

Article

Optimal Allocation of Capacitor Banks and Distributed Generation: A Comparison of Recently Developed Metaheuristic Optimization Techniques on the Real Distribution Networks of ALG-AB-Hassi Sida, Algeria

Khaled Fettah ¹, Talal Guia ¹, Ahmed Salhi ², Souhil Mouassa ^{3,4}, Alessandro Bosisio ^{5,*}
and Rouzbeh Shirvani ⁵

- ¹ Laboratoire des Nouvelles Technologies et le Développement Local (LNTDL), Electrical Engineering Department, University of El Oued, El-Oued 39000, Algeria; khaled-fettah@univ-eloued.dz (K.F.); talal-guia@univ-eloued.dz (T.G.)
 - ² Laboratoire de Génie Electrique de Biskra (LGEB), Electrical Engineering Department, University of Biskra, Biskra 07000, Algeria; a.salhi@univ-biskra.dz
 - ³ Electrical Engineering Department, University of Bouira, Bouira 10000, Algeria; souhil.mouassa@univ-bouira.dz
 - ⁴ Electrical Engineering Department, University of Jaén, 23700 Linares (Jaén), Spain
 - ⁵ Department of Electrical, Computer and Biomedical Engineering, University of Pavia, 27100 Pavia, Italy; rouzbeh.shirvani01@universitadipavia.it
- * Correspondence: alessandro.bosisio@unipv.it

Abstract: Recent advancements in renewable energy technologies, alongside changes in utility infrastructure and progressive government policies, have bolstered the integration of renewable-based distributed generation units within distribution systems. This paper introduces the Energy Valley Optimizer, a novel tool designed for the strategic placement of distributed generation units and capacitor banks. This placement is crucial not only for optimizing energy loss and enhancing bus voltage stability but also for promoting sustainable energy use and reducing environmental impact over the long term. By minimizing energy loss and voltage fluctuations, the optimizer contributes to a more sustainable and resilient energy system. It achieves this through the optimal allocation of resources across various load patterns within a 24 h period and is tested on the ALG-AB-Hassi-Sida 157-bus distribution network in South Algeria. Comparative analysis with existing algorithms—such as the Liver Cancer Algorithm, Walrus Optimization Algorithm, and Zebra Optimization Algorithm—demonstrates the superior performance of the Energy Valley Optimizer. It not only enhances technical and economic efficiencies but also significantly lowers the total cost of energy over 24 years, thus supporting sustainable development goals in energy management.

Keywords: renewable energy; distributed generation; energy optimization; voltage stability; cost efficiency



Citation: Fettah, K.; Guia, T.; Salhi, A.; Mouassa, S.; Bosisio, A.; Shirvani, R. Optimal Allocation of Capacitor Banks and Distributed Generation: A Comparison of Recently Developed Metaheuristic Optimization Techniques on the Real Distribution Networks of ALG-AB-Hassi Sida, Algeria. *Sustainability* **2024**, *16*, 4419. <https://doi.org/10.3390/su16114419>

Academic Editors: Kangli Liu, Yiji Lu, Miltiadis (Miltos) Alamaniotis and Na Chai

Received: 15 April 2024

Revised: 15 May 2024

Accepted: 20 May 2024

Published: 23 May 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The distribution system is an essential area of research, as it represents the crucial connection between the transmission network and end-users. With rapid industrialization and population growth, the electricity demand continues to rise, pushing the line current to its limits.

This situation increases line losses and lower/higher voltage levels at consumer sites. The unpredictable nature of load patterns further complicates maintaining a balanced power flow and ensuring adequate supply voltage while adhering to operational constraints. These challenges ultimately impact power quality and network stability. Moreover, given that many consumer loads are inductive, they introduce a lagging power factor, contributing to increased system losses. Therefore, distribution companies need to minimize line losses and maintain a consistent voltage profile in the system [1].

Reactive power compensation, achieved through shunt capacitors, is an effective strategy for addressing these challenges. Capacitors Banks (CBs) are fundamental tools for improving the distribution system's performance. Furthermore, as the electricity demand continues to grow, it is not always feasible or cost-effective to expand the capacity of transmission and distribution systems. Incentivizing the installation of distributed generation (DG) units near consumer sites can help alleviate the need for new infrastructures. The simultaneous deployment of DG and CBs within a distribution system offers numerous technical and economic advantages, including reducing system losses, maintaining a stable voltage profile, decreasing branch currents, improving the power factor, and enhancing power quality, among other benefits [2].

Moreover, this approach carries environmental benefits since DGs often rely on less polluting renewable energy sources (RESs) than conventional generators.

While integrating DGs and CBs in distribution systems enhances overall system performance, it is crucial to consider potential issues such as overvoltage, bidirectional power flow, and excessive power loss if these components are not placed optimally. The optimal selection of location and size for DG units and CBs is crucial for minimizing losses and ensuring efficient operation within acceptable limits. This involves determining the most suitable locations for installing DG units and CBs to maximize their effectiveness in improving system performance and reliability. Typically, the Distribution System Operator (DSO) is responsible for determining the optimal locations for capacitor banks, as they are primarily used for voltage support and power factor correction across the grid. On the other hand, the location and size of DG units, in particular photovoltaic (PV) systems, are often determined by the end-user or the owner of the PV system. This is because PV systems are usually installed on rooftops or premises owned by individual consumers or businesses, and the decision regarding their location and size depends on factors such as available space, solar resource potential, energy demand, and financial considerations. Therefore, while the DSO focuses on optimizing CB locations to enhance system voltage stability, end-users typically decide on the location and size of PV systems based on their specific energy needs and site conditions.

Optimal Capacitor Bank (OCB) allocation within distribution networks offers a range of technical advantages, including reducing power losses and energy losses and improvements in power quality, particularly in the presence of voltage and current harmonics [3]. Various optimization techniques have been applied to address the OCB allocation problem, encompassing analytical methods, classical/numerical approaches, heuristic/metaheuristic strategies, and artificial intelligence methods [4]. The authors in [5] introduced a Locational Sensitivity Factor (LSF) analysis to identify potential nodes for OCB placement and employed the Particle Swarm Optimization (PSO) algorithm for determining the OCB sizes. In [6], a Plant Growth Simulation Algorithm (PGSA), which requires no parameter tuning, was combined with LSF for OCB sizing. A Clustering-Based Optimization (CBO) algorithm was proposed in [7] to systematically allocate CBs on system busses, minimizing the overall cost of power/energy and CBs. Paper [8] put forward an analytical method for ranking system busses based on the voltage stability index (VSI) and utilized a fuzzy real-coded Genetic Algorithm (GA) for OCB sizing, aiming to maximize savings in power/energy loss and CB expenditure. In [9], a combination of LSF and VSI was employed for OCB placement, and a Bacterial Foraging Optimization Algorithm (BFOA) was suggested for OCB sizing, accounting for load variations. Another approach involved combining two bio-inspired algorithms, the Bat Algorithm (BA) and Cuckoo Search (CS), to allocate OCBs with a focus on reducing network power loss and maximizing savings [10]. The authors in [11] employed the Teaching and Learning-Based Optimization (TLBO) algorithm for OCB allocation, aiming to minimize power/energy loss costs. Reducing power losses and capacitor costs was the primary objective in [12], where the PSO algorithm was used for OCB allocation. The PSO algorithm considered various operators, including Gaussian and Cauchy probability distribution functions, along with chaotic load pattern sequences of the distribution system.

In [13], the authors utilized the LSF to reduce the search space and identify precise CB locations, complemented by the Gravitational Search Algorithm (GSA) for OCB sizing. Lastly, a newly developed Crow Search Algorithm (CSA) was introduced in [14] to address the OCB allocation problem within distribution networks.

It is crucial to investigate the appropriate allocation of DG units and select a suitable optimization tool [15]. Various techniques have been applied to solve the problem of optimal distributed generation unit (ODG) allocation in distribution networks. In [16], an analytical method combined with fuzzy logic was proposed for ODG allocation, with the primary goal of minimizing real power loss. The authors in [17] introduced a novel algorithm that blends GA and PSO for ODG allocation to minimize network loss.

A metaheuristic Harmony Search Algorithm (HSA) was presented in [18] to address the ODG allocation problem with loss minimization as an objective. An Exhaustive Search Algorithm (ESA) was proposed in [19] for single and multiple ODG allocations to minimize both active and reactive power losses. The authors in [20] employed an LSF analysis to locate DG units and utilized the Nature-Inspired Intelligent Water Drop (IWD) optimization algorithm for DG sizing. In [21], the authors considered various load models while solving the ODG allocation problem, using LSF for DG location and the BFOA for DG sizing. In [22], a hybrid optimization algorithm combining Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC) was proposed as a multi-objective technique for ODG allocation. The authors in [23] introduced a new voltage stability index technique for single ODG allocation in the presence of load growth. In [24], a Backtracking Search Optimization Algorithm (BSOA) based on swarm intelligence, with a single control parameter, was proposed for ODG allocation in a radial distribution system. The authors in [25] utilized the BA for the allocation of PV systems, modeling the intermittent generation pattern of solar irradiance using an appropriate probabilistic distribution function. In [26], an LSF analysis was used to identify DG locations, and an Invasive Weed Optimization (IWO) algorithm was employed for DG sizing. In [27], the authors proposed a multiple DG allocation technique that combines PSO with an improved analytical method. In [28], a new Hybrid Grey Wolf Optimizer (HGWO) was employed for the optimal allocation of various DG types, based on power injected from the DG units, with power loss minimization as the objective. The authors in [29] introduced a new metaheuristic optimization algorithm called the Stud Krill Herd Algorithm (SKHA) for ODG allocation in distribution networks.

Authors in [30] utilized the Locational Sensitivity Factor (LSF) to identify the optimal locations for combined DG units and CBs. They employed the BFOA to determine the sizing of DG units and OCBs. The authors in [31] introduced a GA to achieve the optimal allocation of combined DG units and CBs within distribution networks. In [32], an Intersect Mutation Differential Evolution (IMDE) algorithm was proposed for the simultaneous allocation of DG units and CBs, taking into account current flow while ensuring safe operating limits. Authors in [33] developed an Evolutionary Algorithm based on Decomposition (EA/D) to address the combined allocation of DG units and CBs as a multi-objective optimization problem. Their approach aimed to reduce power loss and maintain distribution system reliability.

In [34], the author introduced the Gbest-guided Artificial Bee Colony (GABC) algorithm to allocate DG units and CBs in distribution networks with varying load demands. The authors in [35] presented a Water Cycle Algorithm (WCA) for the simultaneous allocation of DG units and CBs within distribution networks. Their approach sought to achieve techno-economic and environmental benefits.

Many studies on the optimal placement of DG and CBs focus on theoretical models or ideal scenarios that do not always reflect the complexity of real-world grid operations. These models often overlook the variability in demand and generation, which can significantly impact the effectiveness of energy distribution strategies. Real grid systems are subject to daily load fluctuations influenced by various factors including time of day, weather conditions, and consumer behavior, making it critical to incorporate dynamic load analysis rather than relying solely on static peak load conditions. This approach ensures

that energy resources are optimized not just for efficiency but also for resilience, adapting to changes in load with minimal disruption. By using detailed hourly load profiles, planners can better understand and anticipate the effects of load changes on voltage stability and system reliability, enabling more accurate and effective placement of DG units and CBs (Table 1).

Table 1. Summary of various methods for optimal DG units and CBs allocation in distribution systems.

