

Research paper

Techno-economic analysis of battery storage technologies in distribution networks with integrated electric vehicles and solar PV systems

Chukwuemeka Emmanuel Okafor^a, Saheed Lekan Gbadamosi^{a,*}, Senthil Krishnamurthy^a, Mukovhe Ratshitanga^a, Prathaban Moodley^b

^a Department of Electrical, Electronic and Computer Engineering, Cape Peninsula University of Technology, South Africa

^b Applied Energy Research, South African National Energy Development Institute, South Africa



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ABSTRACT

This study presents a simulation, optimization, and assessment of economic impacts of a grid-connected solar PV system with electric vehicles (EVs) and various battery energy storage systems (BESS) for distribution network systems. Four optimization algorithms—Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Direct Search Optimization (DSO), and Grey Wolf Optimizer (GWO) were deployed in determining the optimal parameters for energy storage deployment in the distribution networks integrated with EVs and solar photovoltaic (PV) systems. Two real-world distribution network systems were modeled for time-based (quasi-dynamic) simulations: the 30-bus South African distribution network and the 49-bus distribution network of Baghdad City, Iraq. These models were used to evaluate the impacts of integrating solar PV, electric vehicles (EVs), and battery energy storage systems (BESS) on voltage profiles and active power losses. The simulation results were further optimized to determine the optimal BESS placement within the proposed networks using GA, PSO, DSO and GWO techniques. An economic analysis was conducted to optimize the integration of BESS with EVs and solar photovoltaic (PV) systems. The study considered various battery storage configurations, including grid + time-dependent loads (TDLs), grid + PVs + TDLs, grid + PVs + EVs + TDLs, grid + PVs + TDLs + Li-ion BESS, grid + PVs + TDLs + Surrrette BESS, and grid + PVs + TDLs + Trojan BESS. These configurations were analyzed to assess their impact on power losses and voltage deviations within the distribution networks. The results showed promising outcomes, with the total Net Present Cost (NPC) ranging from \$8.41 million to \$10.03 million across all configurations. Li-ion BESS emerged as the most cost-effective option, achieving the lowest annualized cost. The PSO algorithm outperformed the GA in optimization, determining an optimal BESS size of 0.1126 MW. Systems utilizing Li-ion BESS consistently demonstrated superior performance to those with Surrrette and Trojan BESS, achieving the lowest net energy purchases, peak demands, and energy costs while generating significant revenue from excess energy sales to the grid. Li-ion BESS is the most cost-effective and sustainable solution due to its high efficiency, energy density, and long lifecycle. For the real-world 30-bus South African distribution network, PSO and GWO are preferred due to their efficient utilization of BESS, achieving optimal performance with lower storage investment. For the larger 49 bus network, GWO offers a more balanced and robust solution, effectively maintaining acceptable power losses and voltage quality through appropriate BESS allocation.

1. Introduction

Today, approximately 90 % of people worldwide rely on internal combustion vehicles powered by gasoline or diesel (Deb et al., 2018). These vehicles contribute significantly to CO₂ emissions, exacerbating global warming and climate change. Recently, rising oil prices, the necessity of minimizing greenhouse gas emissions, and the rapid growth of

sustainable energy have accelerated the adoption of EVs (Ma et al., 2017). EVs are increasingly recognized for their potential to reduce traffic congestion, lower carbon emissions, and foster a healthier living environment (Wang et al., 2023; Hajiaghahi-Keshteli et al., 2023). However, a key limitation of EVs is their range, constrained by the limited storage capacity of their batteries. After a certain distance, EVs must recharge at nearby charging stations. Consequently, developing a

* Corresponding author.

E-mail address: gbadamosiadeolu@gmail.com (S.L. Gbadamosi).

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robust and efficient charging infrastructure is essential to accommodate the growing need for EV charging while ensuring stability of the grid and economic sustainability. Poorly planned deployment of EV charging stations can lead to technical and financial challenges, including interference of harmonics, deviations in the supply voltage, and increased peak load demands, potentially destabilizing the grid (Polisetty et al., 2023; Al Wahedi and Bicer, 2022). Thus, determining the optimal locations for EV charging stations is crucial for effective distribution network planning and operation.

