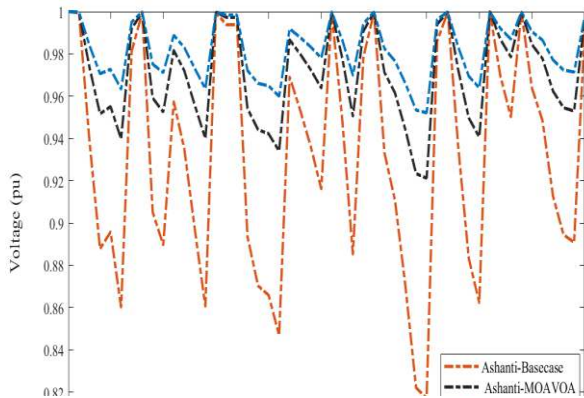
IMOMRFO reduces reactive losses by 85.0%, cutting them from 66,650.18 kVAr or 66.65 MVar to 9.997 MVar, equivalent to releasing over 56.6 MVar of reactive capacity that was previously absorbed by network impedances. This is particularly significant for the ECG Ashanti 33 kV network because reactive power import from the GridCo high-voltage network carries an implicit cost through reactive energy charges and transmission losses.[22] Its elimination, therefore, generates both direct and indirect economic benefits beyond those captured in the 15-year NPV model.

Table 9: Voltage Deviation Index (VDI) Summary

Network	Algorithm	VDI Base (%)	VDI Optimized (%)	VDI Improvement (%)
IEEE 33-Bus	MOAVOA	11.64	3.44	75.43%
IEEE 33-Bus	IMOMRFO	11.64	1.41	87.89%
Ashanti 50-Bus	MOAVOA	37.43	6.94	81.45%
Ashanti 50-Bus	IMOMRFO	37.43	2.56	93.15%

Voltage Profile Improvement

Voltage profile results for the Ashanti network are presented in Fig 7 for a representative selection of buses. Both algorithms achieve complete elimination of voltage

**Fig 1:** Ashanti 50-Bus: Voltage Profile Comparison at Critical Buses

violations (all 29 buses that were below 0.95 p.u. in the base case are restored above the limit), but at substantially different levels of voltage recovery.

IMOMRFO raises the minimum bus voltage from 0.8170 p.u. (Bus 35,) to 0.9521 p.u., a gain of 0.1351 p.u. (16.54%). MOAVOA raises the same bus to 0.9212 p.u., a gain of 0.1042 p.u. (12.75%). Both results exceed the 0.95 p.u. lower bound, meaning IMOMRFO achieves full compliance, while MOAVOA also achieves compliance but with less margin at the critical bus. Bus 21 perceives the largest proportional voltage recovery for IMOMRFO, rising by 0.1131 p.u. from 0.8468 to 0.9599 p.u., a 13.36% improvement driven by the 9,000 kW PV-DG unit sited directly at that bus.

Voltage Deviation Index Improvement

The VDI provides a single scalar measure of the aggregate voltage quality across the entire network, as defined by the second objective function in (2), and the corresponding results are summarized in Table 9.

On the Ashanti 50-bus 33 kV network, IMOMRFO delivers a VDI improvement of 93.15% on the Ashanti Regional network, reducing the index from 37.43% to a residual 2.56%. This is the strongest voltage quality improvement result across all four case combinations and directly demonstrates IMOMRFO's superior capacity to simultaneously exploit reactive and active support opportunities in a large, weakly meshed distribution system. MOAVOA achieves an 81.45% VDI improvement (from 37.43% to 6.94%), also a large improvement, but with a higher residual deviation.

On the IEEE 33-bus network, MOAVOA improves the VDI from 11.64% to 3.44% (75.43%), while IMOMRFO reduces it from 11.64% to 1.41% (87.89%). These results confirm that IMOMRFO consistently attains lower residual VDI on both networks, although the smaller and more uniform IEEE 33-bus system yields less pronounced differences between algorithms than the larger and more heterogeneous Ashanti network.

5.2 Techno-Economic Performance Analysis

Capital Investment Breakdown

Table 10 presents the capital-investment breakdown for all four scenario items, disaggregated into PV-DG, EVCS hub, and capacitor-bank components as defined in the capital-cost objective F_3 in (3)–(6) and the investment model in (16)–(18) and (25). PV-DG capital dominates in every case, reflecting the relatively high per-kW cost assumed for utility-scale PV in the Ghanaian procurement environment (1,000 USD/kW in this study, consistent with recent Sub-Saharan African solar tenders), so even moderate increases in installed PV-DG capacity translate into substantial jumps in total investment. EVCS hub capital is fixed at 80,000 USD

per hub, giving 240.0 kUSD for three hubs in all four scenarios, while capacitor-bank capital remains modest but non-negligible, especially for the Ashanti cases, where the optimal capacitor sizes are substantially larger than on the IEEE 33-bus network, contributing to higher Cap Bank capital yet still a relatively small share of the total.