Author(s) [Ref]	Objective Function(s)	Method	Benefits	Benefit Years	Test System	Real System	Year	CB	PV	CB-PV
Ovidiu et al. [36]	Minimization of energy losses	Sperm-Whale Algorithm (SWA)	Technical	-	IEEE 33-bus system	215-bus EDN from Romania	2019	✓	✗	✗
Anes et al. [37]	Minimization of total annual cost	Equilibrium Optimizer (EO)	Economic	1 year	IEEE 33, IEEE 69	-	2021	✓	✗	✗
Arnab et al. [38]	Minimization of energy losses	SPEA Algorithm	Technical	-	IEEE 33, IEEE 69	-	2020	✗	✓	✗
Mansur et al. [39]	Minimizing the total power and energy losses	Salp Swarm Algorithm (SSA)	Technical	-	IEEE 69	-	2021	✗	✓	✗
Chandrasekaran et al. [40]	Minimizing active power losses, voltage deviation index (VDI), the total cost of electrical energy, and total emissions	a hybrid enhanced grey wolf optimizer and particle swarm optimization (EGWO-PSO)	Technical, Economic, and Envi- ronmental	1 year	IEEE 33, IEEE 69	-	2021	✓	✓	✓
Moradi et al. [41]	Reduction in power losses, cost-effectiveness of electrical energy and enhancement of voltage profile	multi-objective bezier search differential evolution algorithm (MOBSDEA)	Technical, Economic	1 year	IEEE 33, IEEE 69	-	2023	✓	✓	✗
This paper	Minimize the total energy cost over 24 years	the Energy Valley Optimizer (EVO)	Technical, Economic	24 years	-	ALG-AB- Hassi Sida 157-bus	-	✓	✓	✓

Despite the comprehensive exploration of various optimization strategies in the existing literature, many approaches primarily focus on theoretical models or ideal scenarios that do not reflect real-world grid operations. Specifically, these models often overlook the inherent variability in demand and generation, failing to account for the operational dynamics that significantly influence energy distribution strategies. For instance, methods like Particle Swarm Optimization (PSO) and Bacterial Foraging Optimization Algorithm (BFOA) offer robust performance in static scenarios but lack the adaptability required to handle dynamic load conditions. Moreover, traditional algorithms like the Genetic Algorithm (GA) and PSO can require significant parameter tuning, leading to suboptimal performance when managing fluctuations in grid loads.

The proposed Energy Valley Optimizer (EVO) is specifically designed to address these gaps by offering a more flexible and dynamic solution that adapts to the inherent variability of the power distribution network. By incorporating hourly load variations over a 24-h period and minimizing total energy costs across a 24-year lifespan, the EVO ensures accurate optimization of CB and DG placement. This approach accounts for the dynamic changes in load patterns and provides real-time adjustments that align with the system's operational needs, enhancing energy loss reduction and maintaining voltage stability. Thus, the EVO demonstrates superior adaptability, overcoming the limitations of previous methods and offering a practical, comprehensive solution for grid optimization.

This paper applies four recently developed metaheuristic optimization techniques—the Energy Valley Optimizer (EVO), Liver Cancer Algorithm (LCA), Zebra Optimization Algorithm (ZOA), and Walrus Optimization Algorithm (WaOA)—to determine the optimal locations and sizes for CBs and DG units, in particular PV systems, over a 24 h period, accounting for hourly load variations. The ALG-AB-Hassi Sida 157-bus radial distribution test system is used as the case study. A list of sensitive busses is generated and identified as the most suitable candidates based on their voltage profiles. Each algorithm is then applied to identify the optimal solution, considering the system's hourly load variations. The results obtained from these techniques are compared to determine their effectiveness. The main contributions of this paper include the following:

- Investigating the integration of DG units and CBs in the distribution network to enhance technical and economic benefits.
- Achieving technical objectives, which involve reducing energy losses, minimizing voltage deviation, and improving bus voltage stability.
- Addressing economic concerns over a period of 24 years and annually, this study sets three objectives: minimizing the total energy cost over 24 years through the use of (CBs), and a combined implementation of both CBs and DG, evaluated over each year of the 24-year cycle.
- Considering three operational scenarios: DG units only, CBs only, and the simultaneous allocation of DG units and CBs in the distribution network using the EVO.
- Applying the proposed EVO to a real distribution system.

This paper thus provides valuable insights into the optimal allocation of DG units and CBs, considering real-world load variations and multiple technical and economic objectives.

The remainder of this paper is structured as follows: Section 2 presents the mathematical problem formulation considering different constraint factors. Section 3 provides an overview of the proposed methods. The results of the simulation are presented and discussed in Section 4, followed by the conclusion in Section 5.

2. Problem Formulation

2.1. Objective Function

For load flow calculations, the backward/forward sweep method is used [42]. The objective aims to minimize the total energy cost annually over 24 years under three scenarios: the first scenario involves only capacitor banks (CBs), the second scenario includes only distributed generation (DG), and the third scenario combines both CBs and DG units. The objective function for this analysis is detailed in Equation (1):

$$\min \left\{ A + B + C = C_{\text{energy}} \cdot \left[\sum_{t \in T} \sum_{i \in nbr} Re \left| \left(I_{br_i}^t \right)^2 \times Z_i \right| \right] \cdot Tf \right. \\ \left. + C_{cb} \cdot \sum_{j \in ncb} Q_{cb_j} + C_{DG} \cdot \sum_{k \in nDG} P_{DG_k} \right\} \quad (1)$$

2.1.1. Minimizing the Total Energy Cost over 24 Years with Capacitor Banks (Obj1)

Obj1 minimizes the total energy cost over a 24-year period (USD/24 year) with CBs. C_{energy} is the average energy cost (in USD/kWh), T is the hours in a day (in h), nbr is the number of branches, $I_{br_i}^t$ is the current flowing through branch i at time t (in A), Z_i represents the impedance of branch i (in Ω), $Tf = 0.9 \cdot 8760 \cdot 24$ (Tf represents the total hours over a 24-year period, calculated as 0.9 (efficiency factor) multiplied by 8760 (hours in one year) multiplied by 24 (number of years)). The result is expressed in hours (h), C_{cb} is the CB capital cost (in USD/kVAR), ncb is the number of CBs, and Q_{cb_j} is the reactive power of the CB j (in kVAR). Thus, the total energy cost over 24 years with CBs (Obj1) is computed through terms A and B of Equation (1).

2.1.2. Minimizing Total Energy Cost over 24 Years with DG units (Obj2)

Obj2 minimizes the total cost over a 24-year period (USD/year) with DG. C_{DG} is the DG capital cost (in USD/kW), n_{DG} is the number of DG units, and P_{DG_k} is the active power of the DG k . Thus, the total energy cost over 24-year DG (Obj2) is computed through terms A and C of Equation (1).

2.1.3. Minimizing Total Energy Cost over 24 Years with CBs and DG units (Obj3)

In this case, the total energy cost over a 24-year period (Obj3) minimizes the combined cost of CBs and DG units, reflecting the expenses associated with both components over the course of 24 years. By minimizing Obj3, the goal is to identify the optimal allocation and utilization of CBs and DG units within the power network, balancing factors such as purchase costs, energy costs, and system constraints. Thus, the total energy cost over 24 years with CBs and DG units (Obj3) is computed through all the terms (A, B, and C) of Equation (1).

The choice of a 24-year period for evaluating the performance and cost-effectiveness of distributed generation (DG) units and capacitor banks (CBs) in our study is based on several key considerations:

- **Asset Lifespan:** The typical operational lifespan of DG units, particularly photovoltaic (PV) systems, and capacitor banks aligns closely with a 24-year timeframe. This duration allows us to assess the long-term benefits and depreciation impacts, providing a comprehensive view of the economic and technical performance over the asset's usable life.
- **Financial Analysis:** A 24-year period is commonly used in financial projections for infrastructure investments. It enables a detailed analysis of the payback period, return on investment (ROI), and net present value (NPV), which are critical for decision-making in energy sector investments. This timeframe also aligns with the standard practices for calculating lifecycle costs and benefits in utility-scale energy projects.
- **Policy and Regulatory Frameworks:** Many national and international energy policies and agreements span multiple decades. Analyzing the impacts over a 24-year period provides insights that are relevant to current policy cycles, including the achievement of long-term energy and environmental goals set by governments and international bodies.
- **Market Stability and Forecasting Accuracy:** Extending the analysis to 24 years helps in mitigating the short-term volatilities in energy prices, technological advancements, and policy changes, offering a more stable and reliable forecast that is beneficial for strategic planning.

These factors collectively justify the 24-year period as it encompasses the operational, financial, and policy-driven aspects of implementing DG units and CBs in distribution networks. This approach ensures that the results are both scientifically rigorous and practically applicable for stakeholders in the energy sector.

2.2. Equality and Inequality Constraints

Once objective functions have been defined, equality and inequality constraints have to be set up. It is necessary to first ensure that the actual power injection, both real (P_{DG_k}) and reactive (Q_{cb_j}), from DG units and CBs remains within the installed capacity $P_{DG_{k_{max}}}$ and $Q_{cb_{j_{max}}}$. The inequalities are expressed by (2) and (3):

$$0 < P_{DG_k} < P_{DG_{k_{max}}} \quad t \in T, k \in n_{DG} \quad (2)$$

$$0 < Q_{cb_j} < Q_{cb_{j_{max}}} \quad t \in T, j \in n_{cb} \quad (3)$$

In this paper, P_{DG_k} specifically refers to the power installed from PV systems into the grid, while Q_{cb_j} represents the reactive power injection from CBs into the grid.

Additionally, it is vital to ensure that the voltage at every bus and the current flowing through branches stay within acceptable limits, as specified in [43].

$$V_{m_min} < V_m^t < V_{m_max} \quad t \in T, m \in nB \quad (4)$$

$$I_{br_i}^t < I_{br_i_max} \quad t \in T, i \in nbr \quad (5)$$

Here, V_m^t represents the voltage at bus m at hour t , V_{m_min} and V_{m_max} represent the lower and upper voltage bus limits, selected as 10% for all the network busses, and $I_{br_i_max}$ is the thermal capacity limit of the branch. Moreover, as assumed in [44], a threshold for DG penetration is considered using the coefficient K_P , so that the DG units' installed capacity ($\sum_{k \in nDG} P_{DG_k}$) is equal to 50% of the total active power demand in the system P_{D_m} . This relationship is expressed by Equation (6):

$$\sum_{k \in nDG} P_{DG_k} = K_P \cdot \sum_{m \in nB} P_{D_m} \quad (6)$$

The inequality constraints (2) and (3) pertain to the control variables and are automatically managed through the EVO mechanism. However, additional attention is required to address the inequality constraints in Equations (4)–(6).

2.3. Modeling of PV Uncertainty

The solar energy irradiance for each day's hours could be modeled using the beta Probability Density Function (PDF) supported by historical data. For every hour, the PDF irradiance of solar may be defined by the following [45]:

$$f_b(s) = \begin{cases} \frac{\Gamma(A+B)}{\Gamma(A)\Gamma(B)} s^{(A-1)} & 0 \leq s \leq 1, A, B \geq 0 \\ 0 & \text{Otherwise} \end{cases} \quad (7)$$

where A and B can be calculated as in [46]:

$$\begin{aligned} B &= (1 - \mu) \left(\frac{\mu(1-\mu)}{\sigma^2} - 1 \right) \\ A &= \frac{\mu \cdot B}{1 - \mu} \end{aligned} \quad (8)$$

A and B are parameters used to define the shape of the beta PDF, which models the solar irradiance for each hour of the day based on historical data. These parameters are calculated based on the statistical properties of the data, specifically the mean (μ) and standard deviation (σ).