Most of EV charging stations are powered by fossil fuel generators, which contribute to air pollution. To address this issue, renewable energy sources (RES) such as wind and solar power are increasingly integrated into distribution networks as alternatives to fossil fuel generators, aiming to minimize the greenhouse gas emissions (Uthman et al., 2024). However, due to the intermittent nature of RES, battery energy storage systems (BESS) are vital for mitigating power fluctuations during periods of low generation (Gbadamosi and Nwulu, 2020a). Integrating RES and battery energy storage systems into EV charging infrastructure provides a sustainable, long-term solution (Gbadamosi and Nwulu, 2020b). This approach reduces grid strain, minimizes operational costs, and positions EV charging stations as environmentally friendly alternatives to traditional gas stations. By combining renewable energy with advanced storage technologies, South Africa's energy transition goals can be achieved, supporting the broader objectives of the Just Energy Transition Investment Plan (JETIP) and contributing to global efforts to combat climate change. The energy revolution in South Africa presents a transformative opportunity for innovation, industrial growth, and economic diversification, aligned with the country's energy and climate policies. The JETIP seeks to establish long-term partnerships to support shifting to a low-emissions, climate-resilient economy by leveraging public and private resources alongside international financial support. The plan focuses on accelerating the just transition, decarbonizing the electricity system, and creating economic opportunities in areas such as green hydrogen and electric vehicles.

In South Africa globally, the transportation industry is undergoing a significant paradigm shift driven by the rise of shared mobility services, the growing emergence of electrification, and the emergence of autonomous vehicles. These advancements create substantial opportunities and synergies but also demand careful planning in the design of EV charging infrastructure. The increasing adoption of EVs will significantly heighten electricity demand on the power grid, potentially causing congestion and necessitating extensive infrastructure upgrades. However, a literature review reveals that limited research has been conducted in this crucial area. Reference (Solanke et al., 2020) explores various strategies for managing peak load, frequency control, and the charging and discharging of EVs. It highlights the critical role of the charging and discharging states of plug-in electric vehicle (PEV) batteries at charging stations in these strategies. In Reference (Mohsenzadeh et al., 2018), a distinct charging threshold was established to minimize power losses and voltage deviation in a distribution system integrated with distributed generation (DG) at PEV charging stations. Reference (Barhoumi et al., 2023) details the use of HOMER software to design an optimal hybrid refueling station configuration, incorporating a storage device and three wind turbine (WT) setups for efficient hydrogen (H₂) production for fuel cell (FC) vehicles in Oman. Reference (Shafiq et al., 2022) provides a technical and economic assessment of solar PV charging stations in Pakistan, evaluating CO₂ emissions, energy costs, and power reliability. Reference (Alzahrani et al., 2019) utilizes a GA to determine the placement and sizing of BES devices in a distribution system with high PV penetration. In Reference (Yoshida and Farzaneh, 2020), the development of an off-grid mini-power system comprising diesel, battery, PV, and wind components is optimized using PSO technique to minimize costs. Reference (Samy et al., 2022) introduces an innovative solution for optimizing a hybrid isolated microgrid integrated with wind and PV system optimized using advanced techniques and ANN-based decision-making mechanism. Reference (Amusan et al.,

2022) presents an intelligent demand side management and supply system for a Microgrid, incorporating BESS, consumer units and multiple supply sources. To satisfy the EV load demand on Hawai Island, USA, Reference (Singh and Kumar, 2023) looks into the best energy storage sizing for charging EVs. It assesses the viability of hybrid renewable energy sources (HRES), which include PV, DG, WT, and BESS. A novel approach to maximizing household energy expenses in grid-connected EV-powered homes while considering power export limitations was introduced in Ref (Wu et al., 2022). The method incorporates battery energy storage (BES) degradation, power export restrictions, battery recovery value, and changing EV charging patterns into a technical and economic energy system model. Using EV load patterns, Reference (Al-Ghussain et al., 2024) assesses the technical and financial viability of grid-connected solar PV and EV charging infrastructure stations throughout Kentucky. It assesses various PV system locations, sizing, and positioning while examining how electricity prices and energy credit programs affect system profitability. The study also looks at the techno-economic and environmental effects of green EV charging stations and how extra PV energy can be used to charge lithium-ion batteries. A novel strategy for a solar-powered BESS is presented in Ref (Ullah et al., 2024). as a sustainable substitute for conventional demand-side management and time-of-use pricing methods. IoT-based monitoring and control are incorporated into the system's architecture to maximize energy management and utilization. An Internet of Things-enabled prototype has been created to allow for real-time energy storage system monitoring and control. In Ref (Pal and Kunj, 2024)., this paper presents energy management schemes integrating a photovoltaic-based distributed generator and an energy storage system (ESS) at an electric vehicle charging station. An IEEE-33 bus system was remodeled to represent a rural location in Saudi Arabia, and it is used to implement these real-time energy management strategies.

