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Journal of Advances in Science, Engineering and Technology

Optimal Placement and Sizing of Battery Energy Storage System for Loss Reduction in A Power Distribution System Using Chaotic Coyote Optimization Algorithm

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ABSTRACT

The growing global electricity demand and increasing integration of renewable energy have intensified the need for efficient and resilient power distribution systems. Power losses in distribution networks remain a persistent challenge, increasing operational costs and reducing efficiency. This study investigates the optimal placement and sizing of battery energy storage systems to minimize losses in a 148-bus distribution network. A Chaotic Coyote Optimization Algorithm is proposed, which enhances the conventional Coyote Optimization Algorithm by incorporating chaotic maps to improve exploration, prevent local optima trapping, and accelerate convergence. Two scenarios were evaluated: (i) a grid-connected system and (ii) a grid-connected system with solar photovoltaic integration. For each scenario, single-unit and dual-unit battery energy storage configurations were tested using simultaneous and sequential optimization strategies. The Chaotic Coyote Optimization Algorithm consistently outperformed the Coyote Optimization Algorithm, Whale Optimization Algorithm, and Particle Swarm Optimization, achieving faster convergence and greater solution accuracy. Results showed that dual-unit battery energy storage configurations significantly reduced losses compared to single-unit setups, with the best case (dual-unit plus solar photovoltaic integration) achieving a 51.4 percent reduction in active power losses and an improvement in minimum bus voltage from 0.927 per unit to 0.975 per unit. The study demonstrates that combining battery energy storage with renewable integration not only reduces distribution losses but also enhances voltage stability. The proposed Chaotic Coyote Optimization Algorithm framework provides a robust methodology for energy storage optimization, offering valuable insights for utilities in planning sustainable, cost-effective, and resilient smart grids.

ARTICLE INFO

Keywords:
Battery Energy Storage System,
Power Loss Reduction,
Chaotic Coyote Optimization Algorithm,
Optimal Placement and Sizing,
Renewable Energy Integration.

Article History:
Received 5 May 2025
Received in revised form 3 October 2025
Accepted 6 October 2025
Available online 11 October 2025

1. Introduction

The global electricity demand has been on an inclining trend with a growth rate of 2.4% annually and a projected rise to over 50% by 2050 (IEA, 2023; Mir et al., 2020). Despite increased global generation capacity due to the upscale of renewable energy to more than 440 GW (IEA, 2023), energy transfer from the generation side to the demand side remains a challenge in power networks due to power losses (Sadovskaia et al., 2019). Studies have reported that about 10% of power losses occur in transmission and distribution networks, with over 40% of the total power losses occurring in the distribution networks accounting for a total loss of 4% to 37% of the total generated energy (Al-Mahroqi et al., 2012; Tushar et al., 2020; Wu et al., 2022; Yang et al., 2020). Therefore, power loss reduction is imperative in energy utilization and economic development.

Power loss consists of two parts, i.e., technical electrical power losses (Sadovskaia et al., 2019) and commercial (non-technical) power losses (Carr & Thomson, 2022). The former is composed of variable loss and fixed loss in power systems, while the latter is caused by transgressions in energy management, theft, and statistical errors (Wu et al., 2022). This study will consider the technical power losses. Variable technical

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Editor: Victor Odari, Masinde Muliro University of Science and Technology, Kenya.

Citation: Lagat P., Okinda C., & Owuor J. (2025). Optimal Placement and Sizing of Battery Energy Storage System for Loss Reduction in A Power Distribution System Using Chaotic Coyote Optimization Algorithm. Journal of Advances in Science, Engineering and Technology 2(1), 9 – 25.

power loss is proportional to the square of the load current and accounts for $\frac{3}{4}$ to $\frac{2}{3}$ of the total technical losses in a distribution network (Abd el-Ghany et al., 2021), while the fixed technical power loss accounts for 1/4 to 1/3 of the total technical losses in a distribution network (Electrical Equipment, 2023; Gasperic, 2011). The factor of power loss introduces complexities in power system design in matching generation and demand, and the transmission of power losses from generators to loads via networks and transformers, thus resulting in higher electricity costs. Additionally, the annual costs for power losses consist of generation, transmission, and distribution (Abeysinghe et al., 2020; Sadovskaia et al., 2019). Thus, power loss has a negative impact on the whole power system network, and consequently on the whole community. Distribution losses not only reduce the overall efficiency of the system but also result in increased operational costs for utility providers (Wang et al., 2018). Therefore, mitigating distribution losses is essential to improving the overall performance of power distribution systems.

Various conventional techniques have been employed to reduce distribution losses, i.e., network reconfiguration, voltage regulation, and capacitor placement (Agüero, 2012). Additionally, several studies have reported on the solutions to power loss reduction in power distribution networks such as feeder reconfiguration (Abdelaziz et al., 2016; Hesaroor & Das, 2019; Li et al., 2019; Shaheen et al., 2021; Wu et al., 2010; Xie et al., 2021), VAR compensation (Rajičić & Todorovski, 2020; Shaheen et al., 2021; D. Zhang et al., 2008), distributed generation (DG) (Hesaroor & Das, 2019; Ilo et al., 2003; Ufa et al., 2022), and smart metering (Ilo et al., 2003; Mbungu et al., 2020).

However, studies have reported on the shortcomings of these techniques. Feeder reconfiguration suffers from high complexity and cost (Al-Mahroqi et al., 2012; Civanlar et al., 1988; Kashem et al., 2000), disruptions of operations (Anteneh et al., 2021; Jose & Kowli, 2019; Tian et al., 2016), limited applicability (Al-Mahroqi et al., 2012; Kavousi-Fard & Niknam, 2013; Sultana et al., 2016), unsustained effectiveness due to the dynamic nature of loads (Azizivahed et al., 2018, 2019; Lotfi & Shojaei, 2023), and dependency on advanced control systems (Al-Mahroqi et al., 2012; Zhang et al., 2021). Despite VAR compensation and capacitor placement being valuable techniques in loss reduction and voltage control in distribution networks, their applicability is limited by several setbacks, i.e., Capital Intensive (Machowski et al., 2020), complexities in Maintenance (Bansal, 2005; Kothari, 2012), inflexibility to adapt to dynamic load variation (Chakrabarti & Halder, 2022), overcompensation problems (Das, 2002; Liu et al., 2014), and introduction of switching transients into the system (Bisquert, 2023; Jami et al., 2020). Injecting a small amount of DG reduces the power losses to a minimum level (threshold) after which an increase in DG increases the losses in the network (Al-Mahroqi et al., 2012). Therefore, optimal placement and sizing of DG in the distribution network is still a challenge in optimal loss reduction based on DG technology. Additionally, with the current high penetration of renewable energies characterized by high intermittency, the problem of loss reduction in distribution networks has become complex due to frequency fluctuations and voltage quality problems, thus increasing energy losses in the distribution networks (Wu et al., 2022). A report by Adefarati & Bansal (2016) stated that proper sizing and location of renewable units can reduce feeder overload and power losses. Similarly, Marneni et al. (2015) reported that the optimal placement and sizing of DG in the distribution network improves voltage profile, reduces system power losses, improves power quality, relieves power grid congestion, and reduces the associated costs.

Battery Energy Storage Systems (BESS) have emerged as a promising solution for mitigating distribution losses and enhancing grid reliability (Prakash et al., 2022). BESS offers several advantages, including fast response times, flexibility in operation, and compatibility with renewable energy sources (Datta et al., 2021). Therefore, by strategically deploying BESS within distribution networks, utilities can optimize energy flow, reduce peak demand, and improve voltage stability (Kumar et al., 2019). Additionally, BESS can provide ancillary services such as frequency regulation, voltage support, and backup power during outages (Rancilio et al., 2020). Furthermore, BESS can mitigate the effects caused by the intermittency of renewable energy (Dowling et al., 2020; Wong, Ramachandaramurthy, Taylor, et al., 2019). Moreover, they can improve and compensate for the stability and flexibility of the power system during generation loss, load fluctuations, and transmission loss (De Sisternes et al., 2016; Wong, Ramachandaramurthy, Taylor, et al., 2019). Therefore, power loss in a network can be efficiently reduced by the application of BESS to balance the power exchange (Wong, Ramachandaramurthy, Walker, et al., 2019). However, the efficiency of loss reduction is influenced by the size and location of the BESS (Rajamand, 2020; Wong, Ramachandaramurthy, Walker, et al., 2019).