The solar irradiance state (s) probability for each specific hour could be defined as

$$P_s\{G\} = \int_{s_1}^{s_2} f_b(s) ds \quad (9)$$

The output power of the PV module may be expressed as [47]

$$P_{PV_o}(s) = N \cdot FF \cdot V_y \cdot I_y \quad (10)$$

where

- N represents the number of PV modules in the system;
- FF is the fill factor of the PV system;
- V_y represents the voltage generated by the PV system;
- I_y represents the current generated by the PV system.

The fill factor of the PV system:

$$FF = \frac{V_{MPP} \cdot I_{MPP}}{V_{oc} \cdot I_{Sc}} \quad (11)$$

where

- V_{MPP} and I_{MPP} represent the voltage and current at the maximum power point of the PV system.
- V_{oc} and I_{Sc} represent the open-circuit voltage and short-circuit current of the PV system.

The voltage generated by the PV system:

$$V_y = V_{oc} \cdot K_v \cdot T_{cy} \quad (12)$$

where

- V_{oc} represents the open-circuit voltage of the PV system.
- K_v is a coefficient representing the temperature dependence of the open-circuit voltage.
- T_{cy} represents the cell temperature.

The current generated by the PV system:

$$I_y = s [I_{sc} \cdot K_i \cdot (IT_{cy} - 25)] \quad (13)$$

where

- I_{sc} represents the short-circuit current of the PV system.
- K_i is a coefficient representing the temperature dependence of the short-circuit current.
- IT_{cy} represents the temperature of the PV system's cells.

The cell temperature of the PV system:

$$T_{cy} = T_A + s \left(\frac{N_{OT} - 20}{0.8} \right) \quad (14)$$

- T_A represents the ambient temperature.
- N_{OT} represents the total solar radiation received by the PV system.

The total Hybrid Renewable Energy Systems (HRESs) units' output power, based on the (PV) panel's irradiance characteristics and specification, refers to the combined electrical power generated by an integrated system that utilizes multiple renewable energy sources, one of which includes PV panels. This definition highlights the calculation of output power by taking into account the specific performance characteristics of PV panels under varying solar irradiance conditions.

$$P_{PV}(t) = \int_{s_1}^{s_2} P_{PV_0}(s) P_s \{G\} ds \quad (15)$$

Figure 1 shows the daily output power generated that is injected from the PV units.

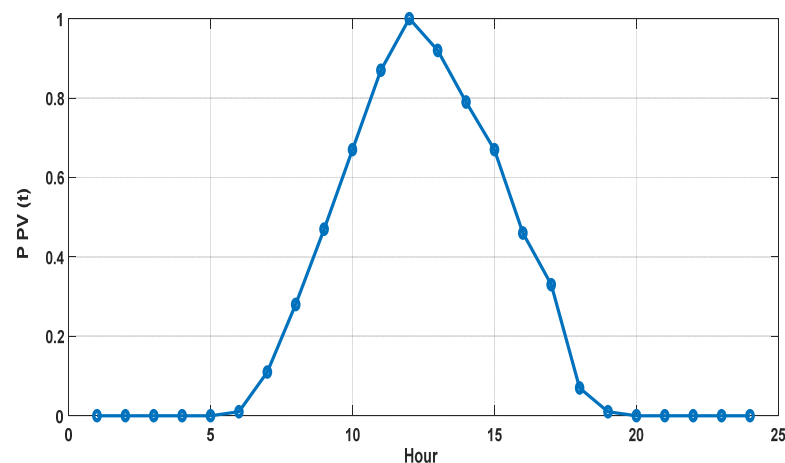


Figure 1. The daily variation of PV output power.

3. Model Mathematics of EVO

In this section, the Energy Valley Optimizer (EVO) algorithm is detailed, employing principles of physics for optimization [48]. The algorithm begins with an initialization process, treating solution candidates as particles in a specific part of the universe. The candidates' positions are determined within defined bounds using random numbers [0, 1].

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_p \\ \vdots \\ X_n \end{bmatrix} = \begin{bmatrix} x_1^1 x_1^2 \cdots x_1^m \cdots x_1^d \\ x_2^1 x_2^2 \cdots x_2^m \cdots x_2^d \\ \vdots \\ x_p^1 x_p^2 \cdots x_p^m \cdots x_p^d \\ \vdots \\ x_n^1 x_n^2 \cdots x_n^m \cdots x_n^d \end{bmatrix}, \begin{cases} p = 1, 2, \dots, n. \\ m = 1, 2, \dots, d. \end{cases} \quad (16)$$

$$x_p^m = x_{p,\min}^m + \text{rand} \cdot (x_{p,\max}^m - x_{p,\min}^m), \begin{cases} p = 1, 2, \dots, n. \\ m = 1, 2, \dots, d. \end{cases}$$

The second step calculates the Enrichment Bound (EB) based on neutron enrichment levels (NELs) of particles.

$$EB = \frac{\sum_{p=1}^n NEL_p}{n}, p = 1, 2, \dots, n \quad (17)$$

Stability levels are then determined, considering the best (BS) and worst (WS) stability levels in the universe.

$$SL_p = \frac{NEL_p - BS}{WS - BS}, p = 1, 2, \dots, n \quad (18)$$

The main search loop of EVO involves decisions based on neutron enrichment levels and stability bounds. If the NEL exceeds the EB, decay processes are considered. Alpha and gamma decay occur for particles with high stability levels, and new candidates are generated accordingly.

$$X_p^{\text{New1}} = X_p (X_{BS}(x_p^m)), \begin{cases} p = 1, 2, \dots, n. \\ m = \text{Alpha Index II.} \end{cases} \quad (19)$$

$$X_p^{\text{New2}} = X_p (X_{Ng}(x_p^m)), \begin{cases} p = 1, 2, \dots, n. \\ m = \text{GammaIndex II.} \end{cases} \quad (20)$$

For lower stability levels, beta decay is applied, causing particles to move towards the best stability level and the center of particles.

$$X_{CP} = \frac{\sum_{p=1}^n X_p}{n}, p = 1, 2, \dots, n. \quad (21)$$

$$X_p^{\text{New1}} = X_p + \frac{(r_1 \times X_{BS} - r_2 \times X_{CP})}{SL_p}, p = 1, 2, \dots, n.$$

Additionally, a controlled movement is conducted toward the best stability level and a neighboring particle for exploration.

$$X_p^{\text{New2}} = X_p + (r_3 \times X_{BS} - r_4 \times X_{Ng}), p = 1, 2, \dots, n. \quad (22)$$

If the NEL is below the EB, random movements are made to simulate electron capture or positron emission.

$$X_p^{\text{New}} = X_p + r, p = 1, 2, \dots, n. \quad (23)$$

At the end of each loop, newly generated vectors are merged with the current population. The algorithm utilizes boundary violation flags and a termination criterion based on the maximum number of evaluations or iterations.

This algorithm introduces three position updating processes in its main loop, balancing exploration and exploitation for improved candidate performance. The unique aspect lies in deriving inspiration from particle decay processes for optimization.

The EVO flowchart is illustrated in Figure 2

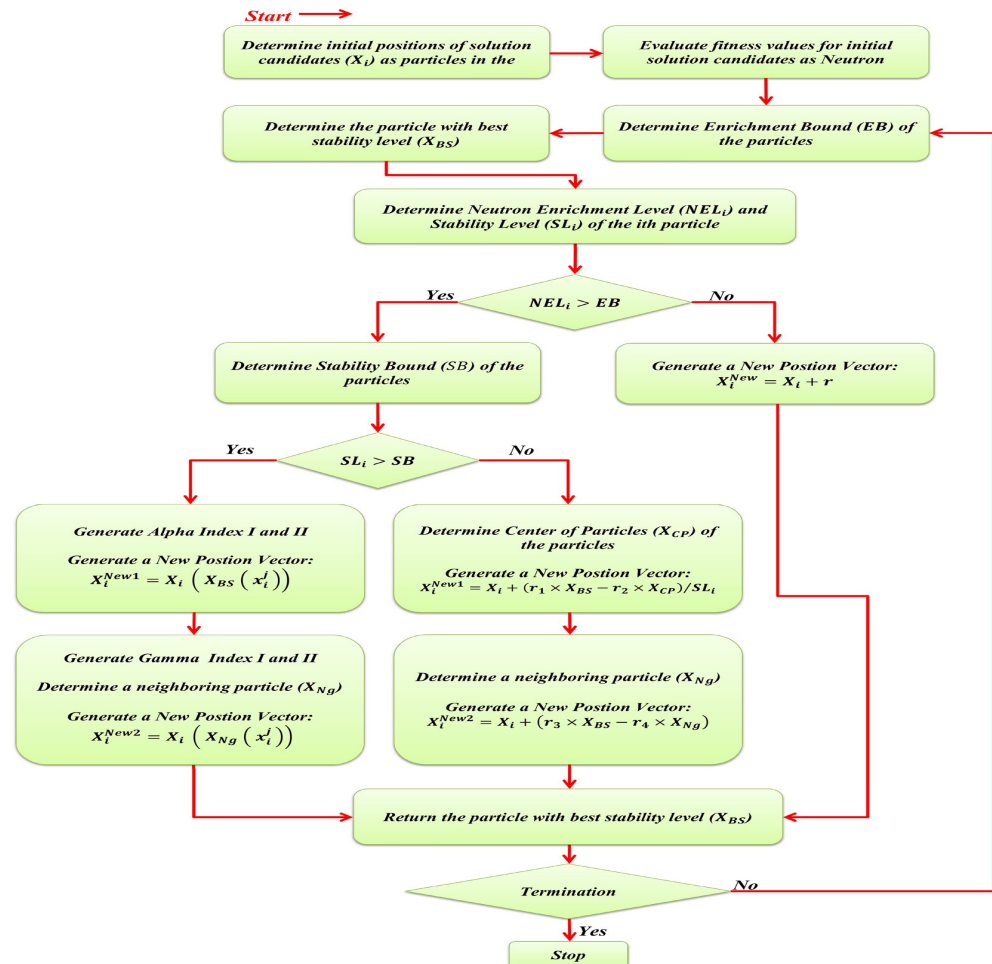


Figure 2. Flowchart of the EVO [48].

In applying the Energy Valley Optimizer (EVO) to our specific case of optimizing the distribution network through the strategic allocation of distributed generation (DG) and capacitor banks (CBs), we interpret the particles (X) in the EVO algorithm as distinct configurations of DG units and CBs within the network. Each particle or solution candidate represents a unique set of locations and sizes for these units, aiming to enhance network performance under our defined criteria, such as minimizing energy losses, improving voltage profiles, or reducing operational costs.

The position of a particle in the solution space is defined by a vector, X , where each component of X corresponds to a decision variable in our optimization problem. For DG units, these decision variables include the locations within the network where DG units could be installed and the capacity or size of each DG unit at those locations. Similarly, for CBs, the decision variables denote the placement locations of CBs and their respective reactive power capacities.

The optimization process involves iteratively adjusting these decision variables (i.e., the particles' positions) following the EVO algorithm's rules, which simulate physical processes such as particle decay, to explore the solution space efficiently. The aim is to find the optimal configuration of DG units and CBs that satisfies our objectives while adhering to the network's operational constraints, such as voltage limits and thermal loading capacities.