Much of the aforementioned literature did not consider both the energy cost of the system and the levelized cost of storage for a distribution network with EV loads integrated with various BESS configurations. However, key questions remain: How do BESS installations impact voltage profile and power losses? How do time-varying EV loads affect the distribution network systems? In prior studies, EV load demand modeling was based on a consistent pattern, assuming no temporal fluctuations and fully charged batteries. Furthermore, the economic performance of the 30-bus distribution system with different BESS configurations and solar PV integration requires detailed analysis. Most existing research does not address the technical impact of power losses and voltage deviation on BESS performance, the integration of solar PVs, of solar PV integration, and real-time EV load data in distribution systems. This paper presents a novel approach for determining the optimal placement of different battery energy storage systems in a grid, solar PV-based distribution network integrated with an EV charging system. Therefore, the key contributions of this research are:

- To develop an approach for identifying the best location for charging an electric vehicle (EV) in the distribution network (DN) to reduce its negative impact on various system performance parameters.
- To Simulate the distribution network with EVs during peak and off-peak periods to investigate EV's effects on the system performance parameters using DigiSilent software.
- Develop a model that considered solar PV and BESS into the DN to reduce the effects of EVs on power loss and voltage deviation to improve the reliability and sustainability of the existing DN.
- Technical and economic assessment of different BESS configurations and the levelized storage cost on the distribution network with EV and Solar PV.
- Develop four optimization algorithms: particle swarm optimization (PSO) algorithm, genetic algorithm (GA), deep sleep optimizer (DSO) algorithm and grey wolf optimizer (GWO) algorithm for reducing the power losses, cost, and voltage deviation in the distribution network systems.

The organization of this paper is as follows: Section 2 presents the mathematical modeling of power quality associated with the proposed system, along with the leveled energy cost. Section 3 outlines the procedure for the optimal placement of various battery energy storage systems (BESS) in the distribution network systems using GA, PSO, DSO and GWO algorithms. Section 4 provides a techno-economic analysis of different BESS configurations integrated with solar PV and EVs on the distribution network. Section 5 discussed the simulated outcomes, and the paper is concluded in Section 6.

2. Problem formulation

Integrating solar PV systems, EVs and battery energy storage into a distribution network reduces total system losses, minimizes voltage fluctuations, and enhances overall system stability, thereby improving the network's performance.

2.1. Optimization of power quality

The multi-objective function considers two key factors: power loss and total voltage deviation. As minimizing system losses is prioritized over improving the voltage profile, the latter is typically enhanced through renewable energy integration. The objective of multi-objective optimization can be expressed as:

- Objective function

The objective function for optimal BESS placement in a distribution network, aimed at reducing active power losses and mitigating voltage deviations, is defined in Eqs. (1) and (2). It seeks to minimize the total cost associated with power losses and voltage deviations. Consequently, the bus that results in the lowest overall system cost is identified as the optimal location for BESS integration. Eqs. (3) and (4) provide cost formulations for line power losses and voltage regulation, respectively.

$$F = \text{MinCost}_{\text{sys}} \quad (1)$$

$$\text{Cost}_{\text{sys}} = \text{Cost}_{\text{loss}} + \text{Cost}_{\text{VR}} \quad (2)$$

$$\text{Cost}_{\text{loss}} = \sum_{t=1}^T \text{Cost}_{\text{loss},t} \alpha_{\text{loss}} \quad (3)$$

$$\text{Cost}_{\text{VR}} = [|V_i - V_{\text{ref}}|] [\alpha_{\text{VR}}] \quad (4)$$

- System constraints

$$V_{\min} \leq V_i(t) \leq V_{\max} \quad (5)$$

$$P_i = \sum_{j=1}^{N_i} V_i V_j Y_{ij} \cos(\theta_{ij} - \delta_i + \delta_j) \quad i = 2 : N_i \quad (6)$$

$$Q_i = \sum_{j=1}^{N_i} V_i V_j Y_{ij} \sin(\theta_{ij} - \delta_i + \delta_j) \quad i = 2 : N_i \quad (7)$$

$$-P_{\text{BESS}}^{\min} \leq P_{\text{BESS}}(t) \leq P_{\text{BESS}}^{\max} \quad (8)$$

$$\text{SOC}_{\min} \leq \text{SOC}(t) \leq \text{SOC}_{\max} \quad (9)$$

- Eq. (5) is the voltage limit, which states that the minimum and maximum voltages throughout the day are determined from the corresponding values for each time step (0.95–1.05). Where $V_{\min}$, $V_{\max}$ represent the minimum and maximum voltage; $V_i(t)$ is the voltage at any bus i (Okafor and Komla, 2023).