The determination of the optimal location and sizing of BESS is a complex non-deterministic polynomial-time problem (Wong, Ramachandaramurthy, Walker, et al., 2019) whose solution is affected by power network requirements, total load demand, network topology, total generation capacity, and the applied BESS technology (Wong, Ramachandaramurthy, Taylor, et al., 2019; Wong, Ramachandaramurthy, Walker, et al., 2019; Yuan et al., 2020). Several studies have applied different techniques to determine the optimal sizes and locations of BESS in power distribution networks for loss reduction. Giannitrapani et al. (2016) developed a clustering technique for the optimal placement and sizing of BESS in a radial electricity network. The study established that the optimal location of the BESS units was on a critical bus. Zhao et al. (2015) introduced a long-term Wind Power Time series technique to optimally locate and determine the capacity of BESS based on the charging and discharging cycles of the BESS. A cost-based approach was presented by Carpinelli et al. (2013) to determine the optimal location and sizing of BESS in an unbalanced low-voltage microgrid. The minimal and maximal loss-sensitive factors (LSF) value was adopted by Sardi et al. (2015) for optimal location selection for BESS. Algorithms such as the Particle Swarm Optimization (PSO) algorithm (Chen et al., 2019; Jin et al., 2020; Rajamand, 2020; Shi & Luo, 2017; Zhu et al., 2018), the genetic algorithm (GA) (Ghofrani et al., 2013; Khaki & Das, 2019), firefly algorithm (FA) (Ai et al., 2014; Wong et al., 2014), bee colony algorithm (Das et al., 2018), bat algorithm (Bahmani-Firouzi & Azizipanah-Abarghooee, 2014), Whale optimization algorithm (WAO) (Wong, Ramachandaramurthy, Walker, et al., 2019), Coyote Optimization Algorithm (COA) (Yuan et al., 2020) have been applied in loss management and to and enhance system performance. However, most of these algorithms suffer from a slow convergence rate due to getting trapped in the local minimum (Jordehi, 2015; Wong, Ramachandaramurthy, Walker, et al., 2019; Yuan et al., 2020). Therefore, there is a need to improve these optimization algorithms with the ability to balance between exploitation and exploration of the meta-heuristics (Cao et al., 2019). The main objective of this research study is to determine the optimal placement and sizing of BESS to reduce the power losses in a distribution network based on the chaotic coyote optimization algorithm (CCOA) in a 148-bus distribution network with a nominal voltage of 11 kV.

2. Materials and methods

This study focuses on the optimal placement and sizing of a BESS in a power distribution network to minimize power losses based on CCOA. For a comparative analysis, two scenarios were explored, i.e., firstly, a grid-connected distribution system (S_G) and secondly, a grid-connected distribution system with a solar photovoltaic (PV) system (S_{PV}). For each scenario, a single BESS (S_{GB1} and S_{PVB1}) and two BESS (S_{GB2} and S_{PVB2}) were implemented for further comparative analysis. Therefore, six simulations (models) were developed. Fig. 1 presents the research design flow for this introduced study.

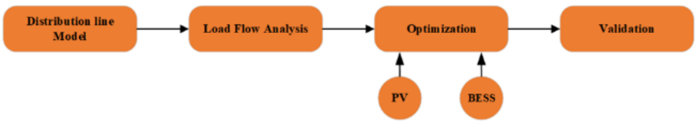

Fig. 1: The research design flow

2.1. Data collection and system modeling

For this study, the Kisumu-Ahero distribution line served as the study area, and the following comprehensive data were collected from the line between the period of September 2024 and December 2024.

Transmission Line Impedance and Configuration: Detailed impedance data for each line section were obtained to model power flow accurately. This data was essential for calculating voltage drops and power losses across the network.

Lamped Load Demand: Real and reactive power demands at each bus were recorded. Accurate load data ensures realistic simulation outcomes and optimizes BESS performance where demand variability is highest (Zhang et al., 2023).

Transformer and Bus Details: All transformer ratings and bus voltage level specifications were collected to reflect real-world conditions (Džafić et al., 2014).

The Electrical Transient Analyzer Program (ETAP®) System (Liu, 2019; Shertukde, 2019) was applied in this study to model the Kisumu-Ahero distribution line. The one-line diagram of the distribution system is given in Fig. 2, and the summary of the data used in the simulation is given in Table 1.

Table 1: A summary of the data used in the simulation of the Kisumu-Ahero distribution line.

Electrical Components	Number
Buses	148
Lamped loads	69
Transmission lines	205
Grid	1

2.2. Chaotic Coyote Optimization Algorithm

2.2.1. *Coyote Optimization*

The COA is a nature-inspired metaheuristic algorithm introduced by Pierezan & Coelho (2018), based on the social and survival behavior of coyotes (*Canis latrans*) whereby multiple agents, "coyotes," work collectively to find optimal solutions to a given problem. Thus, the algorithm mimics the adaptation of coyotes in changing environments, optimizing solutions by evolving over iterations through social learning and adaptation mechanisms (Pierezan & Coelho, 2018). The COA is a population-based technique that applies both swarm intelligence and evolutionary heuristics, thus, the algorithm simulates the coyote's experiences and social structure behavior (Yuan et al., 2020).

Representation of Coyotes in the Algorithm

In COA, each coyote represents a potential solution to the optimization problem (a potential solution in the solution space, characterized by a position vector in a multidimensional space). Each pack of coyotes is represented as a group of individuals with certain "positions," indicating values within the solution space. The position of each coyote changes iteratively, mimicking the search for resources and survival behaviors within a pack. Therefore, these positions are modified iteratively as the algorithm runs, mimicking the movement of coyotes in search of food. The initial coyote positions are typically assigned randomly within the feasible solution space, according to Eq. 1.

$$x_i^j = x_{min}^j + r(x_{max}^j - x_{min}^j) \tag{1}$$

Where x_i^j is the position of the i^{th} coyote in the j^{th} dimension, x_{min}^j and x_{max}^j defines the bounds for each dimension, and r is a random value in the range $[0, 1]$ (Pierezan & Coelho, 2018). The initial position of each coyote is spread across the feasible solution space, enhancing exploration in the early stages of the algorithm (Pierezan & Coelho, 2018).