During the optimization, the fitness of each particle (X) is evaluated based on the objective function, which quantitatively measures the performance of a given configuration of DG units and CBs in the network. Constraints are enforced by penalizing configurations that violate network standards, thus guiding the search towards feasible solutions.

The parameters employed for each were consistently set to maintain a uniform testing environment. Each algorithm utilized a population size of 30 particles, which is critical for preserving a diverse search space. The convergence for all algorithms was governed by a maximum of 100 iterations, providing each with sufficient but bounded opportunities to converge toward an optimal solution. Specifically, each algorithm employed unique parameters tailored to enhance their respective search capabilities:

- The Energy Valley Optimizer (EVO) utilized adaptive mutation rates, designed to enhance exploration in the early phases of the search process and focus on exploitation in later phases to fine-tune solutions.
- The Liver Cancer Algorithm (LCA) featured both mutation and crossover rates, meticulously tuned to strike a balance between exploration and exploitation, ensuring a robust search across the solution landscape.
- The Walrus Optimization Algorithm (WaOA) adjusted exploration and exploitation rates to mimic the behavior of walrus herding, optimizing the search dynamics through this biological inspiration.
- The Zebra Optimization Algorithm (ZOA) incorporated Zebra Herd Dynamics, which influence the movement and decision-making patterns of the virtual herd within the search landscape, adding a unique dimension to the algorithm's strategy.

These tailored parameters are critical as they leverage the unique mechanisms of each algorithm to effectively search and optimize within the problem space. These settings are selected based on extensive preliminary trials and sensitivity analyses, which demonstrated that these configurations provide an optimal balance between solution quality and computational efficiency across different scenarios within the test system. This ensures that our comparisons between algorithms are fair and highlight the advantages of the EVO algorithm due to its innovative approach rather than disparities in parameter settings.

4. Simulation and Results

The proposed Energy Valley Optimizer (EVO) algorithm has been employed to minimize the total energy cost over a 24-year period for the ALG-AB-Hassi Sida 157-bus system. This approach accounts for variations in distributed generator and fixed capacitor bank outputs, as well as daily load fluctuations. It has been rigorously tested across three distinct scenarios:

- Scenario 1: The EVO is utilized for the allocation of 13 CBs, aiming to minimize the objective function (Obj1) as defined in Equation (1). This scenario is compared against other optimization methods, including the Liver Cancer Algorithm (LCA) [49], the Walrus Optimization Algorithm (WaOA) [50], and the Zebra Optimization Algorithm (ZOA) [51].
- Scenario 2: In this scenario, the EVO is applied for the optimal placement of 10 DG units, with the objective (Obj2) of reducing the total energy cost over a 24-year period as outlined in Equation (1). The results are compared with those obtained using the LCA, ZOA, and WaOA.
- Scenario 3: This scenario integrates the allocation strategies of the first two scenarios, utilizing the EVO to place 13 CBs and 10 DG units (Objective 3). Its goal is to reduce the total energy cost over a 24-year period, as specified in Equation (1), and benchmark its performance against the previously mentioned optimization techniques.

In each of these scenarios, the EVO algorithm is configured to run for 100 iterations with 30 search spaces. An important constraint set for the analysis is that the voltage at any node should not deviate by more than 10% from the nominal voltage.

The selection of 13 CBs and 10 DG units was influenced by a deep reservoir of experience and a methodical, data-driven analysis process. This configuration emerged as the most effective after extensive simulations and scenario testing, designed to strike an optimal balance between cost efficiency, system reliability, and performance under varying operational conditions. The analysis leveraged years of accumulated expertise in power distribution optimization, adopting a comprehensive approach that included evaluating system behavior under daily load fluctuations, the variability of DG outputs, and the strategic placement of CBs to ensure voltage stability across the network.

The ALG-AB-Hassi Sida 157-bus system, comprising 156 distribution sections and 157 nodes, is a comprehensive representation of a typical rural distribution network.

The technical specifications of branches and bus bars in the network are meticulously detailed in the referenced literature [52]. To provide a clear visual understanding, Figure 3 in this study illustrates the network diagram. Each scenario is depicted with a nominal voltage of 12.66 kV, showcasing the network's configuration and the specific placements of DG units and CBs as determined by the EVO algorithm.

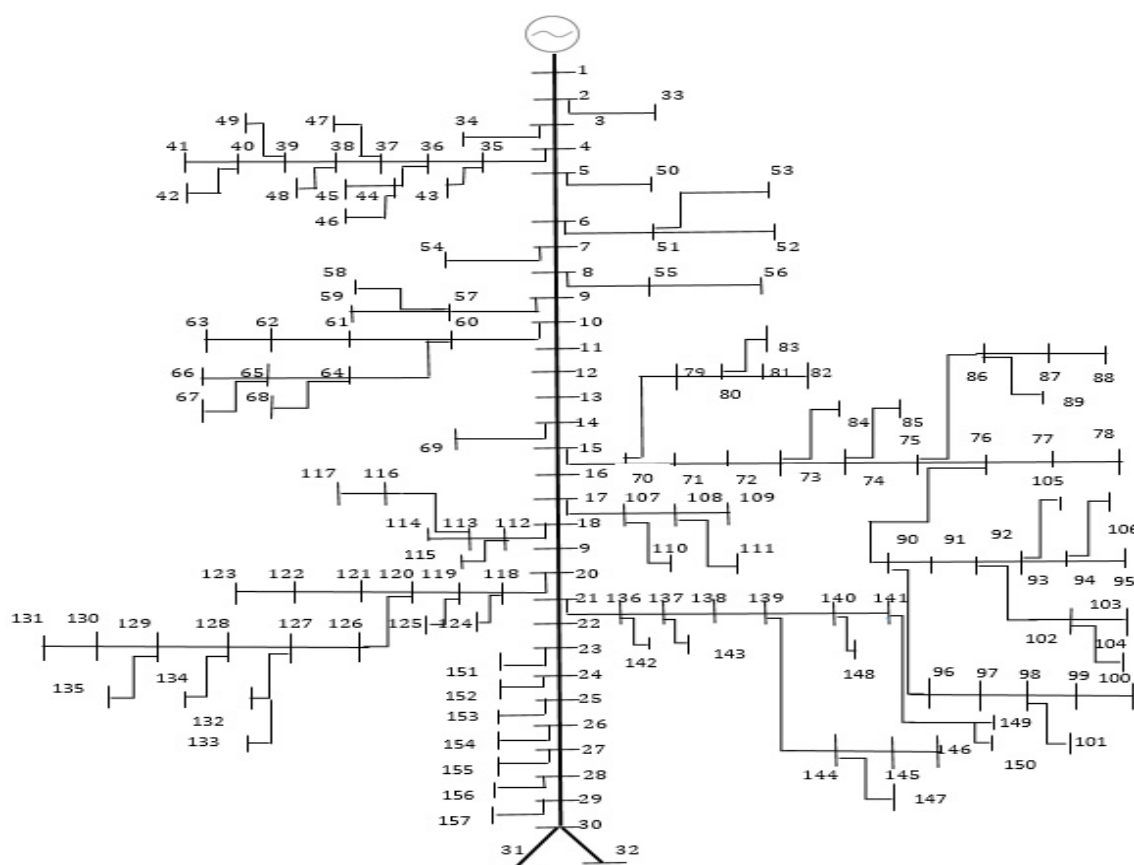


Figure 3. Configurations of the ALG-AB-Hassi Sida 157-bus distribution systems.

This study underscores the effectiveness of the EVO algorithm in optimizing the distribution network, highlighting its potential in enhancing both the technical and economic performance of power systems. The strategic selection of 13 CBs and 10 DG units, guided by the EVO algorithm, reflects our commitment to achieving the highest standards of efficiency and reliability in power distribution, backed by a profound base of expertise and rigorous analytical practices.

The 24-h load variation is illustrated in Figure 4. The voltage profiles of each hour are shown in Figure 5 with 24 different colors for 24 h to emphasize the differences between them as a result of the hourly load variation in the network.

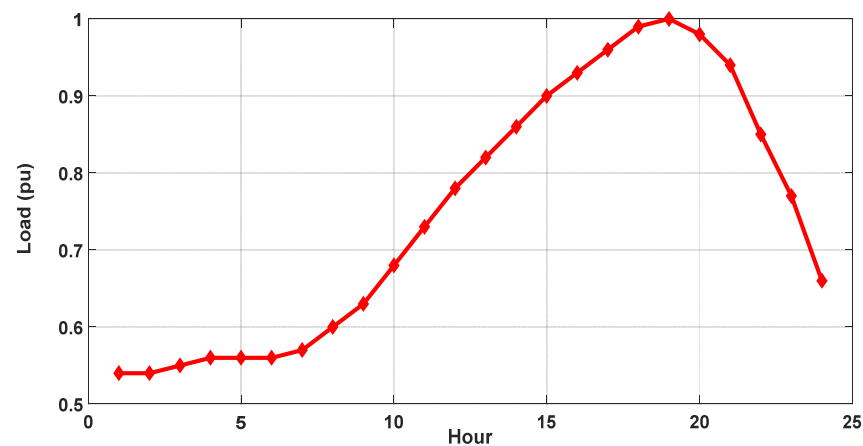


Figure 4. Annual daily average variations of for ALG-AB-Hassi Sida 157-bus network.

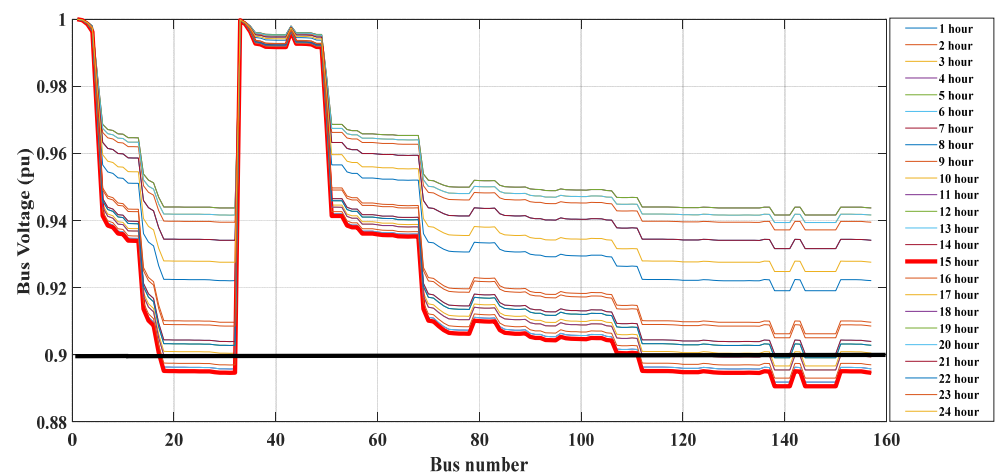


Figure 5. Hourly voltage profile over a 24 h period for the ALG-AB-Hassi Sida 157-bus network.

The ALG-AB-Hassi Sida 157-bus distribution network, chosen as the testing platform for the EVO algorithm, represents a particularly challenging case study due to its complex topology and significant load variability. This network is characterized by a high number of bus connections, which introduces intricate power flow dynamics and multiple potential points for voltage instability and power loss. Such complexity makes it an ideal candidate for testing advanced optimization algorithms like EVO. Additionally, the network's diverse load profiles, which include residential, commercial, and industrial demands, mimic real-world conditions that are crucial for assessing the practical applicability of optimization algorithms.