- Eqs. (6) and (7) are the flow of active and reactive power at each bus respectively, and they should adhere to the boundary limits as part of the optimization process. Where V , δ stand for voltage and its angle at any bus, P_i for injected active power at bus i , Q_i for injected reactive power at the same bus, and Y , δ for branch admittance and angle, respectively.
- The capacity of each BES unit is assumed to be within acceptable limits as stated in Eq. (8). Where $P_{\text{BESS}}^{\max}$ is the maximum BES power, and $P_{\text{BESS}}(t)$ is the BES power at any given time. It is important to note that the BES unit supplies power when discharging and consumes power during charging.
- Eq. (9) shows the charging limits. Charging or discharging depends on the system conditions and each battery's state of charge (SoC) (Nadeeshani et al., 2016).

where α_{loss} represents the cost rate of active power losses, set at 0.284 \$/kWh (Nadeeshani et al., 2016), while α_{VR} denotes the cost rate for voltage regulation, valued at 0.142 \$/pu (Nadeeshani et al., 2016). V_i refers to the voltage measured at hourly intervals over 24 h.

2.2. Levelized cost of energy

The LCOE is determined by dividing the total lifetime costs of a system by its total lifetime energy production. This metric enables a consistent comparison of electricity generation costs between conventional and renewable energy sources (Smallbone et al., 2017). LCOE is especially valuable for assessing technologies with varying capacities, costs over the lifespan, and potential revenues. The Levelized Cost of Energy Storage Systems (LCOESS) is an improved and modified version of the Levelized Cost of Storage (LCOS) framework presented in (Eid et al., 2021; Pawel, 2014; Schmidt et al., 2019), derived from the LCOE formulation. This study incorporates the impact of deterioration on the battery storage system's lifespan energy output $E_{\text{BESS}}(t)$, highlighting the critical importance of considering degradation when selecting hybrid storage systems for specific projects. The LCOES formulation is expressed as follows (Gbadegehin et al., 2019):

$$\text{LCOES} \left(\frac{\$}{\text{kWh}} \right) = \frac{\text{TEIC} + \sum_{n=1}^N \frac{\text{TOM} + \text{TREP}}{(1+r)^n}}{\sum_{n=1}^N \frac{E_{\text{BESS}}}{(1+r)^n}} \quad (10)$$

$$k_n = \frac{CR_n}{365 * m} \quad (11)$$

$$i_{\text{rep}} = \frac{\text{Project Lifetime}}{\sum_{n=1}^N k_n} \quad (12)$$

$$E_{\text{BESS}} = \sum_{n=1}^N (df_n * E_o) * \left(\frac{CR_n}{m} \right) \quad (13)$$

where E_{BESS} represents the anticipated energy produced from the BESS after accounting for degradation, TREP stands for total replacement costs, TOM for total operating and maintenance costs, and TEIC for total equipment and installation costs. The project duration (n) is assumed to be 20 years with a discount rate (r) of 8 %. The data required for calculations in the LCOS analysis include daily cycles, deterioration factors, and the related range of cycles for the storage systems over the project duration. E_o is the energy produced at the start of operation, prior to any degradation. The formula in Eq. (8) can calculate the BESS's total energy output up to the project's completion.

According to System modeling, the daily number of cycles is denoted by m , and the cycle range is connected to the degradation factor df_n is represented by CR_n and k_n stands for the years of operation of the system with the matching df_n, k . The total of all the k_n values yield the opera-

tional lifetime (measured in years) for which the BESS can function as expressed in Eq. (11). t_{rep} provides the replacements time needed over the system's operating lifetime as expressed in Eq. (12). E_{BESS} is represented in Eq. (13) as the total dischargeable energy from the battery energy storage system over its lifespan, with E_o being the first energy released from the storage system on the start of operation.

3. Optimal placement of battery energy storage system

The optimization procedure for determining the optimal location for the BESS in the studied network is outlined in the six steps below, with the corresponding flowchart presented in Fig. 1:

- Input the network data and algorithm parameters.
- Select one candidate location for the predetermined BESS capacity.
- Perform a load flow analysis with the BESS placed at the selected bus.
- Evaluate the objective function and update the best solution.
- If all buses have been evaluated, proceed to step 6; otherwise, return to step 2.
- Identify the optimal BESS location as the bus that yields the minimum value of the objective function.