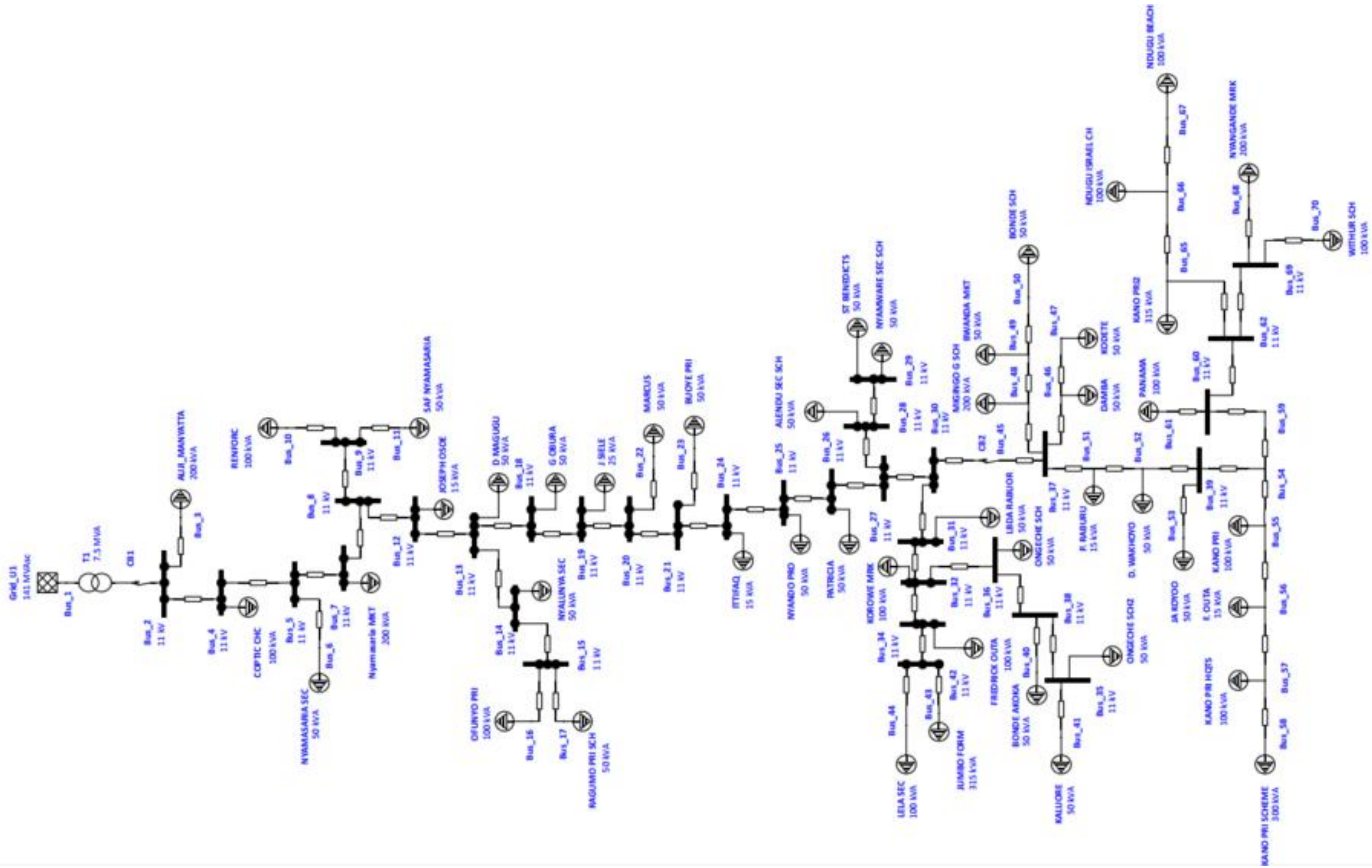

Fig. 2: The modeled Kisumu-Ahero distribution line

Social Learning in the Pack

Coyotes exhibit pack behavior, a critical aspect of COA. Within each iteration, social interaction among coyotes allows them to learn from one another, updating their knowledge and improving their solutions towards optimal solutions. This interaction is mathematically represented by calculating the social position of the pack, which acts as a guide for individual coyotes. The social position (x_{social}) is calculated as the median of the positions of all coyotes in the pack, shown in Eq. 2

$$x_{social} = median(\{x_i\}_{i=1}^{N}) \tag{2}$$

Where N is the number of coyotes in the pack. The algorithm better handles outliers and creates a more robust search process by focusing on the median rather than the mean (Pierezan & Coelho, 2018).

Adaptation Mechanism and Mutation

The adaptation mechanism and mutation process are central to enabling coyotes (representing solutions) to explore the solution space effectively. The adaptation mechanism allows each coyote to adjust its position based on social information, while mutation introduces randomness to prevent premature convergence.

Adaptation Mechanism

The adaptation mechanism in COA allows each coyote to learn from the pack's social position, x_{social}. The updated position for each coyote incorporates this social influence along with its current position (x_i), leading to gradual improvements toward an optimal solution. The new position for the i^{th}coyote is computed according to Eq. 3.

$$x_i^{new} = x_i + r_1(x_{social} - x_i) \tag{3}$$

Where $x_i^{new}$is the updated position, x_i is the current position, x_{social} is the social position of the pack, and r_1 is a random value in the range $[0, 1]$ that adds variability to the learning rate (Pierezan & Coelho, 2018). Each coyote is pulled towards the pack's social position, but allows some degree of variation due to r_1, which introduces adaptability without rigidly enforcing convergence.

Mutation Process

Each coyote undergoes a mutation process, ensuring diversity in the search and avoiding premature convergence. This prevents the algorithm from stagnating and encourages exploration. This is achieved by randomly selecting another coyote from the pack and generating a new candidate position, i.e., each coyote randomly selects another coyote's position x_{random}, from the pack and modifies its position based on it. The new position is calculated according to Eq. 4.

$$x_i^{new} = x_i + r_1(x_{social} - x_i) + r_2(x_{random} - x_i) \tag{4}$$

Where x_{random} is the position of a randomly selected coyote, and r_2 are random values in the range $[0, 1]$ adding stochasticity (Pierezan & Coelho, 2018). The adaptation term $r_1(x_{social} - x_i)$ aligns each coyote toward the social position, encouraging the coyotes to converge toward the median knowledge of the pack. This helps balance exploration and exploitation, moving coyotes toward potentially optimal areas of the search space. The mutation term $r_2(x_{random} - x_i)$ introduces randomness, encouraging exploration by moving the coyote away from the current position in the direction of another random coyote's position. The combination of adaptation and mutation helps COA maintain a balance between exploration (searching new areas) and exploitation (refining known areas). After generating the new position x_i^{new}, the coyote's fitness is evaluated to determine if it should keep this new position. This process is essential in selecting better solutions over iterations, leading to convergence towards the optimal solution.

Selection and Survival of Coyotes

The selection and survival of coyotes is a critical phase that ensures only the fittest solutions are retained for future generations. This process mimics natural selection, where coyotes (potential solutions) with better fitness survive, while others are eliminated, guiding the algorithm toward optimal solutions. Therefore, once new candidate solutions are generated, a fitness function is applied to evaluate each solution. Coyotes with better fitness survive to the next iteration, simulating natural selection. This selection process refines the population, pushing the coyotes toward optimal solutions. The algorithm terminates when a stopping criterion, such as a maximum number of iterations or a desired fitness level, is met.

To evaluate the quality of each coyote (solution), a fitness function $f(x_i)$ is applied, the fitness function depends on the specific optimization problem; for instance, it could represent the objective function in minimization or maximization tasks. Each coyote's fitness is calculated according to Eq. 5.

$$f(x_i) = Obj\ (x_i) \tag{5}$$

During the Adaptation Mechanism and Mutation phase, each coyote in the pack generates a candidate position x_i^{new}. Once the candidate position is created, its fitness $f(x_i^{new})$ is calculated and compared with the original position $f(x_i)$. The selection process keeps the position with the better fitness as given in Eq. 6.

$$x_i = \begin{cases} x_i^{new} & iff(x_i^{new}) < f(x_i) \\ x_i & otherwise \end{cases} \tag{6}$$

In each generation, a few random coyotes are replaced to maintain diversity in the population. This replacement mechanism mimics the introduction of new coyotes into the pack, enhancing exploration. For a given coyote x_k, it is randomly replaced with a new position within the feasible space according to Eq. 7. This ensures a portion of the population is periodically refreshed, preventing local optima entrapment.

$$x_k = x_{min} + r(x_{max} - x_{min}) \tag{7}$$

After applying selection and replacement, the pack is updated with the fittest coyotes to proceed to the next iteration. The survival process is governed by the principle of retaining the best solutions while introducing new ones to maintain a balance between exploration and exploitation. This selection and survival approach in COA enables it to efficiently explore the solution space while converging toward optimal solutions, making it effective in solving complex optimization problems.

2.2.2. Chaotic Coyote Optimization

The Chaotic Coyote Optimization Algorithm (CCOA) is an evolutionary computation technique that combines traditional optimization mechanisms with chaotic mapping to enhance search efficiency and avoid local minima, making it highly effective in solving complex, multimodal optimization problems (Pierezan et al., 2021; Zhang et al., 2023).

The CCOA hybrid approach takes advantage of chaotic maps, which are deterministic yet appear random, offering improved randomness over standard pseudorandom number generation. Chaos theory, introduced by Lorenz (1963), indicates that even simple deterministic systems can exhibit unpredictable, chaotic behavior over time. Therefore, this property makes chaotic maps a valuable tool in optimization, allowing CCOA to explore the search space more effectively than traditional approaches (Naanaa, 2015).

Principles of Chaotic Behavior

Chaotic behavior can be defined as deterministic yet highly sensitive to initial conditions, leading to a butterfly effect where small changes in input can produce vastly different outcomes (Cattani et al., 2016; Lorenz, 1963). In optimization, chaotic maps (Eq. 8) help prevent the algorithm from becoming stuck in local minima by maintaining diversity within the population (Wang et al., 2023).

$$x_{n+1} = f(x_n) = r x_n (1 - x_n) \quad (8)$$

Where f is a nonlinear function, i.e., logistic map, r is a control parameter, typically between 3.57 and 4.0, to ensure chaotic behavior.