The ALG-AB-Hassi Sida network also features varied geographical and climatic conditions, impacting solar generation from photovoltaic systems and the efficiency of distributed generators, thereby providing a comprehensive environment to evaluate the adaptability and effectiveness of the EVO algorithm under dynamic and challenging operational scenarios.

4.1. Scenario 1

In Scenario 1, Table 2 from the ALG-AB-Hassi Sida 157-bus network offers a thorough comparative study on the optimal placements and sizes for CBs across a 24-year timeframe. Utilizing several advanced optimization techniques, including the LCA, WaOA, ZOA, and the EVO, this research conducts a strategic analysis that covers both technical and economic facets. The placement and sizing of the CBs, specified by particular bus locations and capacities, aim to enhance the network's operational efficacy. The evaluation takes into account a maximum capacitor size of 150 kVAR, within an energy cost parameter of

USD 0.06/kWh. This study highlights a strategic approach that balances operational performance with cost-effectiveness, demonstrating a total expenditure of USD 8.5123 million over two decades.

The EVO method proves to be particularly efficient, raising the minimum voltage to 0.902 p.u, equating to an impressive net saving of 22.08% through optimizations in 12 bus locations. This approach not only outperforms traditional methods but also exhibits the potential for significant operational and economic improvements via a comprehensive system optimization technique. The EVO's ability to consider various elements for holistic system improvement sets a new benchmark for efficiency and cost savings over time.

Moreover, Table 2 outlines the significant financial benefits brought by each optimization algorithm. The EVO strategy improves technical metrics, like voltage stability, and also delivers substantial economic benefits. For example, it decreases the energy loss costs to USD 6.5098 million over 24 years, signifying a noteworthy enhancement compared to the base case. An in-depth look at the costs linked to capacitors and overall expenses underlines the strategic importance of focused infrastructure investments for operational and fiscal efficiency.

Table 2. Comparison table for optimal locations and sizes of capacitor banks in ALG-AB-Hassi Sida 157-bus network.

Comparison Criteria	Base Case	Techniques							
		LCA		WaOA		ZOA		EVO	
		Bus of Cbs	Size of Cbs	Bus of Cbs	Size of Cbs	Bus of Cbs	Size of Cbs	Bus of Cbs	Size of Cbs
Optimal location and size of capacitors in kVAR	-			19	150			19	150
		19	100	28	150	19	100	28	150
		28	150	72	150	28	150	72	150
		72	150	78	150	72	100	78	150
		78	150	94	150	78	150	94	150
		101	150	101	150	94	100	101	150
		112	50	112	150	101	150	112	150
		142	150	129	150	112	100	129	150
		147	100	134	150	129	150	134	150
		156	150	142	150	134	100	147	150
				147	150	156	150	150	50
				156	150			156	150
Net injected (kVAR)	-	1150		1800		1250		1700	
Minimum voltage (pu)	0.89	0.8960		0.90		0.8984		0.9029	
Cost of energy loss (M USD/24 years)	8.512354	7.5181		6.5104		7.1637		6.5098	
Cost of energy loss (M USD/year)	0.354681	0.3132		0.2712		0.2984		0.2712	
Capital cost of CBs (M USD/kvar)	-	0.000003		0.000003		0.000003		0.000003	
Capacitors cost (M USD/24 years)	-	0.0828		0.1296		0.09		0.1224	
Capacitors cost (M USD/year)	-	0.003450		0.0054		0.003750		0.0051	
Total cost (M USD/24 years)	8.512354	7.6009		6.64		7.253		6.6322	
Total cost (M USD/year)	0.354681	0.3166		0.2766		0.3021		0.2763	
Net savings (M USD/24 years)	-	0.9114		1.8723		1.2593		1.88	
Net savings (M USD/year)	-	0.03808		0.0780		0.05258		0.07838	
Net savings (%) for 24 years	-	10.70		21.99		14.79		22.08	
Net savings (%) for 1 year	-	10.73		21.99		14.82		22.09	

This comparative research goes beyond simple numerical analysis to shed light on the strategic importance of applying sophisticated optimization methods within energy systems. It champions a nuanced approach that emphasizes technical optimization and fiscal acuity, setting the stage for sustainable, long-term progress in the industry.

Figures 6 and 7 complement the table's findings by illustrating the implications and effectiveness of these optimization techniques within the ALG-AB-Hassi Sida 157-bus networks.

Figure 6 provides a visual representation of the optimization algorithms' convergence characteristics, showcasing the superior performance of both the EVO and WaOA methods.

These methods demonstrate faster and more consistent convergence towards optimal capacitor positions and sizes, vividly demonstrating the EVO method's dominance in achieving rapid and reliable reductions in energy losses and total annual costs. Conversely, Figure 7 likely portrays the hourly voltage profile over a 24 h period, offering insights into the stability and efficiency improvements brought by the EVO method compared to other techniques. It illustrates the method's ability to maintain a higher and more stable voltage level, ensuring network reliability and performance.

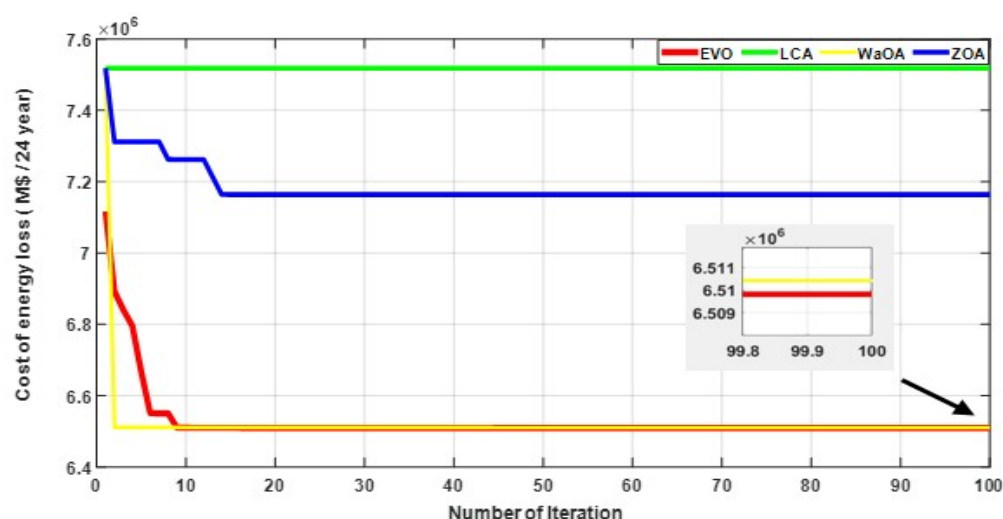


Figure 6. Convergence characteristics of the optimization algorithms for ALG-AB-Hassi Sida 157-bus network (Scenario 1).

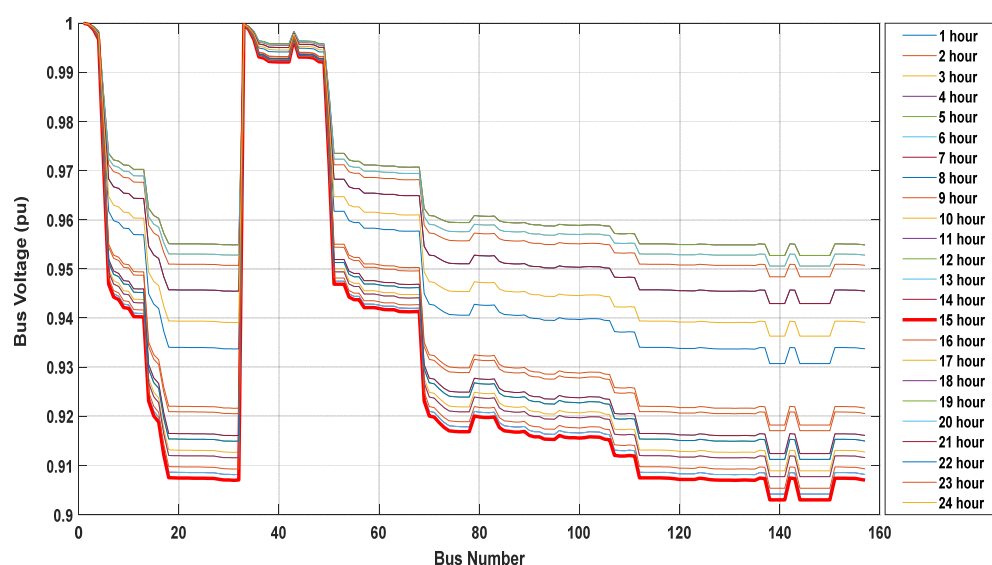


Figure 7. Hourly voltage profile for the first scenario over a 24-h period in the ALG-AB-Hassi Sida 157-bus network.

4.2. Scenario 2

In Scenario 2, Table 3 of the ALG-AB-Hassi Sida 157-bus network study provides an extensive comparison of the optimal locations and sizes for distributed generators (DG units) using a variety of optimization methods, including LCA, WaOA, ZOA, and EVO. This analysis highlights key operational parameters, with DG capacities set to a maximum of 750 kW and an energy cost of 0.06/kWh. The table details a significant total cost reduction over a 24-year period, demonstrating the substantial impact of these optimization strategies.

Table 3. Comparison table for optimal locations and sizes of distributed generation in ALG-AB-Hassi Sida 157-bus network.

Comparison Criteria	Base Case	Techniques							
		LCA		WaOA		ZOA		EVO	
		Bus of DG units	Size of DG units	Bus of DG units	Size of DG units	Bus of DG units	Size of DG units	Bus of DG units	Size of DG units
Optimal location and size of DG units in kW	-	17	750	2023	750	29	750	13	750
		22	750		750	64	750	23	750
		30	750		750	70	750	30	750
		32	750		750	79	750	70	750
		78	750		750	112	750	108	750
		115	750		750	113	750	113	750
		130	750		750	124	750	118	750
		137	750		750	125	750	121	750
		142	750		750	127	750	128	750
		151	750		750	136	750	151	750
Minimum voltage (pu)	0.89	0.933		0.93		0.933		0.934	
Cost of energy loss (M USD/24 years)	8.512354	2.4331		2.4242		2.4237		2.4232	
Cost of energy loss (M USD/year)	0.354681	0.1013		0.1010		0.1009		0.100	
Capital cost of DG units (M USD/kvar)	-	0.000005		0.000005		0.000005		0.000005	
DG units cost (M USD/24 years)	-	0.9		0.9		0.9		0.9	
DG units cost (M USD/year)	-	0.037500		0.037500		0.037500		0.037500	
Total cost (M USD/24 years)	8.512354	3.333		3.3242		3.3237		3.3232	
Total cost (M USD/year)	0.354681	0.1388		0.1385		0.1384		0.1375	
Net savings (M USD/4 years)	-	5.1793		5.1881		5.1886		5.1891	
Net savings (M USD/year)	-	0.21588		0.2161		0.2162		0.2171	
Net savings (%) for 24 years	-	60.84		60.94		60.95		60.95	
Net savings (%) for 1 year	-	60.86		60.92		60.97		61.23	

The EVO method stands out for its exceptional performance, achieving a remarkable increase in the minimum voltage level from 0.89 per unit (p.u) to 0.934 p.u. These results underscore the effectiveness of the EVO method in enhancing network efficiency and stability. It results in the lowest total cost over 24 years at USD 2.4232 million and the highest net savings percentage of 60.95%. The table indicates that each optimization technique recommends different optimal bus locations and sizes for DG units, with the EVO method identifying ten specific bus locations for deployment, showcasing a strategic and well-considered optimization approach.