The test systems considered in this study are two real-world distribution network systems integrated with EVs and PVs. The system operates at a frequency of 50 Hz, and the BESS has a capacity of 0.15 MW. The concepts of regression analysis are employed for the sizing of BESS in this study, as outlined in (Ling et al., 2023). The mathematical formulation for a polynomial function, presented in Eqs. (14) to (18), was derived using regression analysis, a mathematical model was developed to represent the relationship between power losses, voltage deviation, and the BESS multiplier.

$$Y_i = a + bX_i + cX_i^2 + dX_i^3 \quad (14)$$

$$\sum_i Y_i = a \sum_i 1 + b \sum_i X_i + c \sum_i X_i^2 + d \sum_i X_i^3 \quad (15)$$

$$\sum_i X_i Y_i = a \sum_i X_i + b \sum_i X_i^2 + c \sum_i X_i^3 + d \sum_i X_i^4 \quad (16)$$

$$\sum_i X_i^2 Y_i = a \sum_i X_i^2 + b \sum_i X_i^3 + c \sum_i X_i^4 + d \sum_i X_i^5 \quad (17)$$

$$\sum_i X_i^3 Y_i = a \sum_i X_i^3 + b \sum_i X_i^4 + c \sum_i X_i^5 + d \sum_i X_i^6 \quad (18)$$

Eqs. (14) to (18) can be solved using MATLAB software to determine the values of a , b , c , and d , from which the third-order polynomial is derived.

As defined in the placement methodology, the BESS reference size of 0.15 MW is connected to the optimal location (bus STN CNT) identified earlier. DigSILENT Power Factory is then used for simulation. The reference size of the BESS is scaled incrementally using the BESS multiplier (λ_{BESS}), ensuring that Eq. (19) holds for each scaled BESS size:

$$BESS_{size}(MW) = \lambda_{BESS} \times BESS_{reference\ size} = 0.15\lambda_{BESS} \quad (19)$$

Each BESS size is connected to the optimal location, and the power system software conducts a time-dependent (quasi-dynamic) load flow analysis to evaluate the power losses and voltage deviations. Initially, the network's power loss without any BESS connection is 0.922663 MW.

3.1. Genetic algorithm

GAs are evolutionary-based methods inspired by Darwin's concept of original selection and are often employed to address optimization problems. In this paper, GAs was utilized for optimal sizing and placement of BESS, with the construction of the objective function serving as the optimization criterion.

A random population of possible solutions to the problem is created at the beginning of the GA process, as shown in Fig. 2. Every member of this initial population has their fitness evaluated, and those who are more fit have a higher chance of surviving. As the algorithm develops, new possible solutions—known as offspring—are produced using the prior generation of parents through genetic processes like crossover, mutation, and selection (Mirsaeidi et al., 2023; Liu et al., 2020).

By offering approximations, GAs is beneficial for resolving challenging optimization issues. Three core ideas serve as their foundation (McCall, 2005):

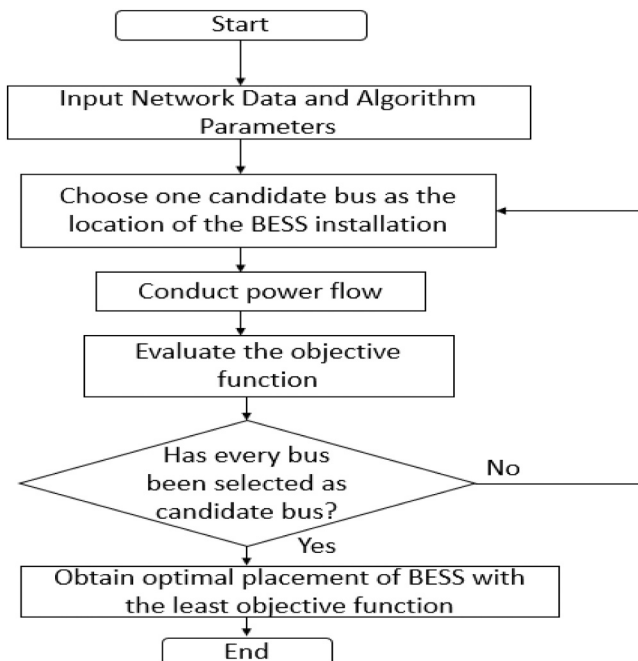


Fig. 1. Flowchart of the proposed approach for optimal BESS placement.