Coyotes' Social Structure and Optimization

Coyotes, highly social animals, live in packs with a hierarchy and specific roles (Gifford et al., 2017). This social behavior, when adapted to CCOA, means that each candidate solution, or coyote, in the optimization process is part of a virtual pack (Naveen & Prathap, 2023). The algorithm is initialized by creating multiple packs, where each coyote represents a potential solution (Wu et al., 2022). During each iteration, coyotes within a pack communicate, updating their positions based on pack leaders and other members (Nguyen et al., 2021). The position update of each coyote x_i is performed according to Eq. 9.

$$x_{i,j}(t+1) = x_{i,j}(t) + \alpha\left(l_j - x_{i,j}(t)\right) + \beta\left(p_j - x_{i,j}(t)\right) \quad (9)$$

Where $x_{i,j}(t)$ is the position of the j^{th} coyote in the i^{th} dimension at iteration t, l_j represents the pack leader's position, and p_j is a random position influenced by other coyotes within the pack. Parameters α and β are random weights between 0 and 1, ensuring exploration and avoiding local minima (Abd Elaziz et al., 2021).

Algorithm 1: The Chaotic Coyote Optimization Algorithm

Input: Number of packs (P),
Number of coyotes per pack (N),
Chaotic map (γ_{t+1})
Max iterations (T)
Control parameter (r) for chaotic map
Objective function (f)
Output: Position and fitness of the best coyote as the optimal solution

```
Initialize each coyote's position randomly in the search space.
For each P
    Calculate the fitness (objective function value) of each coyote.
    Identify the coyote with the best fitness as the pack leader.
end
Set iteration t = 1
While t ≤ T do
    Find x_{i,j}(t+1)
    Find γ_{t+1} = r γ_t (1 − γ_t)
    Set chaotic factors α = γ_t and β = 1 − γ_t
    For each coyote i in N
        Update x_i^{new} = x_i + r_1(x_{social} − x_i) + r_2(x_{random} − x_i)
        Find f(x_i) = Obj(x_i)
        Update x_i
    end
    Randomize coyote behavior γ_{t+1} = r γ_t (1 − γ_t)
    Update x_{i,j}(t+1) = x_{i,j}(t) + γ_t (α (l_j − x_{i,j}(t))) + β (p_j − x_{i,j}(t))
end
```

Chaotic Integration in CCOA

To integrate chaotic behavior, the position update is modified by incorporating chaotic maps (Açikkapi & Özkaynak, 2020). The algorithm introduces controlled randomness in the update equation by using a chaotic sequence, which enhances exploration (Açikkapi & Özkaynak, 2020). Eq. 10 presents the incorporation of the logistic map for generating chaotic sequences.

$$\gamma_{t+1} = r\gamma_t(1 - \gamma_t) \quad (10)$$

Where γ_t is the chaotic parameter at iteration t. This chaotic sequence can influence α and β in the position update, ensuring diverse movements (Heidari et al., 2020).

$$x_{i,j}(t+1) = x_{i,j}(t) + \gamma_t\left(\alpha\left(l_j - x_{i,j}(t)\right)\right) + \beta\left(p_j - x_{i,j}(t)\right) \quad (11)$$

The updated chaotic position is performed according to Eq. 11. Therefore, the algorithm explores the search space more effectively, leveraging chaotic behavior to avoid premature convergence. The CCOA is summarized below in Algorithm 1.

2.2.3. Optimization Problem Formulation

The optimal placement and sizing of BESS in a power distribution network is a complex optimization problem that aims to minimize power losses while satisfying the technical and operational constraints. This study formulates the problem mathematically, defining the objective function, decision variables, and constraints, and finally, integrates the CCOA to solve the problem efficiently.

The primary objective of this study was to minimize the total active power losses in the distribution network. The power loss (P_{loss}) in a distribution system can be calculated using the bus conductance and voltage values according to Eq. 12 (Shaheen et al., 2021; Wu et al., 2022)

$$P_{loss} = \sum_{i=1}^{N_b}\sum_{j=1}^{N_b} G_{ij}(V_i^2 + V_j^2 - 2V_iV_j cos(\theta_i - \theta_j) \quad (11)$$

Where, N_b is the total number of buses in the system, G_{ij} is the conductance between the i^{th} and j^{th} bus, V_i, V_j are the voltage magnitudes at the i^{th} and j^{th} bus, respectively, and θ_i, θ_j are voltage angles at the i^{th} and j^{th} bus, respectively. Therefore, the objective function f is the minimization of the P_{loss} as given in Eq. 13.

$$f = min(P_{loss}) \quad (12)$$

Additionally, the optimization problem may also consider other objectives such as improving voltage profiles, reducing operational costs, or enhancing system reliability. However, for this study, the focus remains on minimizing power losses, as it directly impacts the efficiency and economic performance of the distribution network (Sadovskaia et al., 2019; Wu et al., 2022).

The decision variables for this study were the location of BESS (L_k) and the size of BESS (S_k). L_k is a binary variable indicating whether a BESS is installed at a specific bus, while S_k is the rated power (kW) and energy capacity (kWh) at each selected location. Therefore, for a given distribution system with k BESS units, the decision variables can be represented in a vector form given in Eq. 13, where each x_k corresponds to the L_k and $S_k$of the k^{th} BESS unit. The optimization algorithm searches for the optimal combination of these variables to minimize f.

$$X = [x_1, x_2, x_3, \dots, x_k] \quad (13)$$

The optimization problem was subject to several technical and operational constraints to ensure feasible and practical solutions. These constraints include: Power Balance Constraints (The total power injected into the network must equal the sum of the total power demand and losses, i.e., nodal power balance for real and reactive power (Džafić et al., 2014)), voltage constraints (The voltage magnitude at each bus must remain within permissible limits to ensure system stability and compliance with standards for this study it was set to 1.00 pu (Kumar et al., 2019)), BESS capacity constraints (The size of each BESS unit must be within feasible limits based on available technology and economic considerations, i.e., the physical limits of BESS in terms of charging and discharging capacities and energy storage limits (Rajamand, 2020)), and BESS placement constraints (Each BESS unit can only be placed at a bus that is pre-qualified based on load demand, accessibility, and technical viability).

The optimization was performed over a 148-bus network with a nominal voltage of 11 kV, modeled using ETAP®. The decision space was large due to the high number of buses and potential BESS sizes, thus necessitating a robust search algorithm. The use of CCOA provides enhanced exploration and exploitation through chaotic dynamics, as it avoids premature convergence by integrating randomness from logistic maps (Açikkapi & Özkaynak, 2020; Pierezan et al., 2021). For each candidate solution (set of BESS placements and sizes), the power flow analysis was conducted. The fitness value was computed based on the total P_{loss} resulting from the configuration. If multiple BESS were used, the fitness was aggregated over the contribution of each unit. The candidate solutions were ranked, and the best-performing ones were retained and evolved through CCOA processes such as chaotic mutation, pack learning, and survival dynamics.

To handle constraint violations and to discourage the algorithm from selecting infeasible solutions while allowing for soft constraint handling, penalty functions were incorporated into the objective function. The modified fitness function is given in Eq. 14, where, λ_1 and λ_2 are the penalty coefficients for voltage and BESS size violations, respectively, and H_v and H_{bess} are the penalties for voltage and BESS size violations, respectively.

$$F = P_{loss} + \lambda_1 H_v + \lambda_2 H_{bess} \quad (14)$$

As already mentioned, the study considered two scenarios, i.e., S_{1B1} and S_{2B1} and S_{1B2} and S_{2B2} as summarized in Table 2. Additionally, under these scenarios, two optimization techniques procedures were applied, i.e., Simultaneous Optimization (*Sim_Op*) step and Sequential Optimization (*Seq_Op*) step regarding the location and size of BESS.

Table 2: A summary of all the established models and a description of their objective function

Scenario	PV Integrated	`BESS Units	Objective
S_1	No	1	Minimize $P_{loss}^{(1)}$
S_1	No	2	Minimize $P_{loss}^{(1)}$
S_2	Yes (2 PV)	1	Minimize $P_{loss}^{(2)}$
S_2	Yes (2 PV)	2	Minimize $P_{loss}^{(2)}$

Where $P_{loss}^{(1)}$ power loss in S_G and $P_{loss}^{(2)}$ power loss in S_{PV}

Simultaneous Optimization Steps

In the *Sim_Op* step, both location and size are treated as decision variables in a single vectorized solution space, optimized concurrently using the CCOA. Therefore, the decision variable vector becomes $[x_k] = [L_k, S_k]$, for a single BESS while $[x_k] = [L_k, S_k, L_k, S_k]$ for a two BESS and the objective function is given in Eq. 15 for S_G and Eq. 17 for S_{PV} as given in Table 3.