Table 10: Capital Investment Breakdown (k\$)

Item	IEEE33 MOAVOA	IEEE33 IMOMRFO	Ashanti MOAVOA	Ashanti IMOMRFO
PV-DG Capital	1,040.0	977.0	13,400.0	26,080.0
EVCS Hub Capital	240.0	240.0	240.0	240.0
Capacitor Bank Capital	36.0	43.74	123.6	283.0
Total Capital Investment	1,316.0	1,260.74	13,763.6	26,603.0

NPV Revenue and Cost Analysis

Table 11 presents the complete 15-year discounted cash-flow breakdown for the Ashanti network scenarios under both algorithms. The dominant benefit streams are PV energy savings and loss-reduction savings, which together account for most of the total NPV inflows, reflecting the scale of the Ashanti network's base-case losses and the grid-energy tariff of 0.15 USD/kWh used for the techno-economic assessment.

Table 11: 15-Year NPV Economic Breakdown (k\$)
Ashanti 33kV Network

PV-DG Capital Cost	MOAVOA (BCS)	IMOMRFO (BCS)
PV-DG Capital Cost	13,400.0	26,080.0
EVCS Hub Capital Cost	240.0	240.0
Capacitor Bank Capital Cost	124.2	283
Total Capital Investment	13764.2	26603
PV O&M NPV (15 yr)	4385.60	8535.54
PV Inverter Replacement NPV	419.20	815.79
EVCS O&M NPV (15 yr)	210.40	210.40
PV Energy Savings NPV	21610.01	42058.89
Loss Reduction Savings NPV	19763.70	26030.16
EV Charging Margin NPV	4768.03	4768.03
NET 15-yr NPV PROFIT (k\$)	27,362.37	36,692.34

Using the net-profit values in Table 11, the IMOMRFO

best-compromise solution yields a 15-year net present profit of 36.69 MUSD from a 26.60 MUSD investment, whereas MOAVOA delivers 27.36 MUSD of net profit from 13.76 MUSD of capital expenditure. The Ashanti economic analysis also underlines the central role of the two energy-related benefit streams defined in (24)–(27) and aggregated in the overall NPV expression in (35). IMOMRFO's 81% active-loss reduction lowers technical losses from 14.53 MW to 2.76 MW, and when this reduction is converted to annual energy savings using the adopted loss factor and grid tariff, it produces the loss-reduction NPV values in Table 10 (19.76 MUSD for MOAVOA and 26.03 MUSD for IMOMRFO). PV energy savings are of comparable magnitude: IMOMRFO's 26,080 kW of PV-DG, operated at a 26.25% capacity factor as in (24), generates tens of gigawatt-hours per year, which, when valued at 0.15 USD/kWh and discounted over 15 years, yields PV-energy NPV contributions of 21.61 MUSD for MOAVOA and 42.06 MUSD for IMOMRFO. The EV charging margin, computed from (28)–(33), is smaller but remains positive, with both algorithms producing the same 4.77 MUSD NPV from EVCS operation, providing an additional, stable revenue stream that supports ECG's business case for investing in fast-charging infrastructure.

Net Profit and Payback Period

The IMOMRFO solution delivers a 15-year net NPV profit of approximately 36.69 MUSD against a capital investment of 26.60 MUSD, corresponding to a strong NPV-based return on investment over the project life. Simple payback on the Ashanti IMOMRFO investment occurs very early in the project, as the combined annual PV-energy and loss-reduction savings are large relative to the initial capital outlay; even on a discounted-cash-flow basis with a 20% real discount rate, the break-even point falls within Years 2–3 of the 15-year horizon. The MOAVOA solution yields a 15-year net profit of about 27.36 MUSD from a lower capital investment of 13.76 MUSD, implying a higher NPV-based ROI percentage than IMOMRFO because it deploys substantially less capital despite achieving a smaller absolute NPV. Both solutions, therefore, present very strong business cases for ECG under the adopted tariff and discount-rate assumptions. All Ashanti network net present values are evaluated with a single real discount rate of 20% over a 15-year horizon, applied consistently to both MOAVOA and IMOMRFO, so that their techno-economic performance is compared on a common basis. This relatively high discount rate reflects a conservative utility-planning

assumption for the Ghanaian context and avoids overstating the present worth of future benefits, ensuring that the reported projects remain clearly profitable while corresponding to different investment strategies: MOAVOA attains a positive 15-year NPV with a lower capital requirement, whereas IMOMRFO requires a higher upfront investment but delivers the larger absolute NPV together with greater overall technical improvement. The final best-compromise solutions are selected from the multi-objective Pareto archives using TOPSIS with fixed weights of 0.25, 0.25, and 0.50 on active power loss, voltage deviation index, and capital investment cost, respectively, a weighting pattern that slightly favours affordability while still keeping network-loss reduction and voltage-profile improvement explicitly in the decision.