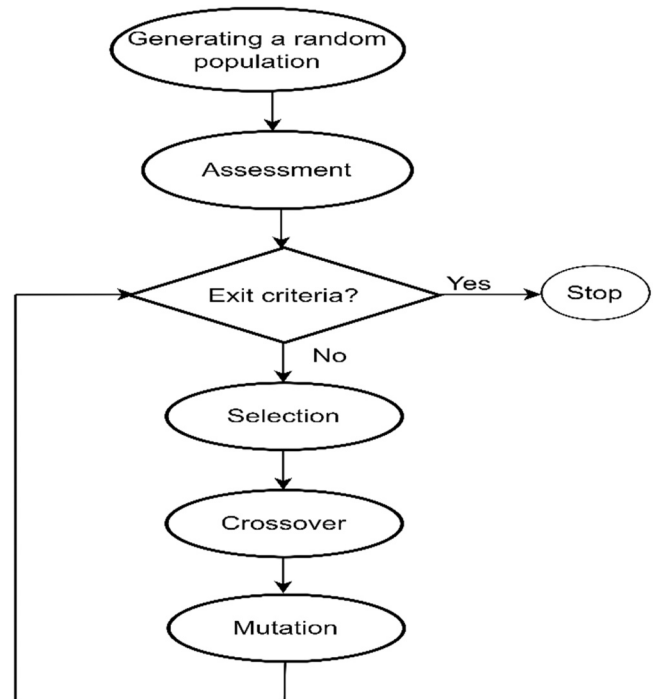


Fig. 2. Description of genetic algorithm.

- **Variation Principle:** The selection process heavily relies on the unique characteristics of each member of a population.
- **Adaptation Principle:** People are more inclined to procreate if they possess better survival skills.
- **Heredity Principle:** For traits to be passed on to children and allow the population to evolve toward desirable characteristics, they must be inheritable.

GAs is used extensively in optimization; however, they have several drawbacks. They may experience modest rates of convergence and local trapping, especially when the population is not diverse. If the population members are overly similar, GAs may miss the global optimum and undergo early convergence.

It is necessary to explain a few basic terms before going into detail about how GAs operate:

- **Population:** The collection of all potential answers.
- **Individual:** A population-wide single solution.
- **A chromosome** is a part that symbolizes a solution.
- **Gene:** A particular quality or feature of a solution.

GAs have recently been widely used to solve sizing and energy management optimization issues, demonstrating their value in tackling practical issues.

3.2. Particle swarm optimization algorithm

PSO is a widely used swarm intelligence algorithm introduced by Dr. Kennedy and Eberhart in 1995 (Dipesh and Lini). Inspired by the social behavior of flocks of birds, PSO is designed to find optimal solutions for complex optimization problems (Naderi et al., 2019; Gandoman et al., 2018; Saini et al., 2024). In this algorithm, particles move within a search space, mimicking a swarm's behavior to find the ideal spot for food, which represents the best course of action. Each particle in PSO has a position, X_{it} representing a promising solution, and a velocity U_i , which determines its movement. As particles navigate the search space, they continuously update their positions and velocities to achieve better solutions. By comparing their current and previous positions, particles identify their best personal positions (P_{best}). Additionally, they share information with the swarm, allowing them to identify the best global position (G_{best}), which represents the optimal solution found by the entire swarm.

PSO integrates cognitive and social components, enabling cooperation among particles to achieve high levels of problem-solving efficiency. The cognitive component focuses on a particle's individual experience (P_{best}), while the social component incorporates the collective experience of the swarm (G_{best}). Acceleration coefficients govern the particles' movements (a_1 and a_2) and random factors (b_1 and b_2) to balance exploration and exploitation. An inertia factor (w) controls the influence of a particle's previous velocity on its current movement. Eqs. (18) and (19) describe how the positions and velocities of particles are updated as they explore the search space.

The iterative process of PSO involves the following steps:

- **Fitness Evaluation:** Calculate each particle's fitness value at its current position, corresponding to the objective function value at that position.
- **Update Best Positions:** Update each particle's personal best fitness (P_{best}) and the swarm's global best fitness (G_{best}).
- **Position and Velocity Update:** Use predefined equations to adjust each particle's velocity and position for the next iteration.

Initially, particle positions are evenly distributed across the search space to cover all potential values of the decision variables. During each iteration, particles receive a fitness value based on the objective function and retain their best values throughout optimization. The particle with

the best fitness value is updated at every iteration by comparing its current fitness with the global best from previous iterations. Common stopping criteria for PSO include a predefined number of iterations or a tolerance for minimal changes in the optimal fitness value (Saini et al., 2024). Through this iterative approach, particles progressively converge toward the optimal solution, demonstrating PSO's efficiency in tackling diverse optimization problems.

$$U_i^{t+1} = wU_i^t + a_1b_1(P_{best,i}^t - X_i^t) + a_2b_2(G_{best,i}^t - X_i^t) \quad (20)$$

$$X_i^{t+1} = X_i^t + U_i^{t+1} \quad (21)$$

3.3. Grey Wolf optimization (GWO) algorithm

The Grey Wolf Optimization (GWO) algorithm, proposed by Seyedali Mirjalili in 2014 (Herwan and Mustaffa, 2022), is inspired by the social hierarchy and hunting behavior of grey wolves in nature. The hierarchy comprises four levels: the alpha (leader), beta (advisor to the leader), delta (subordinate), and omega (follower). This structured leadership model guides the algorithm's decision-making process. GWO effectively balances exploration and exploitation, making it suitable for solving complex, non-linear optimization problems. It has been widely applied in various domains, including power system optimization, engineering design, and image processing.