Figures 8 and 9 further elucidate the data presented in Table 3 by offering visual insights into the performance and impact of the optimization techniques on the ALG-AB-Hassi Sida 157-bus network. Figure 8 demonstrates the exceptional convergence characteristics of the EVO method, identifying the optimal locations and sizes for DG units

swiftly and consistently, leading to the most substantial reduction in energy losses and total energy costs over 24 years. This visually emphasizes the method's superiority over others, which may show slower or less stable convergence paths. Meanwhile, Figure 9 presents the hourly voltage profile over a 24 h period, likely highlighting the improved voltage stability and reliability achieved through the EVO optimization. It provides a granular view of how voltage levels fluctuate throughout the day under various optimization methods, underlining the enhanced network performance facilitated by the EVO method. The incorporation of specific parameter values and financial metrics into the discussion ensures a comprehensive understanding of the economic and technical ramifications of DG placement within the distribution network, highlighting the nuanced balance between optimizing for efficiency and managing costs.

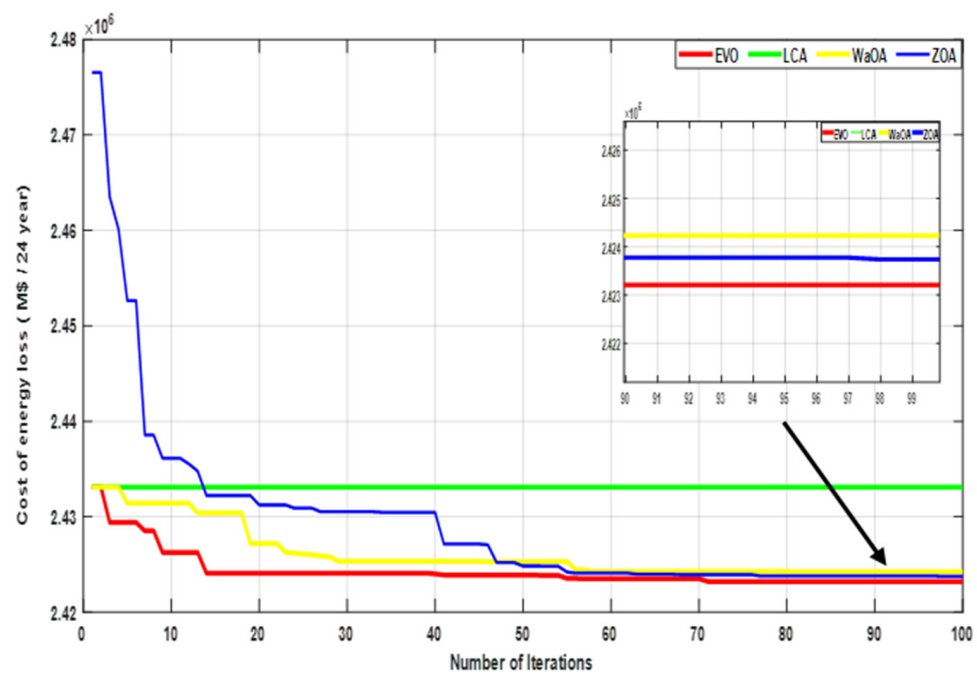


Figure 8. Convergence characteristics of the optimization algorithms for ALG-AB-Hassi Sida 157-bus network-(Scenario 2).

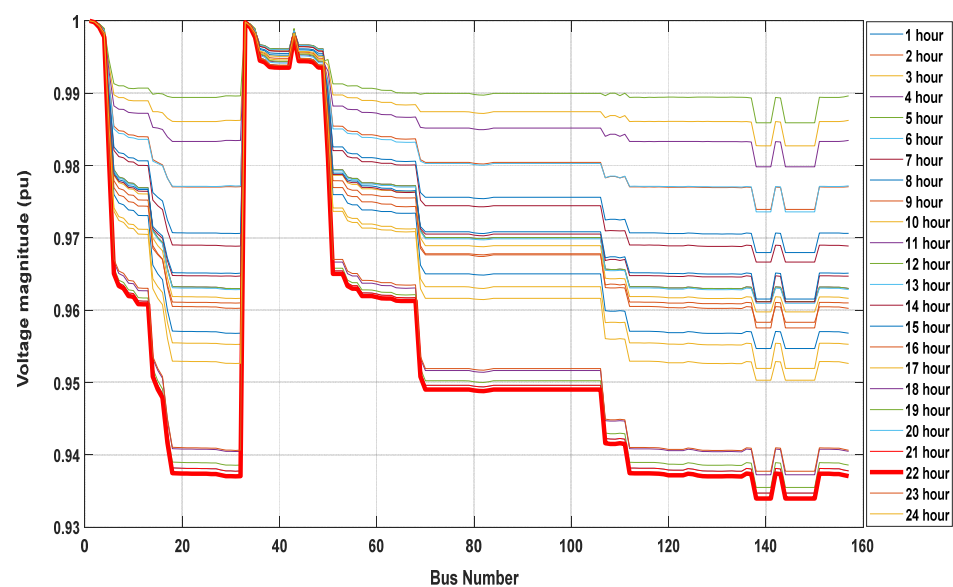


Figure 9. Hourly voltage profile for the second scenario over a 24-h period in the ALG-AB-Hassi Sida 157-bus network.

4.3. Scenario 3

In Scenario 3, Table 4 of the ALG-AB-Hassi Sida 157-bus network study offers a detailed examination of the optimal locations and sizes of DG units and CBs utilizing various optimization techniques, including the LCA, WaOA, ZOA, and the EVO. The table meticulously defines operational parameters, setting the maximum sizes for CBs at 150 kVAR and that for DG units at 750 kW, within an energy cost framework (C_{energy}) of USD 0.06/kWh. It also reveals the total energy cost over 24 years, recorded at USD 8.512354 million.

The EVO method emerges as a significant breakthrough, increasing the minimum voltage from 0.87 per unit (pu) to 0.94 pu. This impressive performance highlights EVO's unmatched efficiency in enhancing network efficiency and reliability, achieving the lowest total energy cost over 24 years at USD 1.9080 million and the highest net savings percentage of 65.53%. The table provides a specific enumeration of bus locations and sizes for DG units and CBs for each method, showcasing a tailored and strategic approach to optimization.

Figures 10 and 11 further augment the insights provided in Table 4 by offering a visual exploration of the optimization techniques' performance and their impact on the ALG-AB-Hassi Sida 157-bus network. Figure 10 showcases the exceptional convergence characteristics of the EVO method, rapidly and reliably pinpointing the optimal placements and capacities for both DG units and CBs. This effectively leads to the most substantial reduction in energy losses and total energy costs over 24 years, graphically highlighting the EVO method's dominance over alternative techniques, which may demonstrate slower or more erratic convergence trends. Meanwhile, Figure 11 presents the hourly voltage profile over a 24 h cycle, likely illustrating the improved voltage stability and reliability attained through EVO optimization. It offers an intricate depiction of how voltage levels fluctuate throughout the day under various optimization strategies, accentuating the superior network performance enabled by the EVO method. The inclusion of these specific parameter values and financial metrics ensures a thorough comprehension of the economic and technical implications of the combined deployment of DG units and CBs within the distribution network, showcasing a sophisticated balance between optimizing for efficiency and managing operational costs.

In our simulations, stability is a critical metric, especially given the stochastic nature of the algorithms like EVO, LCA, WaOA, and ZOA. To assess the stability and minimize the potential for random outcomes, we conducted multiple runs (30 trials) for each algorithm under identical conditions. The results are analyzed for variance and consistency to ensure that the conclusions drawn are based on not only optimal but also repeatable outcomes.

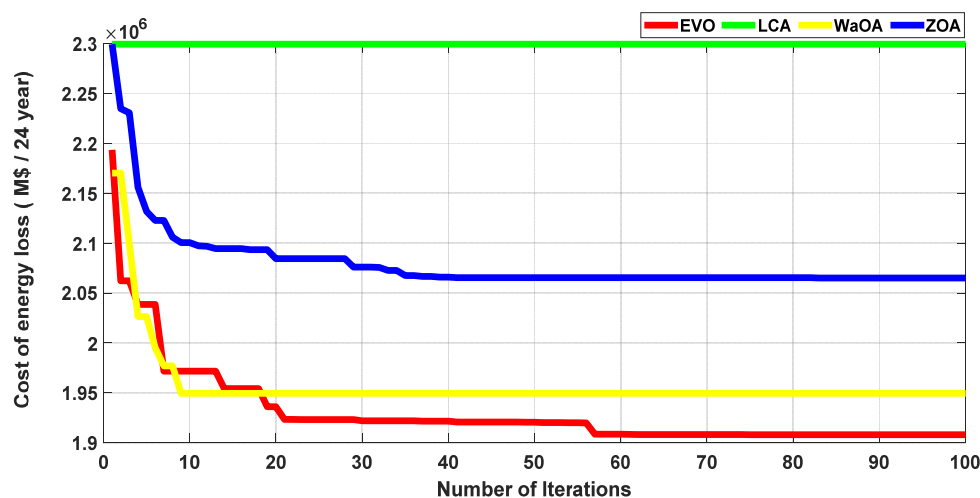


Figure 10. Convergence characteristics of the optimization algorithms for ALG-AB-Hassi Sida 157-bus network (Scenario 3).

Table 4. Comparison table for optimal locations and sizes of distributed generation and capacitor banks in ALG-AB-Hassi Sida 157-bus network.

Comparison Criteria	Base Case	Techniques															
		LCA				WaOA				ZOA				EVO			
		Bus of CBs	Size of CBs	Bus of DG units	Size of DG units	Bus of CBs	Size of CBs	Bus of DG units	Size of DG units	Bus of CBs	Size of CBs	Bus of DG units	Size of DG units	Bus of CBs	Size of CBs	Bus of DG units	Size of DG units
Optimal location and size of capacitors in kVAR and DG units in kW	-	19	50	11	750	19	150	12	750	19	100	55	750	19	150	57	750
		28	50	24	750	28	150	21	750	28	100	61	750	28	150	94	750
		78	100	65	750	78	100	57	750	72	150	72	750	94	150	110	750
		112	50	75	750	112	150	110	750	112	50	83	750	101	100	113	750
		134	50	91	750	129	100	112	750	129	150	112	750	112	150	125	750
		142	50	118	750	134	150	121	750	134	100	116	750	129	150	126	750
		142	150	119	750	142	150	128	750	142	100	118	750	134	150	130	750
		150	50	125	750	147	150	142	750	147	50	119	750	142	150	137	750
		156	50	151	750	150	150	147	750	150	50	122	750	147	150	142	750
				156	750	156	150	151	750	156	150	133	750	150	150	155	750
Net injected (kVAR)	-			550				1400				1000				1750	
Minimum voltage (pu)	0.89			0.9355				0.9393				0.9381				0.9399	
Cost of energy loss (M USD/24 years)	8.512354			2.2995				1.9495				2.0651				1.9080	
Cost of energy loss (M USD/year)	0.886703			0.09581				0.081				0.086				0.0795	
Capital cost of capacitors (M USD/kvar)	-			0.000003				0.000003				0.000003				0.000003	
Capacitor cost (M USD/24 years)	-			0.039600				0.100				0.072				0.126	
Capacitor cost (M USD/year)	-			0.001650				0.004200				0.003				0.005250	
Capital cost of DG units (M USD/kvar)	-			0.000005				0.000005				0.000005				0.000005	
DG unit cost (M USD/24 years)	-			0.9				0.9				0.9				0.9	
DG unit cost (M USD/year)	-			0.037500				0.037500				0.037500				0.037500	
Total cost (M USD/24 years)	8.512354			3.2391				2.9495				3.0371				2.934	
Total cost (M USD/year)	0.886703			0.13496				0.1229				0.1265				0.12225	
Net savings (M USD/24 years)	-			5.2732				5.5628				5.4752				5.5783	
Net savings (M USD/year)	-			0.7517				0.7640				0.7602				0.7644	
Net savings (%) for 24 years	-			61.94				65.35				64.32				65.53	
Net savings (%) for 1 year	-			84.77				86.16				85.73				86.20	