Sequential Optimization Steps

In this approach, the location of the BESS is optimized first, assuming a predefined size. Once the location(s) are fixed, sizing is optimized in a second phase, using a narrowed-down search space. With a fixed BESS size (S_{fixed}) assumed, the decision variable contains only the location L_k. Thus, the objective function is given in Eq. 16 for S_G and Eq. 19 for S_{PV}. Once the optimal location(s) are identified, sizing becomes the next optimization step. The decision variable contains only the size S_k.Therefore, the objective function is given in Eq. 17 for S_G and Eq. 20 for S_{PV}.

Table 3: The objective function for each optimization problem

Scenario		Objective function Description	
S_1	Sim_Op	$min\ F = f(L_k, S_k)\ \forall k \in \{1\ or\ 2\}$	(15)
	Seq_Op	$min\ F_1 = f(L_k)\ S_{fixed}$ is fixed	(16)
		$min\ F_2 = f(S_k \mid L_k = L_k^{opt})$	(17)
S_2	Sim_Op	$min\ F = f(L_k, S_k, P_{pv1}, P_{pv2})$	(18)
	Seq_Op	$min\ F_1 = f(L_k, P_{pv1}, P_{pv2})$	(19)
		$min\ F_2 = f(S_k \mid L_k = L_k^{opt}, P_{pv})$	(20)

2.2.4. Optimization Evaluation

This study aims to optimally place and size BESS in a power distribution system to minimize losses in the network. A grid-connected distribution system was applied as the base case (S_G) in this study. Therefore, a comparative analysis was performed between S_G, S_{GB1}, S_{GB2}, S_{PV}, S_{PVB1}, S_{PVB2}. The performance of the models was evaluated based on the established Power Loss values. The task being a minimization task, the best model had the lowest Power Loss. Additionally, a comparison with other optimization techniques, i.e., COA, WOA, and PSO, was also performed to evaluate the performance of the proposed CCOA technique.

2.2.5. Particle Swarm Optimization (PSO) Algorithm

PSO is one of the most widely used algorithms in this domain is the PSO algorithm. Inspired by the collective behavior of birds flocking or fish schooling, PSO models each candidate solution as a "particle" in the search space that adjusts its position based on its own experience and that of neighboring particles (Cuevas et al., 2020; Neshat, Adeli, Sepidnam, Sargolzaei, & Toosi, 2012). PSO has been used effectively to minimize power losses and improve voltage stability by identifying optimal BESS sizes and locations (Chen et al., 2019; Jin et al., 2020; Rajamand, 2020). However, PSO has limitations, particularly its tendency to become trapped in local optima, especially in high-dimensional or multimodal objective functions, which undermines its reliability in complex optimization tasks (Jordehi, 2015).

In PSO, each particle represents a potential solution in the search space (Shami et al., 2022). It operates by initializing a group (or "swarm") of particles that move through the problem's solution space to find the optimal solution. Each particle represents a potential solution and is characterized by two vectors, i.e., the position vector x_i (representing the current solution) and velocity vector v_i (representing the direction and magnitude of the particle's movement in the solution space) as given in Eq. 21.

$$\begin{aligned} v_i^{t+1} &= \omega v_i^t + c_1 r_1 (p_i^{best} - x_i^t) + c_2 r_2 (g^{best} - x_i^t) \\ x_i^{t+1} &= x_i^t + v_i^{t+1} \end{aligned} \tag{21}$$

Where ω is the inertia weight (linearly decreased over iterations), balancing global and local search. A larger ω encourages exploration, while a smaller ω promotes exploitation. c_1 and c_2 are acceleration coefficients, guiding the particle toward personal and global best positions, respectively. r_1 and r_2 are random numbers in [0, 1] that introduce stochasticity into the movement, preventing deterministic traps.

Each particle adjusts its trajectory based on two key pieces of information: Its own best-known position p_i^{best} and the globally best-known position g^{best} found by the swarm. $c_1 r_1 (p_i^{best} - x_i^t)$ is a Cognitive Component whose task is to encourage the particle to return to the best solution it has found so far. While $c_2 r_2 (g^{best} - x_i^t)$ is the Social Component that encourages movement toward the best solution found by the swarm. To ensure particles do not escape the feasible space, boundary conditions are enforced by clamping velocities by setting $v_i^{t+1} \in [-v_{max}, v_{max}]$ and restricting positions to problem constraints, i.e., voltage boundaries.

2.2.6. Whale Optimization Algorithm (WOA)

The WOA is popular for its simplicity and search strategy, which is based on the bubble-net feeding method of humpback whales (Abualigah et al., 2024; Amiriebrahimabadi & Mansouri, 2024; Majumdar, Mitra, Mirjalili, & Bhattacharya, 2024). Wong et al. (2019) used WOA to reduce losses through optimal BESS configuration and found it more effective than traditional PSO and GA methods. However, WOA can also get stuck in convergence under certain conditions, showing a need for better hybrid or adaptive variants (Majumdar et al., 2024; Nadimi-Shahraki, Zamani, Asghari Varzaneh, & Mirjalili, 2023).

The WOA algorithm operates in two phases. The first phase is the Exploitation stage, which includes the Shrinking Encircling Mechanism and Spiral Updating Position. The second phase is the Exploration stage, which focuses on the Search for Prey.

In the Exploitation stage, the Humpback whales locate and encircle prey, a behavior reminiscent of the WOA algorithm. Operating on the assumption that the precise location of the optimal design within the search space is unknown, the algorithm regards the current best solution as representative of the target prey or as being close to the optimal solution. Upon ascertaining the best solution, the remaining search agents adjust their positions toward this optimum solution. This process is formally defined by Eq. 22.

$$\begin{aligned} \vec{D} &= \left|\vec{C} \cdot \vec{X}^*(t) - \vec{X}(t)\right| \\ \vec{X}(t+1) &= \vec{X}(t) - \vec{A} \cdot \vec{D} \end{aligned} \tag{22}$$

Where t is the number of iterations, $\vec{X}^*$ is the position vector of the current best solution, $\vec{X}$ is the position vector, and $\vec{A}$ and $\vec{C}$ are coefficient vectors and are computed based on Eq. 23 (Mirjalili & Lewis, 2016)

$$\begin{aligned} \vec{A} &= 2\vec{a} \cdot \vec{r} - \vec{a} \\ \vec{C} &= 2 \cdot \vec{r} \end{aligned} \tag{23}$$

Where $\vec{r}$ is a random vector within the range of zero to one and $\vec{a}$ is linearly decreased from two to zero during iteration. The shrinking encircling mechanism is realized through the decrease of $\vec{a}$. Therefore, $\vec{A}$ is decreased throughout the iteration within the interval $[-a \quad a]$. Hence, the next updated position for a search agent can be any point between the current position of the agent and the position of the current best candidate when $|\vec{A}| \leq 1$ (Mirjalili & Lewis, 2016).

In the Exploitation stage, the updating of the spiral movement (helix-shaped movement) was performed by the spiral equation in Eq. 24 based on the location of whales and prey (Mirjalili & Lewis, 2016).

$$\vec{X}(t) = \vec{D}^{i} \cdot e^{bl} \cdot cos(2\pi l) + \vec{X}^{*}(t) \tag{24}$$

Where, $\vec{D}^{i} = |\vec{X}^{*}(t) - \vec{X}(t)|$ is the distance between the prey and the whale at the i^th iteration, b is a constant that defines the shape of the logarithmic spiral, and l is a random number within the interval [−1,1]. Humpback whales employ a strategy where they swim around prey within a shrinking circle while also following a spiral-shaped path. Consequently, there is a 0.5 probability of selecting either the shrinking encircling mechanism or the spiral model to update the whale's position during optimization (Mirjalili & Lewis, 2016). The comprehensive equation for updating the position, inspired by the hunting behavior of humpback whales during the exploitation stage, is provided in Eq. 25, where p is the probability of between [0,1] (Mirjalili & Lewis, 2016).

$$\vec{X}(t+1) = \begin{cases} \vec{X}^{*}(t) - \vec{A} \cdot \vec{D} & if\ p < 0.5 \\ \vec{D}^{i} \cdot e^{bl} \cdot cos(2\pi l) + \vec{X}^{*}(t) & if\ p \leq 0.5 \end{cases} \tag{25}$$

The Exploration stage simulates humpback whales searching for prey randomly, based on each other's position. In the exploration stage, $\vec{A}$ is used with random values greater than 1 or less than −1 to force the search agent to move far away from a reference whale. During the Exploitation stage, the positions of the search agents are updated according to the best candidate acquired. Conversely, in the Exploration stage, the positions of the search agents are updated based on a randomly selected search agent. This enables the algorithm to conduct a global search, as described in Eq. 26, where, $\vec{X}_r$ is a random position vector selected from the current population (Mirjalili & Lewis, 2016).

$$\begin{gathered} \vec{D} = |\vec{C} \cdot \vec{X}_r(t) - \vec{X}(t)| \\ \vec{X}(t+1) = \vec{X}_r(t) - \vec{A} \cdot \vec{D} \end{gathered} \tag{26}$$

3. Results

The study focused on the optimal placement and sizing of BESS in a power distribution network to minimize power losses using the CCOA. This study was conducted on a 148-bus distribution network with a nominal voltage of 11 kV, modeled using ETAP®. Two primary scenarios were investigated, i.e., S_G and S_{PV}. For each scenario, the performance of single and dual BESS configurations was evaluated using *Sim_Op* and *Seq_Op* steps.