5.3 Algorithm Performance Comparison Solution Quality: IMOMRFO vs. MOAVOA

Table 12 provides a direct head-to-head comparison of the TOPSIS best-compromise solution quality across both networks and all three objective dimensions

Table 12: IMOMRFO and MOAVOA: Best Compromise Solution Quality

Metric	IEEE33 MOAVOA	IEEE33 IMOMRFO	Ashanti MOAVOA	Ashanti IMOMRFO
Active Loss (kW)	76.72	22.25	5,594.05	2,760.70
Active Loss Reduction (%)	62.0	88.98	68.0	81.0
Reactive Loss Reduction (%)	74.5	91.5	68.0	85.0
VDI (%)	3.44	1.41	6.94	2.56
VDI Improvement (%)	87.89	87.89	81.45	93.15
Min. Voltage (p.u.)	0.9699	0.9699	0.9212	0.9521
Min. Voltage Improvement (%)	6.18	6.18	12.75	16.54
Buses < 0.95 p.u.	0	0	0	0
Capital Investment (k\$)	1,316.0	1,260.74	13,763.6	26,602.4
15-yr Net Profit (k\$)	4,822.16	4,918.88	27,362.37	36,692.34
TOPSIS CC Score	0.8034	0.94	0.86	0.93

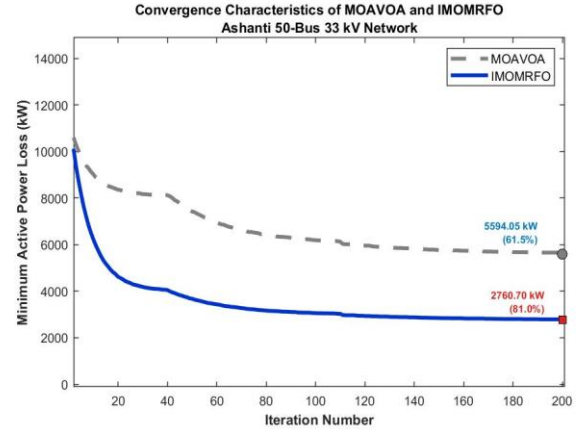


Fig 8: IMOMRFO and MOAVOA: Best Compromise Solution Quality

Overall, IMOMRFO delivers stronger technical improvements and higher long-term profit on both networks, whereas MOAVOA achieves these benefits with lower upfront capital investment.

IMOMRFO consistently outperforms MOAVOA on the loss and economic dimensions across both networks. On the IEEE 33-bus network, IMOMRFO achieves an active-loss reduction of 88.98% versus 62.0% for MOAVOA, a difference of 26.98 percentage points, despite deploying slightly less capital (1,261.34 k\$ and 1,316.6 k\$). On the Ashanti network, the margin narrows to 19.5 percentage points (81.0% for IMOMRFO and 61.5% for MOAVOA) but is even more consequential in absolute terms: 11,769 kW for IMOMRFO versus 8,936 kW for MOAVOA of loss reduction. IMOMRFO's superior technical performance is reflected in its TOPSIS closeness coefficient, which reaches 0.94 (IEEE 33-bus) and 0.93 (Ashanti), compared with 0.8034 and 0.86 for MOAVOA.

Convergence Characteristics

Fig 8 presents the convergence curves of MOAVOA and IMOMRFO on the Ashanti 50-bus 33 kV network over 200 iterations, both starting from a base-case active power loss of 14,530 kW. IMOMRFO demonstrates markedly superior convergence speed and solution quality, descending steeply from about 10,879 kW at iteration 1 to below 4,000 kW by iteration 40 and converging to a final best value of 2,760.70 kW, an 81.0% reduction, with the curve effectively plateauing from around iteration 130. MOAVOA follows a considerably shallower descent, with meaningful improvement continuing beyond iteration 150 and a final best of 5,594.05 kW (61.5% reduction), so IMOMRFO's final solution outperforms MOAVOA's

best result at every point in its run. This consistent advantage is attributed to IMOMRFO's chaotic tent-map initialization in (39), Lévy-flight mutation in (42) for escaping local optima, and an adaptive somersault factor that decays from 2.0 to 0.5 to balance exploration and exploitation as implemented through (40) and (41), mechanisms that collectively prove more effective than MOAVOA's satiation-rate control and leader-companion updates in (43)–(45) on the complex nine-asset, 50-bus optimisation.