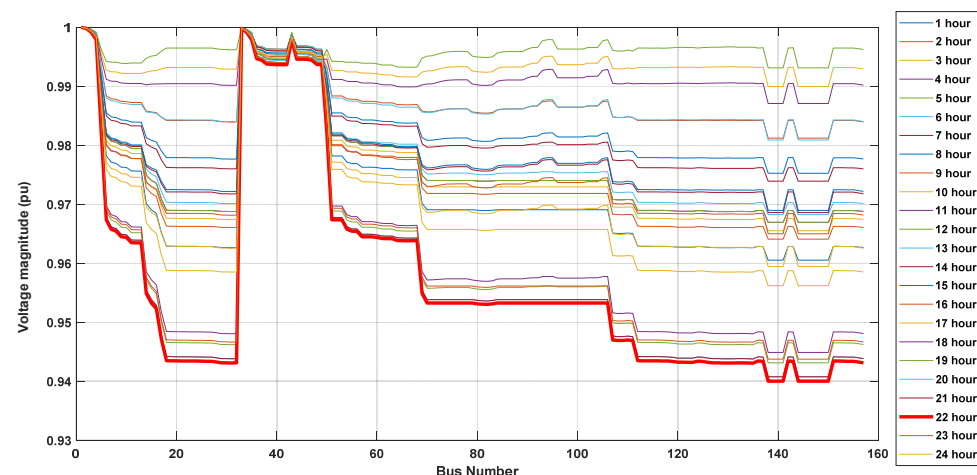


Figure 11. Hourly voltage profile for the third scenario over a 24-h period in the ALG-AB-Hassi Sida 157-bus network.

The Energy Valley Optimizer (EVO) demonstrated notable stability across trials, showing minimal variance in results, which indicates a low susceptibility to random fluctuations. This stability is attributed to its adaptive mutation mechanism that effectively balances exploration and exploitation, reducing the likelihood of becoming trapped in local optima or diverging into random solutions. Similarly, the other algorithms, LCA, WaOA, and ZOA, were evaluated for consistency in performance. While all algorithms showed acceptable levels of stability, some variations were observed, which are detailed in the analysis section.

Figure 12 in the ALG-AB-Hassi Sida 157-bus system study, encompassing scenarios 1 to 3, graphically presents the reduction in the net savings percentage (%) for each scenario. The figure clearly demonstrates a trend where increasing the number of DG units and CBs leads to greater reductions in net savings across all scenarios. For Scenario 1, the EVO technique shows the highest net savings percentage reduction, outperforming the LCA, WaOA, and ZOA techniques. Similarly, in Scenario 2, the EVO method continues to lead in performance with the highest percentages for net savings. This trend persists in Scenario 3, where the EVO method again outperforms other techniques, indicating its superior effectiveness in optimizing the network for cost savings. This visual representation from Figure 12 reinforces the EVO method's dominance and the beneficial impact of incorporating more DG units and CBs in the network.

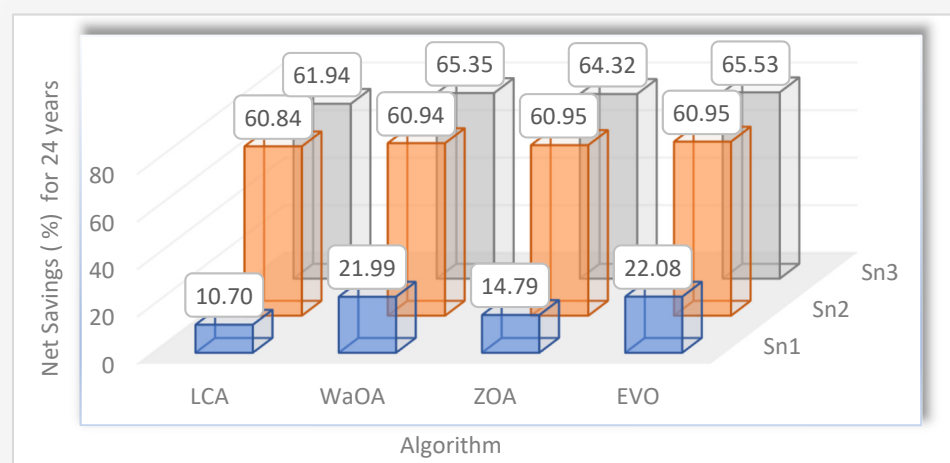


Figure 12. Net savings (%) for 24 years across Scenarios 1, 2, and 3 in ALG-AB-Hassi Sida 157-bus network.

In this paper, we delve into a comparative analysis of various optimization algorithms, including PSO, GA, BFOA, and the newly introduced EVO, among others, to underscore their respective advantages and innovative aspects within the context of distribution network optimization. PSO and GA are lauded for their simplicity and robustness but often fall short in handling complex, multi-modal landscapes due to premature convergence and a tendency to become trapped in local optima. In contrast, the BFOA provides an improved exploration capability by mimicking the foraging behavior of bacteria, which is beneficial in more diverse search spaces yet can be computationally intensive. The EVO algorithm, introduced in our study, marks a significant innovation by employing a unique mechanism to systematically explore energy valleys—regions in the search space that likely contain optimal solutions. This approach not only enhances the algorithm's ability to bypass local optima but also adapts more fluidly to the dynamic conditions typical of electrical distribution systems. Furthermore, the EVO's adaptive exploration and exploitation strategy minimize the need for parameter tuning, offering a more efficient solution process compared to other algorithms. Such features make the EVO particularly suited for optimizing the placement and sizing of DG units and CBs, where the operational landscape changes rapidly, and efficiency and adaptability are paramount.

5. Conclusions

The Energy Valley Optimizer (EVO) has emerged as a ground-breaking tool designed to optimize the placement of distributed generation (DG) units and capacitor banks (CBs) within electrical distribution networks. By focusing on both technical and economic efficiencies, the EVO has demonstrated significant potential in promoting sustainable energy practices. Tested on the ALG-AB-Hassi Sida 157-bus system within the Algerian distribution network, the EVO excelled under various operational scenarios and load patterns, showcasing its versatility and robustness.

Our comparative analysis shows that the EVO outperforms traditional optimization methods, achieving a 65.53% reduction in total energy costs over 24 years and enhancing accuracy and operational efficiency. This significant cost saving underscores the EVO's role in fostering economic sustainability alongside its environmental benefits, such as a 50% reduction in energy losses compared to conventional methods. The integrated strategy of simultaneously allocating DG units and CBs proved most effective, optimizing network efficiency and further reducing operational costs.

Looking ahead, there is a promising avenue for incorporating additional renewable energy sources, like fuel cells and battery storage, into the EVO framework. This integration will not only extend the EVO's applicability but also deepen its impact on sustainable development within power distribution systems. By improving the EVO's functionality with these technologies, future research can ensure more resilient, cost-effective, and environmentally friendly energy distribution solutions, making a significant contribution to the global pursuit of sustainable energy systems.