Table 4: The comparison of the performance of different Optimization algorithms in Power Loss Reduction

Algorithm	Model	Power Loss (kW)	
		Sim_Op	*Seq_Op*
CCOA	S_{GB1}	139.6	143.8
	S_{GB2}	121.4	124.9
	S_{PVB1}	118.2	122.4
	S_{PVB2}	97.8	101.3
COA	S_{GB1}	144.5	149.2
	S_{GB2}	128.1	131.7
	S_{PVB1}	124.6	128.3
	S_{PVB2}	103.5	107.8
WOA	S_{GB1}	147.3	152.5
	S_{GB2}	132.2	135.9
	S_{PVB1}	126.8	130.4
	S_{PVB2}	106.1	110.9
PSO	S_{GB1}	150.7	155.6
	S_{GB2}	135.5	139.2
	S_{PVB1}	130.4	134.7
	S_{PVB2}	109.3	114.2

3.1. Optimization model evaluation

The CCOA demonstrated superior performance compared to conventional COA, WOA, and PSO as presented in Table 4. The CCOA had the lowest Power Loss in all the observed scenarios. The integration of chaotic dynamics significantly improved the convergence rate and diversity in solution space. The simulations achieved stable convergence in under 45 iterations (Fig. 3 (a)), with average computation time ranging between 1.7 to 2.3 minutes per epoch. The fitness function in this study was based on the minimization of total active power loss and penalization of constraint violations. Additionally, from Fig. 3 (b), the CCOA under *Sim_Op* yielded the most optimal and feasible solutions across all scenarios.

3.1.1. Analysis of Simultaneous and Sequential Optimization Steps

The *Sim_Op* consistently achieved better results (lowest Power loss) by considering location and size interdependencies as given in Table 4. However, it demanded more computational resources. However, The *Seq_Op* was faster, making it suitable for real-time applications where computational time is critical. Therefore, for large-scale networks, *Seq_Op* may be preferred due to its lower computational burden, while *Sim_Op* is ideal for offline planning where accuracy is paramount.

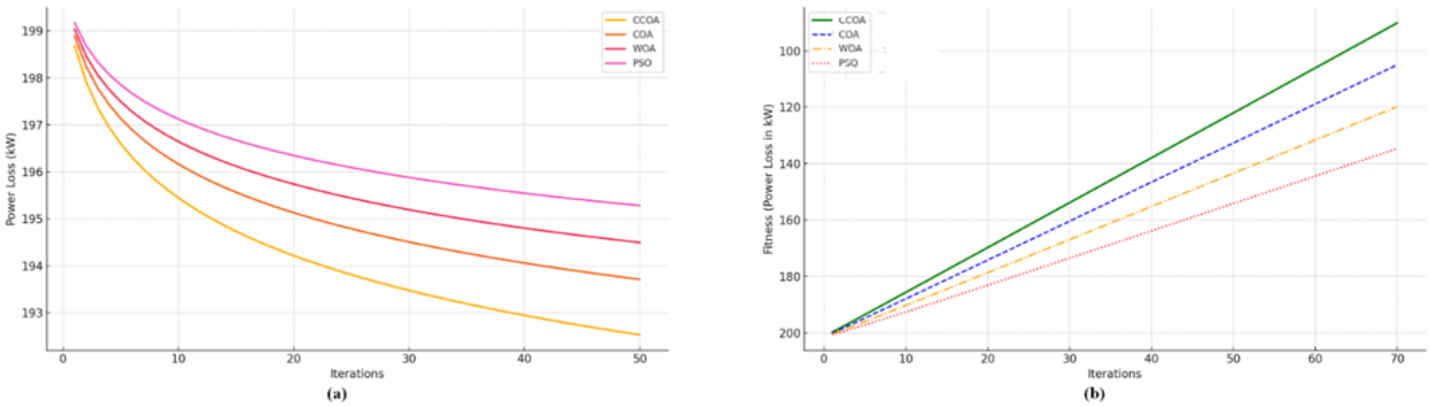

Fig. 3: The comparison of the performance of CCOA, COA, WOA, and PSO (a) Convergence graph comparing over 50 iterations (b) Convergence curve comparing fitness (power loss in kW) across optimization iterations using *Sim_Op* steps

3.2. Power Loss Reduction Evaluation

3.2.1. Analysis of Grid-Connected Distribution System with Single BESS Unit (S_{GB1})

In *Sim_Op*, the location and size of a single BESS were simultaneously optimized. The algorithm identified Bus 87 as the optimal location for BESS placement with a capacity of 1400 kWh and rated power of 420 kW. The total active power loss was reduced from 201.3 kW in S_G to 139.6 kW, representing a 30.64% reduction in losses as shown in Fig. 4 and Fig. 5. Additionally, the voltage profile across the network improved, with the minimum bus voltage increasing from 0.927 pu to 0.954 pu, highlighting enhanced voltage regulation.

When the location was optimized first (*Seq_Op*) with a fixed size of 1000 kWh, the optimal bus was again identified as Bus 87, validating the selection of Bus 87. Subsequent optimization of the size yielded an optimal configuration of 1250 kWh at 410 kW. The resulting power losses were 143.8 kW, slightly higher than in the simultaneous case, but still a 28.6% reduction from S_G as shown in Fig. 4 and Fig. 5.

3.2.2. Analysis of Grid-connected System with Two BESS Units (S_{GB2})

The introduction of a second BESS unit allowed for more distributed energy support. The optimal placement was determined at Bus 63 and Bus 107, with sizes of 900 kWh (270 kW) and 1100 kWh (330 kW), respectively, using the *Sim_Op*. The losses were significantly reduced to 121.4 kW, reflecting a 39.68% improvement compared to the base case. The S_{GB2} configuration outperformed the S_{GB1} setup by 9.05% as shown in Fig. 5. Additionally, the minimum voltage across the network was improved to 0.971 pu from 0.937 pu, and voltage deviation across all buses was more uniform, demonstrating the value of multi-node energy injection.

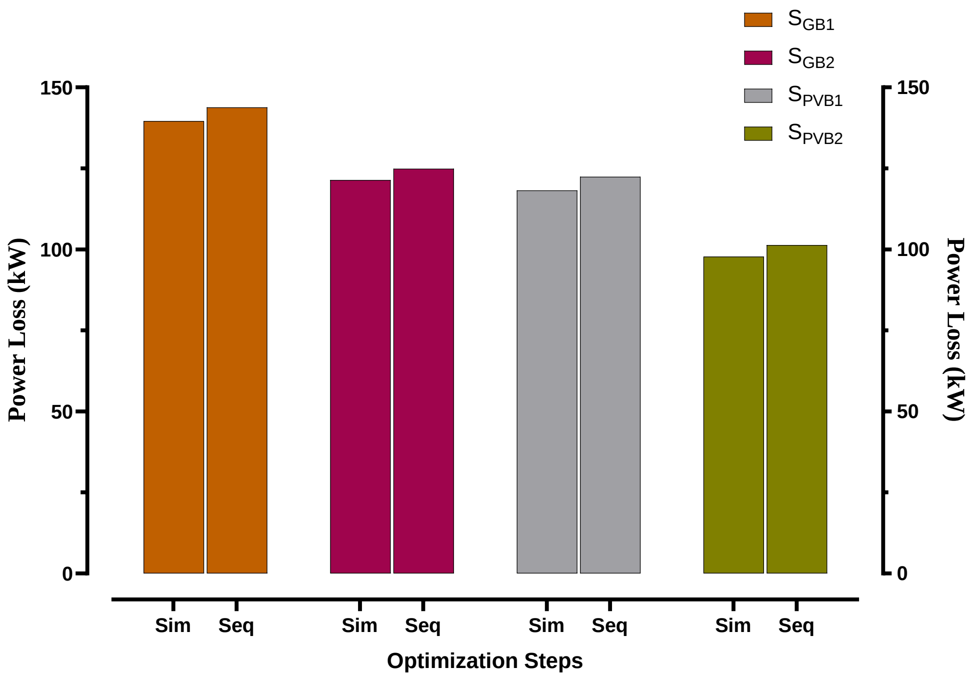

Fig. 4: The total Power Loss in the system for different scenarios using CCOA for both *Sim_Op* and *Seq_Op*