3.4. Deep Sleep optimizer (DSO) algorithm

The Deep Sleep Optimization (DSO) algorithm is a recent meta-heuristic introduced in 2023. It is a nature-inspired optimization technique modeled after the human deep sleep cycle (Mirjalili et al., 2014). DSO employs a two-phase strategy: random exploration during the "dream phase" and solution refinement during the "memory strengthening phase," enabling it to effectively escape local optima and explore the solution space more comprehensively. Notable features of DSO include:

- When the algorithm detects stagnation in the search for an optimal solution, it transitions into a deep sleep state, thereby reducing unnecessary computational effort.
- DSO avoids redundant evaluations by halting iterations that are unlikely to improve the solution, thus enhancing computational efficiency.
- The sleep mechanism enables a balance between global exploration and local exploitation by alternating between active search and rest periods.
- This mechanism also helps the algorithm escape local optima by suspending the search and introducing solution diversity upon reactivation.

3.5. Test system

This study utilizes two test distribution systems: the real-world 30-bus and 49-bus networks (Chong et al., 2013). Both systems are integrated with electric vehicles (EVs) and photovoltaic (PV) plants, operating at a system frequency of 50 Hz. The network topologies are illustrated in Fig. 4 and Fig. 5, respectively.

4. Techno-economic analysis of various BESS configurations in a 30-bus South Africa distribution network with PV and EVs

This section analyses the technical and economic impacts of integrating a BESS with the grid, solar PVs, and EVs in a 30-bus South Africa DN. The study addresses the increasing electricity demand driven by the growing EV infrastructure while reducing the problems with instability of the grid caused by unexpected load spikes, higher electrical losses,

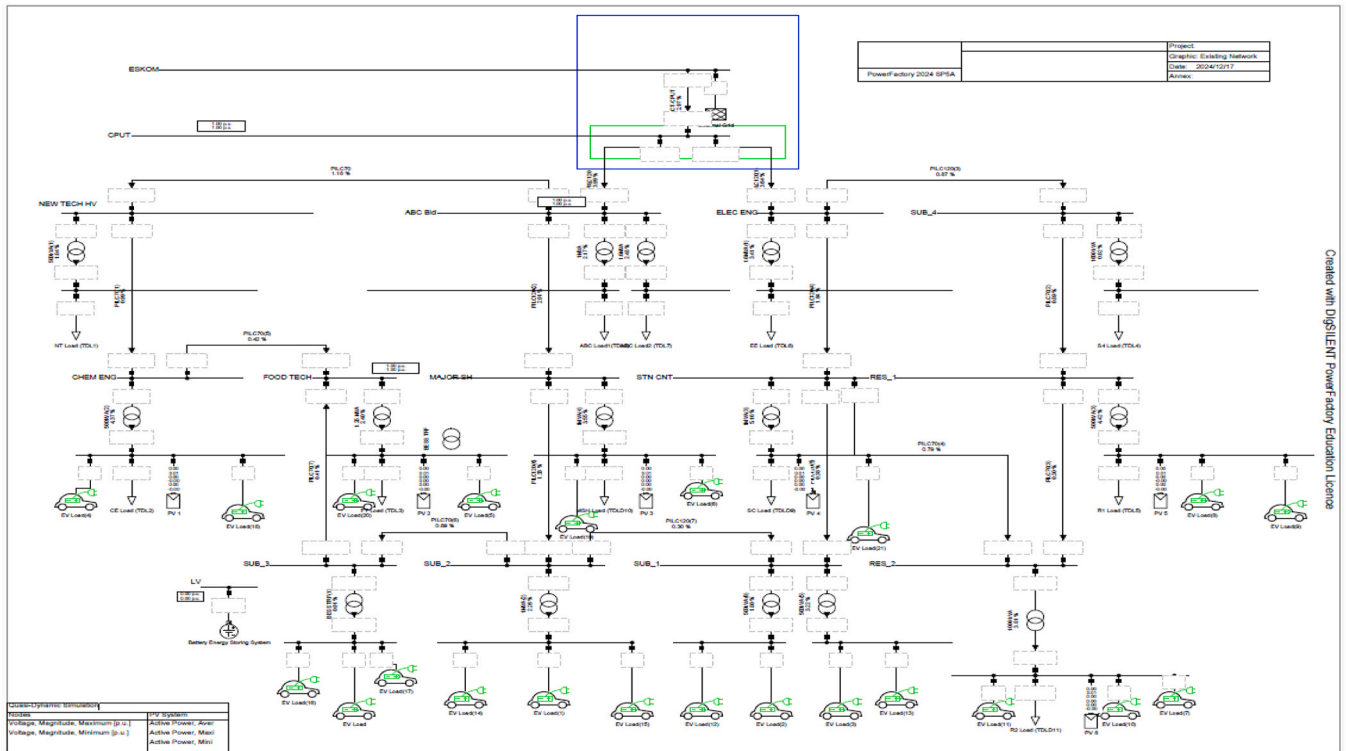


Fig. 3. Topology of the 30-bus distribution test system using DigSILENT Power Factory software.