Author Contributions: Methodology, S.M.; Software, A.S.; Resources, S.M.; Writing—original draft, K.F.; Writing—review & editing, A.B. and R.S.; Visualization, A.S.; Supervision, T.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Acknowledgments: I would like to warmly thank Souhil MOUASSA from the Higher Polytechnic School of Linares University of Jaén at Spain and University of Bouira from Algeria for his invaluable discussions, guidance, and bright comments on research Gate and WhatsApp application.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Abou El-El, A.A.; El-Sehiemy, R.A.; Kinawy, A.M.; Mouwafi, M.T. Optimal capacitor placement in distribution systems for power loss reduction and voltage profile improvement. *IET Gener. Transm. Distrib.* **2016**, *10*, 1209–1221. [\[CrossRef\]](#)
2. Devabalaji, K.R.; Ravi, K.; Kothari, D.P. Optimal location and sizing of capacitor placement in radial distribution system using bacterial foraging optimization algorithm. *Int. J. Electr. Power Energy Syst.* **2015**, *71*, 383–390. [\[CrossRef\]](#)
3. Masoum, M.A.; Ladjevardi, M.; Jafarian, A.; Fuchs, E.F. Optimal placement, replacement and sizing of capacitor banks in distorted distribution networks by genetic algorithms. *IEEE Trans. Power Deliv.* **2004**, *19*, 1794–1801. [\[CrossRef\]](#)
4. Aman, M.M.; Jasmon, G.B.; Bakar, A.H.A.; Mokhlis, H.; Karimi, M. Optimum shunt capacitor placement in distribution system—A review and comparative study. *Renew. Sustain. Energy Rev.* **2014**, *30*, 429–439. [\[CrossRef\]](#)
5. Prakash, K.; Sydulu, M. Particle swarm optimization-based capacitor placement on radial distribution systems. In Proceedings of the Power Engineering Society General Meeting, Tampa, FL, USA, 24–28 June 2007; pp. 1–5.
6. Rao, R.S.; Narasimham, S.V.L.; Ramalingaraju, M. Optimal capacitor placement in a radial distribution system using plant growth simulation algorithm. *Int. J. Electr. Power Energy Syst.* **2011**, *33*, 1133–1139. [\[CrossRef\]](#)
7. Vuletić, J.; Todorovski, M. Optimal capacitor placement in radial distribution systems using clustering based optimization. *Int. J. Electr. Power Energy Syst.* **2014**, *62*, 229–236. [\[CrossRef\]](#)
8. Abul'Wafa, A.R. Optimal capacitor placement for enhancing voltage stability in distribution systems using analytical algorithm and Fuzzy-Real Coded GA. *Int. J. Electr. Power Energy Syst.* **2014**, *55*, 246–252. [\[CrossRef\]](#)
9. Fettah, K.; Talal, G.; Salhi, A.; Betka, A.; Saidi, A.; Teguvar, M.; Ali, E.; Bajaj, M.; Dost, M.; Shir, A.; et al. A pareto strategy based on multi-objective optimal integration of distributed generation and compensation devices regarding weather and load fluctuations. *Sci. Rep.* **2024**, *14*, 10423. [\[CrossRef\]](#) [\[PubMed\]](#)
10. Injeti, S.K.; Thunuguntla, V.K.; Shareef, M. Optimal allocation of capacitor banks in radial distribution systems for minimization of real power loss and maximization of network savings using bio-inspired optimization algorithms. *Int. J. Electr. Power Energy Syst.* **2015**, *69*, 441–455. [\[CrossRef\]](#)
11. Sultana, S.; Roy, P.K. Optimal Capacitor Placement in Radial Distribution Systems Using Teaching Learning-Based Optimization. *Int. J. Electr. Power Energy Syst.* **2014**, *54*, 387–398. [\[CrossRef\]](#)
12. Lee, C.S.; Ayala, H.V.H.; dos Santos Coelho, L. Capacitor Placement of Distribution Systems Using Particle Swarm Optimization Approaches. *Int. J. Electr. Power Energy Syst.* **2015**, *64*, 839–851. [\[CrossRef\]](#)
13. Shuaib, Y.M.; Kalavathi, M.S.; Rajan, C.C.A. Optimal Capacitor Placement in Radial Distribution System Using Gravitational Search Algorithm. *Int. J. Electr. Power Energy Syst.* **2015**, *64*, 384–397. [\[CrossRef\]](#)
14. Askarzadeh, A. Capacitor Placement in Distribution Systems for Power Loss Reduction and Voltage Improvement: A New Methodology. *IET Gener. Transm. Distrib.* **2016**, *10*, 3631–3638. [\[CrossRef\]](#)
15. Doostan, M.; Navaratnan, S.; Mohajeryami, S.; Cecchi, V. Concurrent Placement of Distributed Generation Resources and Capacitor Banks in Distribution Systems. In Proceedings of the 2016 North American Power Symposium (NAPS), Denver, CO, USA, 18–20 September 2016; pp. 1–6.
16. Injeti, S.; Kumar, S.; Kumar, N.P. Optimal Planning of Distributed Generation for Improved Voltage Stability and Loss Reduction. *Int. J. Comput. Appl.* **2011**, *15*, 40–46.
17. Moradi, M.H.; Abedini, M. A Combination of Genetic Algorithm and Particle Swarm Optimization for Optimal DG Location and Sizing in Distribution Systems. *Int. J. Electr. Power Energy Syst.* **2012**, *34*, 66–74. [\[CrossRef\]](#)
18. Rao, R.S.; Ravindra, K.; Satish, K.; Narasimham, S.V.L. Power Loss Minimization in Distribution System Using Network Reconfiguration in the Presence of Distributed Generation. *IEEE Trans. Power Syst.* **2013**, *28*, 317–325. [\[CrossRef\]](#)
19. Mahmoud Pesaran, H.A.; Zin, A.A.B.M.; Khairuddin, A.B.; Shariati, O. Optimal Sizing and Siting of Distributed Generators by Exhaustive Search. *Distrib. Gener. Altern. Energy J.* **2015**, *30*, 29–56.
20. Prabha, D.R.; Jayabarathi, T.; Umamageswari, R.; Saranya, S. Optimal Location and Sizing of Distributed Generation Unit Using Intelligent Water Drop Algorithm. *Sustain. Energy Technol. Assess.* **2015**, *11*, 106–113. [\[CrossRef\]](#)
21. Kowsalya, M. Optimal Size and Siting of Multiple Distributed Generators in Distribution System Using Bacterial Foraging Optimization. *Swarm Evol. Comput.* **2014**, *15*, 58–65.
22. Kefayat, M.; Ara, A.L.; Niaki, S.N. A Hybrid of Ant Colony Optimization and Artificial Bee Colony Algorithm for Probabilistic Optimal Placement and Sizing of Distributed Energy Resources. *Energy Convers. Manag.* **2015**, *92*, 149–161. [\[CrossRef\]](#)
23. Murty, V.V.S.N.; Kumar, A. Optimal Placement of DG in Radial Distribution Systems Based on New Voltage Stability Index Under Load Growth. *Int. J. Electr. Power Energy Syst.* **2015**, *69*, 246–256. [\[CrossRef\]](#)
24. El-Fergany, A. Optimal Allocation of Multi-Type Distributed Generators Using Backtracking Search Optimization Algorithm. *Int. J. Electr. Power Energy Syst.* **2015**, *64*, 1197–1205. [\[CrossRef\]](#)
25. Sudabattula, S.K.; Kowsalya, M. Optimal Allocation of Solar Based Distributed Generators in Distribution System Using Bat Algorithm. *Perspect. Sci.* **2016**, *8*, 270–272. [\[CrossRef\]](#)
26. Prabha, D.R.; Jayabarathi, T. Optimal Placement and Sizing of Multiple Distributed Generating Units in Distribution Networks by Invasive Weed Optimization Algorithm. *Ain Shams Eng. J.* **2016**, *7*, 683–694. [\[CrossRef\]](#)
27. Kansal, S.; Kumar, V.; Tyagi, B. Hybrid Approach for Optimal Placement of Multiple DGs of Multiple Types in Distribution Networks. *Int. J. Electr. Power Energy Syst.* **2016**, *75*, 226–235. [\[CrossRef\]](#)

28. Sanjay, R.; Jayabarathi, T.; Raghunathan, T.; Ramesh, V.; Mithulananthan, N. Optimal Allocation of Distributed Generation Using Hybrid Grey Wolf Optimizer. *IEEE Access* **2017**, *5*, 14807–14818. [\[CrossRef\]](#)
29. ChithraDevi, S.A.; Lakshminarasimman, L.; Balamurugan, R. Stud Krill Herd Algorithm for Multiple DG Placement and Sizing in a Radial Distribution System. *Eng. Sci. Technol. Int. J.* **2017**, *20*, 748–759. [\[CrossRef\]](#)
30. Kowsalya, M. Optimal Distributed Generation and Capacitor Placement in Power Distribution Networks for Power Loss Minimization. In Proceedings of the 2014 International Conference on Advances in Electrical Engineering (ICAEE), Vellore, India, 9–11 January 2014; pp. 1–6.
31. Saonerkar, A.K.; Bagde, B.Y. Optimized DG placement in radial distribution system with reconfiguration and capacitor placement using genetic algorithm. In Proceedings of the 2014 International Conference on Advanced Communication Control and Computing Technologies (ICACCCT), Ramanathapuram, India, 8–10 May 2014; pp. 1077–1083.
32. Khodabakhshian, A.; Andishgar, M.H. Simultaneous placement and sizing of DGs and shunt capacitors in distribution systems by using IMDE algorithm. *Int. J. Electr. Power Energy Syst.* **2016**, *82*, 599–607. [\[CrossRef\]](#)
33. Biswas, P.P.; Mallipeddi, R.; Suganthan, P.N.; Amaratunga, G.A. A multiobjective approach for optimal placement and sizing of distributed generators and capacitors in distribution network. *Appl. Soft Comput.* **2017**, *60*, 268–280. [\[CrossRef\]](#)
34. Dixit, M.; Kundu, P.; Jariwala, H.R. Incorporation of distributed generation and shunt capacitor in radial distribution system for techno-economic benefits. *Eng. Sci. Technol. Int. J.* **2017**, *20*, 482–493. [\[CrossRef\]](#)
35. El-Ela, A.A.A.; El-Sehiemy, R.A.; Abbas, A.S. Optimal Placement and Sizing of Distributed Generation and Capacitor Banks in Distribution Systems Using Water Cycle Algorithm. *IEEE Syst. J.* **2018**, *1*, 1–8. [\[CrossRef\]](#)
36. Ivanov, O.; Neagu, B.; Grigoras, G.; Gavrilas, M. Optimal Capacitor Bank Allocation in Electricity Distribution Networks Using Metaheuristic Algorithms. *Energies* **2018**, *12*, 4239. [\[CrossRef\]](#)
37. Bouhanik, A.; Salhi, A.; Naimi, D. Optimal Capacitor Allocation Based On Hourly Load Variation Via New Optimization Algorithms. In Proceedings of the 2022 19th International Multi-Conference on Systems, Signals & Devices (SSD), Sétif, Algeria, 6–10 May 2022; pp. 2035–2040. [\[CrossRef\]](#)
38. Arnab Pal, Ajoy Kumar Chakraborty, and Arup Ratan Bhowmik, Optimal placement and sizing of DG considering power and energy loss minimization in distribution system. *Int. J. Electr. Eng. Inform.* **2020**, *12*, 624–653. [\[CrossRef\]](#)
39. Hasanov, M.; Suyarov, A.; Urinboy, J.; Boliev, A. Optimal Integration of Photovoltaic Based DG Units in Distribution Network Considering Uncertainties. *Int. J. Acad. Appl. Res. (IJAAR)* **2021**, *5*, 195–198, ISSN: 2643-9603. Available online: <https://ssrn.com/abstract=3837826> (accessed on 14 April 2024).
40. Venkatesan, C.; Kannadasan, R.; Alsharif, M.H.; Kim, M.-K.; Nebhen, J. A Novel Multiobjective Hybrid Technique for Siting and Sizing of Distributed Generation and Capacitor Banks in Radial Distribution Systems. *Sustainability* **2021**, *13*, 3308. [\[CrossRef\]](#)
41. Moradi, M.; Najafi, M.; Kakavand, A.; Falehi, A.D. MOBSDEA-Based Optimal Sizing and Siting of Renewable Energy-based Distributed Generation Units to reduce: Power losses, Electrical Energy Cost and Voltage Profile deviation. *Environ. Eng. Manag. J. (EEMJ)* **2023**, *22*, 1913.
42. Parmar, P.; Patel, C. *Optimal Placement of Capacitor Using backward forward Sweep Method*; Springer Nature Singapore Pte Ltd.: Singapore, 2018; pp. 255–262.
43. Rekioua, D.; Matagne, E. Modeling of Solar Irradiance and Cells. In *Optimization of Photovoltaic Power Systems, Green Energy and Technology*; Springer: London, UK, 2012.
44. Nasef, A.; Shaheen, A.; Khattab, H. Local and remote control of automatic voltage regulators in distribution networks with different variations and uncertainties: Practical cases study. *Electr. Power Syst. Res.* **2022**, *205*, 107773. [\[CrossRef\]](#)
45. Maya, N.K.; Jasmin, E.A. Optimal integration of distributed generation (DG) resources in unbalanced distribution system considering uncertainty modelling. *Int. Trans. Electr. Energy Syst.* **2017**, *27*, e2248.
46. Hung, D.Q.; Mithulananthan, N.; Lee, K.Y. Determining PV penetration for distribution systems with time varying load models. *IEEE Trans. Power Syst.* **2014**, *29*, 3048–3057. [\[CrossRef\]](#)
47. Soroudi, A.; Aien, M.; Ehsan, M. A probabilistic modelling of photo voltaic modules and wind power generation impact on distribution networks. *IEEE Syst. J.* **2012**, *6*, 254–259. [\[CrossRef\]](#)
48. Azizi, M.; Aickelin, U.; AKhorshidi, H.; Baghalzadeh Shishehgharkhaneh, M. Energy valley optimizer: A novel metaheuristic algorithm for global and engineering optimization. *Sci. Rep.* **2023**, *13*, 226. [\[CrossRef\]](#) [\[PubMed\]](#)
49. Houssein, E.H.; Oliva, D.; Samee, N.A.; Mahmoud, N.F.; Emam, M.M. Liver Cancer Algorithm: A novel bio-inspired optimizer. *Comput. Biol. Med.* **2023**, *165*, 107389. [\[CrossRef\]](#) [\[PubMed\]](#)
50. Trojovský, P.; Dehghani, M. Walrus Optimization Algorithm: A New Bio-Inspired Metaheuristic Algorithm. *Res. Sq.* **2022**, preprint. [\[CrossRef\]](#)
51. Trojovská, E.; Dehghani, M.; Trojovský, P. Zebra Optimization Algorithm: A New Bio-Inspired Optimization Algorithm for Solving Optimization Algorithm. *IEEE Access* **2022**, *10*, 49445–49473. [\[CrossRef\]](#)
52. Algerian National Electricity Company “Sonelgaz”. Available online: www.sonelgaz-distribution.dz (accessed on 14 April 2024).

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.