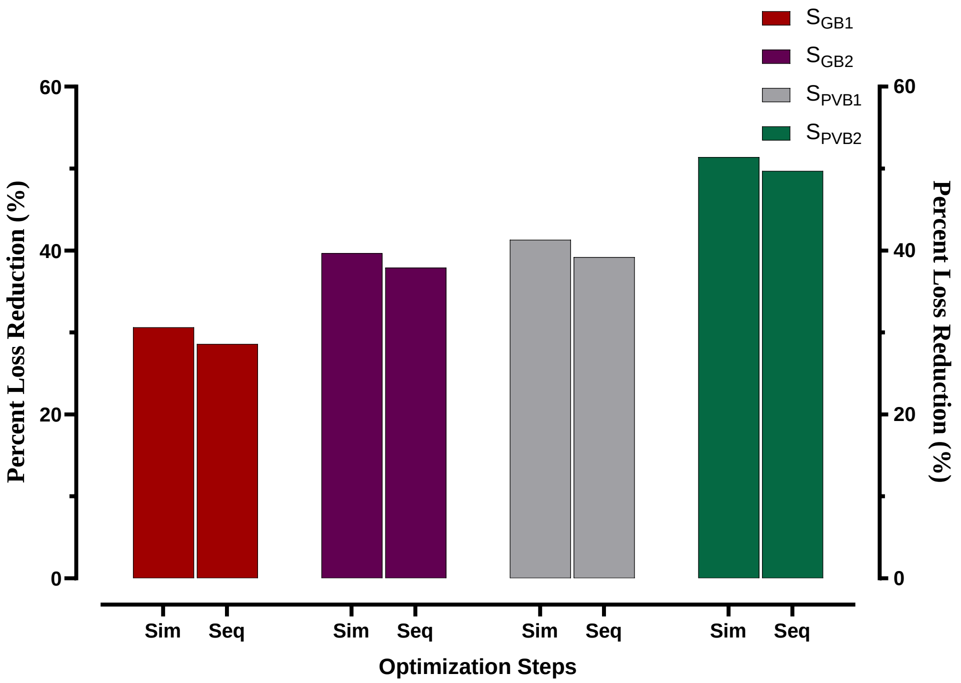

Fig. 5: Loss Reduction Percentage per Scenario using the CCOA

The *Seq_Op* was applied with initial fixed BESS sizes of 800 kWh each, location optimization suggested Bus 61 and Bus 106. Size tuning in the next step yielded 880 kWh (260 kW) and 1150 kWh (345 kW), respectively. The resulting loss was 124.9 kW, slightly higher than the simultaneous method but still showing a 37.9% reduction. The summary of the results is given in Table 5.

3.2.3. Analysis of Grid-Connected Distribution System with PV and Single BESS Unit (S_{PVB1})

This scenario incorporated two PV generation units placed at Bus 34 and Bus 77; each rated at 350 kW (the most stable Buses with the highest pu). The total system Power Loss of the S_{PV} Configuration alone before the BESS integration was established to be 164.5 kW, lower than the 201.3 kW in S_G as shown in Fig. 6.

The integrated PV systems helped flatten the load profile, which in turn influenced BESS optimization. Applying the *Sim_Op*, the optimization algorithm located the BESS at Bus 95 with an optimal capacity of 1000 kWh and rated output of 300 kW. Losses were reduced to 118.2 kW, a 41.3% reduction from S_G setup Fig. 5. Compared to the S_{PV} configuration (164.5 kW losses), this configuration improved efficiency by 28.1%. The voltage profile was significantly improved, especially in sections near Bus 77 (0.921 to 0.967 for Bus 77), due to the localized generation and energy storage support. The application of *Seq_Op* fixed the BESS size at 950 kWh, and the optimal location was determined to be Bus 93. After size optimization, the best configuration was 1020 kWh (310 kW). This led to losses of 122.4 kW, translating to a 39.2% improvement, slightly less than the simultaneous strategy.

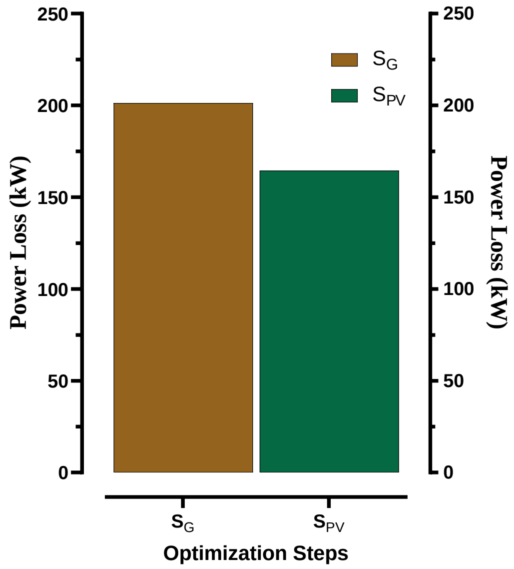

Fig. 6: The comparison in Total Power Loss in the distribution system between the base case (S_G)and PV intergrated system (S_{PV})

3.2.4. Analysis of Grid-connected System with PV and Two BESS Units (S_{PVB2})

This scenario had the highest complexity with combined PV and dual BESS systems. It best reflects future smart grid implementations where diverse energy sources interact. The *Sim_Op* determined the optimal locations as Bus 91 and Bus 123, with BESS sizes of 800 kWh (240 kW) and 950 kWh (285 kW), respectively. Losses dropped to an impressive 97.8 kW, the lowest across all scenarios Fig. 4 and Fig. 5. This marked a 51.4% improvement relative to the base case and a 40.5% improvement over the S_{PV} configuration. Additionally, power factor improvements were observed due to reactive power support from both PV inverters and BESS units, stabilizing voltage swings and reducing reactive power demand. The application of *Seq_Op* fixed the BESS sizes of 850 kWh, optimal locations were found at Bus 89 and Bus 121. After sizing, the values were adjusted to 820 kWh (250 kW) and 980 kWh (290 kW). The losses were slightly higher at 101.3 kW, yielding a 49.7% reduction.

Table 5: Power Loss Reduction in all Scenarios

Scenario	Optimization Step	Loss (kW)	Loss Reduction (%)
S_{1B1}	*Sim_Op*	139.6	30.6%
	Seq_Op	143.8	28.6%
S_{1B2}	*Sim_Op*	121.4	39.7%
	Seq_Op	124.9	37.9%
S_{2B1}	*Sim_Op*	118.2	41.3%
	Seq_Op	122.4	39.2%
S_{2B2}	*Sim_Op*	97.8	51.4%
	Seq_Op	101.3	49.7%

Loss in S_G is 201.3 kW and in S_{PV} is 164.5 kW

3.2.5. Evaluation of the effect of BESS Configurations

The comparative analysis between single and dual BESS configurations revealed significant differences in system performance. Dual-BESS systems consistently outperformed their single-unit counterparts in both S_G and S_{PV} scenarios. Specifically, the dual-BESS configuration reduced power losses by an additional 9.1% in the S_G setup and 10.1% in the S_{PV} Configuration Fig. 5. This superior performance is attributed to the distributed nature of energy injection, which allows better voltage support across the network and minimizes localized overloading. Moreover, dual-BESS setups improved the voltage profile across all buses more effectively, maintaining minimum voltage levels consistently above 0.95 pu compared to the 0.94–0.95 pu range observed in single-BESS cases, and 0.927 pu in the S_G as shown in Fig. 7. This uniform voltage regulation helps mitigate voltage violations, enhancing overall grid stability. The benefit of improved voltage profiles is especially evident in PV-integrated systems, where the variability in generation is better compensated by the flexibility of multiple BESS units. Despite higher implementation complexity and cost, dual-BESS systems present a compelling case for enhanced operational reliability, scalability, and energy loss reduction. Therefore, in high-demand or renewable-rich distribution networks, deploying dual or multi-point BESS configurations proves to be an effective strategy for maximizing efficiency and resilience.