Pareto Front Distribution for both algorithms on the Ashanti regional 33kV network

Fig 9 presents the Pareto-optimal solutions obtained by MOAVOA and IMOMRFO for the Ashanti 50-bus 33 kV network in the three-objective space of active power loss, voltage deviation index (VDI), and capital investment cost in (1)–(3) and the vector F in (7). MOAVOA's Pareto front is concentrated in a region with relatively high active-power losses (approximately 5.3–8.4 MW) and moderate VDIs (about 5.5–7.7%), but with comparatively low investment requirements in the range 13.8–18.0 MUSD; its TOPSIS best-compromise solution achieves 5,594.05 kW of loss and VDI = 6.94% at a capital cost of 13.76 MUSD, with a closeness coefficient of 0.86. In contrast, IMOMRFO generates a Pareto set located much deeper in the low-loss, low-VDI region, reducing active-power loss to roughly 2.5–4.9 MW and VDI to about 1.8–3.6%, while incurring higher investment costs between 26.1 and 32.0 MUSD; its best-compromise solution attains 2,760.70 kW of loss and VDI = 2.56% at 26.60 MUSD, with a closeness coefficient of 0.93, clearly dominating the MOAVOA BCS in both technical objectives. Overall, the distribution of Pareto points indicates that MOAVOA is more attractive in strictly budget-constrained settings, offering lower-cost but higher-loss solutions, whereas IMOMRFO systematically pushes the Pareto front towards lower losses and smaller voltage deviations and provides a denser set of high-performance alternatives for utilities that prioritize technical reinforcement over minimum capital expenditure, which justifies its higher TOPSIS score and its selection as the preferred planning tool for the Ashanti network.

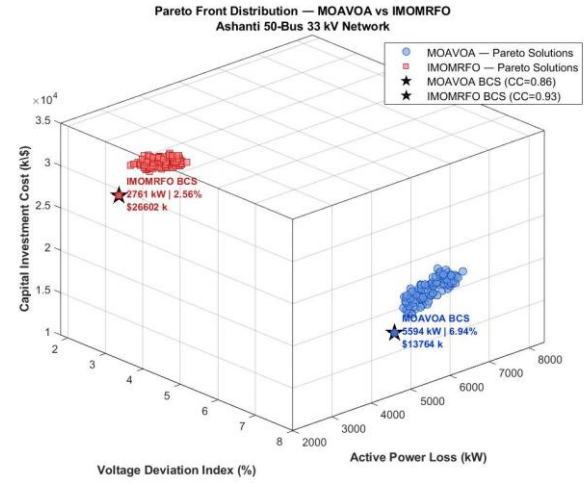


Fig 9: Pareto Front Distribution for MOAVOA and IMOMRFO

Conclusion

This paper proposed a unified techno-economic multi-objective framework for the simultaneous siting and sizing of PV-DG units, capacitor banks, and fast EVCS hubs in radial distribution networks, using active power loss, voltage deviation index, and capital investment cost as planning objectives. The approach combined Pareto-based optimisation with TOPSIS and a 15-year discounted cash-flow model and was applied to both the IEEE 33-bus test network and the ECG Ashanti Regional 50-bus 33 kV network.

On the IEEE 33-bus system, IMOMRFO achieved the best compromise solution, sharply reducing losses and voltage deviation while delivering the highest 15-year net profit compared with MOAVOA.

On the Ashanti network, coordinated placement of PV-DG, CAP BANK, and EVCSs transformed a weak, high-loss base case into an acceptable operating state, with the IMOMRFO best-compromise plan cutting active power loss by about 81%, eliminating all voltage violations, and yielding strong long-term net profit from a realistic investment level.

Overall, the results show that treating PV-DG, capacitor banks, and EVCSs as interacting decision variables within a single optimisation and economic-evaluation framework enables utilities such as ECG and NEDCO to rehabilitate high-loss, undervoltage networks while obtaining attractive long-term financial returns.

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Mante Bismark conducted the core research and prepared the original draft. Patrick N. Ayambire, Albert K. Awopone, Isaac Prempeh, and Ernest Fiko Morgan supervised the work and contributed to reviewing and revising the manuscript.

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The datasets generated and/or analyzed during the current study are not publicly available due to restrictions from the data providers but are available from the corresponding author on reasonable request.

Ethical approval

This study did not involve human participants, human data, or animals. Therefore, ethical approval was not required for this research.

Consent to participate

Not applicable. This study did not involve human participants.

Consent to publish

Not applicable. This manuscript does not contain any individual person's data in any form.

Conflict of Interest

The author declares no conflicts of interest.

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