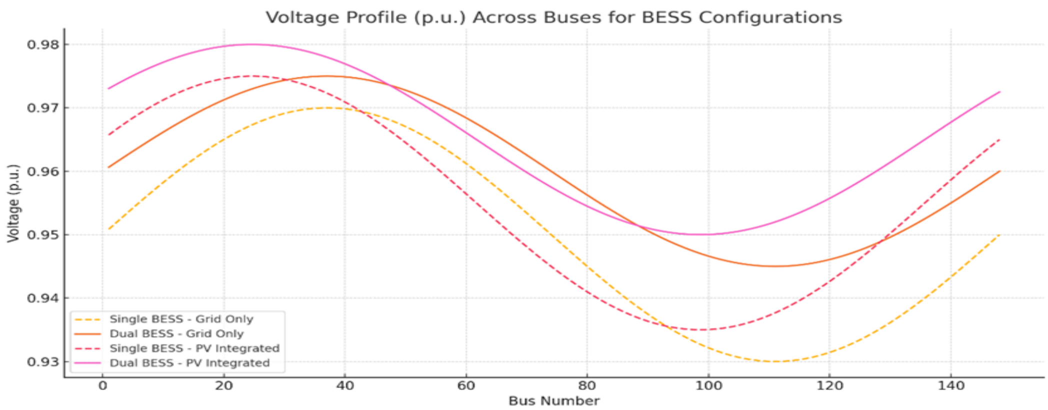

Fig. 7: The voltage profiles (pu) across the 148-bus distribution network for both single and dual BESS configurations

4. Discussions

The results demonstrate the efficiency of CCOA in optimizing BESS configurations, outperforming traditional optimization techniques such as the COA, WOA, and PSO. The CCOA consistently achieved the lowest power losses across all scenarios, validating its superiority over conventional optimization methods, e.g., in the S_{GB1}, the CCOA reduced power losses by 30.64% (from 201.3 kW to 139.6 kW) under *Sim_Op*. This outperformed COA (144.5 kW), WOA (147.3 kW), and PSO (150.7 kW) under the same conditions. The chaotic dynamics integrated into CCOA enhanced its ability to escape local minima, ensuring a more thorough exploration of the solution space (Açikkapi & Özkaynak, 2020; Pierezan et al., 2021). This aligns with previous studies that highlight the advantages of chaotic maps in improving metaheuristic algorithms' convergence and diversity (Heidari et al., 2020).

The dual-BESS configuration, i.e., S_{GB2} further reduced losses to 121.4 kW (39.68% reduction), demonstrating the benefits of distributed energy storage. This result concurs with the report by Wong et al. (2019), which emphasized that multi-point BESS placement mitigates localized overloading and improves voltage regulation. The CCOA's ability to handle such complex, high-dimensional problems underscore its robustness in real-world applications.

The integration of PV systems with BESS (S_{PVB1} and S_{PVB2}) yielded even greater reductions in power losses. The S_{PVB1} scenario achieved a 41.3% loss reduction (118.2 kW), while S_{PVB2} achieved 51.4% (97.8 kW). These results corroborate the findings of Adefarati & Bansal (2016), who noted that renewable energy units, when optimally sized and located, significantly reduce feeder overload and power losses. The PV systems flattened the load profile, reducing peak demand and enabling BESS to operate more efficiently (Kumar et al., 2019). Moreover, the dual-BESS configuration in PV-integrated systems (S_{PVB2}) outperformed the single-BESS setup (S_{PVB1}) by an additional 10.1%. This highlights the synergistic effect of combining distributed generation with distributed storage, as noted by Dowling et al. (2020) that the flexibility of multiple BESS units compensates for the intermittency of PV generation, ensuring stable grid operation (Wong, Ramachandaramurthy, Taylor, et al., 2019).

The study also established significant improvements in voltage profiles across the 148-bus network. In the S_G , the minimum voltage was 0.927 pu, which improved to 0.954 pu with a single BESS (S_{GB1}) and 0.971 pu with dual BESS (S_{GB2}). The PV-integrated scenarios (S_{PVB1} and S_{PVB2}) further enhanced voltage stability, with minimum voltages of 0.967 pu and 0.975 pu, respectively. These improvements are critical for maintaining grid reliability and compliance with voltage standards (Kumar et al., 2019). The dual-BESS configuration provided more uniform voltage regulation, mitigating voltage violations in remote or heavily loaded buses. This aligns with the report by Rajamand (2020), which emphasized that distributed BESS placement enhances voltage support across the network. The results also concur with those of Shaheen et al. (2021), who demonstrated that optimal BESS sizing and placement improve voltage profiles while reducing losses.

The proposed study compared two optimization approaches, i.e., *Sim_Op* and *Seq_Op*. *Sim_Op*, which optimizes BESS location and size concurrently, consistently achieved better results but required higher computational resources. For example, in S_{GB1} *Sim_Op* reduced losses to 139.6 kW, while Seq_Op achieved 143.8 kW. This difference arises because Sim_Op accounts for the interdependencies between location and size, leading to more globally optimal solutions (Pierezan & Coelho, 2018). *Seq_Op*, on the other hand, is computationally less intensive and may be more suitable for real-time applications. However, its performance is limited by the initial assumptions (e.g., fixed BESS size in the first step). This trade-off between accuracy and computational efficiency must be carefully considered in practical implementations, especially for large-scale networks (Sadovskaia et al., 2019).

Generally, the findings of this study have several practical implications for power distribution systems. First, the superior performance of CCOA suggests its potential for widespread adoption in grid planning and operation. Its ability to handle complex, non-linear problems makes it suitable for other optimization tasks, such as capacitor placement or feeder reconfiguration (Ghofrani et al., 2013). Second, the demonstrated benefits of dual-BESS configurations highlight the importance of distributed energy storage in modern grids. As renewable energy penetration increases, utilities should consider multi-point BESS deployments to enhance system resilience and efficiency (De Sisternes et al., 2016). Third, the integration of PV with BESS offers a viable pathway for decarbonizing power systems while improving operational efficiency. Policymakers and grid operators should incentivize such hybrid systems to accelerate the energy transition (Datta et al., 2021).

5. Conclusion

This study investigated the optimal placement and sizing of BESS in a 148-bus power distribution network to minimize power losses using the CCOA. The research demonstrated that CCOA outperformed COA, WOA, and PSO optimization techniques by achieving the lowest power losses across all tested scenarios. The integration of chaotic dynamics enhanced the algorithm's ability to balance exploration and exploitation, preventing premature convergence and improving solution accuracy. The results established that dual-BESS configurations significantly reduced power losses compared to single-BESS setups, with reductions of up to 51.4% in PV-integrated systems. The optimal placement of BESS units at strategic buses (e.g., Bus 87 for single-BESS and Buses 63 & 107 for dual-BESS) improved voltage stability, maintaining minimum voltages above 0.95 pu across the network. Furthermore, the combination of BESS with solar PV generation further enhanced loss reduction, highlighting the synergistic benefits of hybrid renewable-storage systems in modern grids. The study also compared two optimization approaches, *Sim_Op* and *Seq_Op*, revealing that *Sim_Op* provided superior results by considering location and size interdependencies, while *Seq_Op* offered computational efficiency for real-time applications. These insights are crucial for utilities and grid operators in planning cost-effective and resilient power distribution systems. The proposed CCOA-based optimization framework provides a robust methodology for integrating BESS into distribution networks, particularly in renewable-rich environments. Future research should explore the following: Firstly, the economic feasibility of large-scale BESS deployment, including cost-benefit analysis. Secondly, the dynamic load and generation scenarios are used to assess real-time performance under varying conditions. Lastly, the integration of other renewable sources (e.g., wind) with BESS for a more comprehensive energy management strategy. This study contributes to the development of smarter, more efficient power grids, supporting global energy transition goals by advancing optimization techniques and hybrid energy solutions. The findings highlight the importance of intelligent BESS placement and sizing in achieving sustainable and resilient power distribution systems.

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