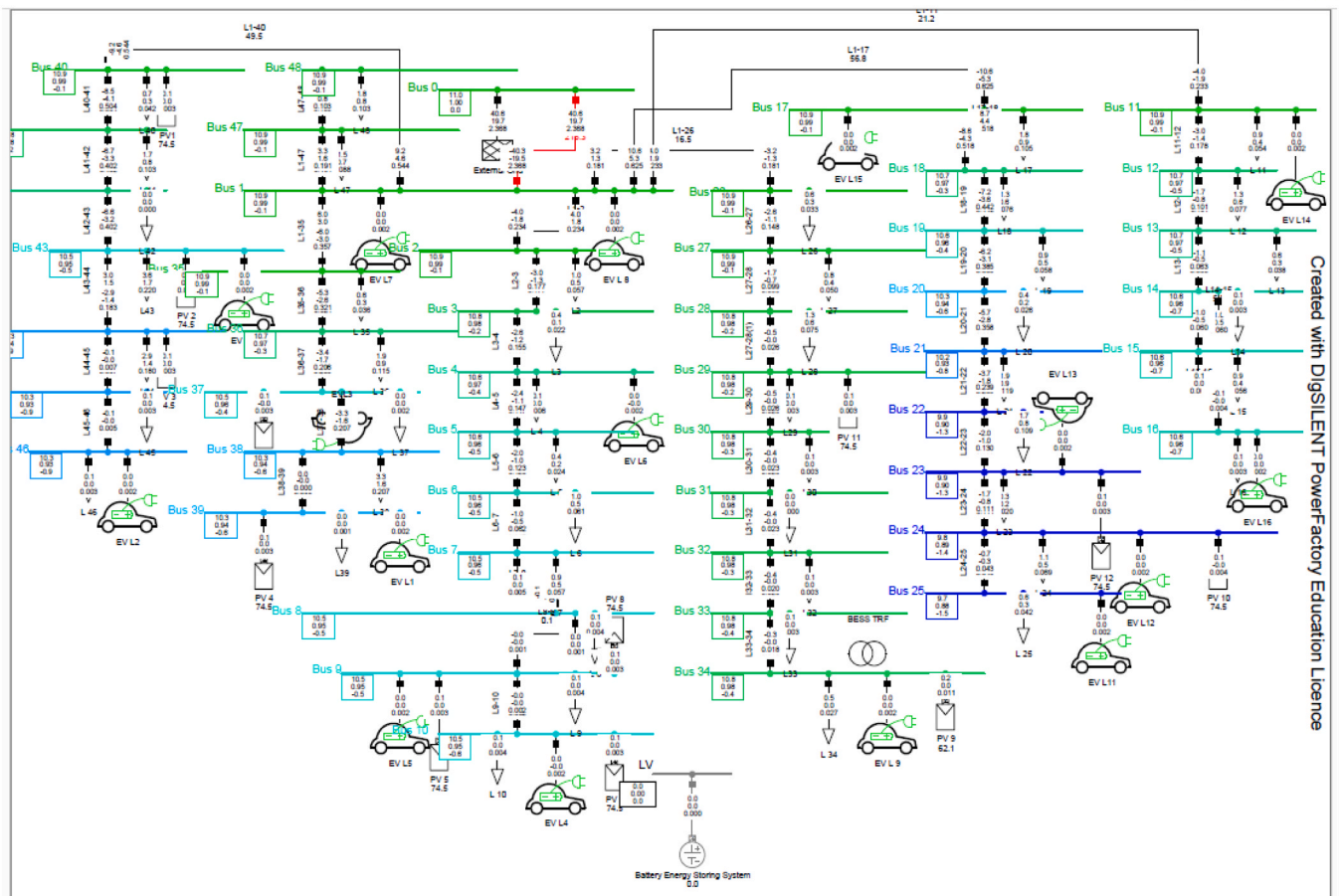


Fig. 4. Topology of the 49-bus distribution test system using DigSILENT Power Factory software.

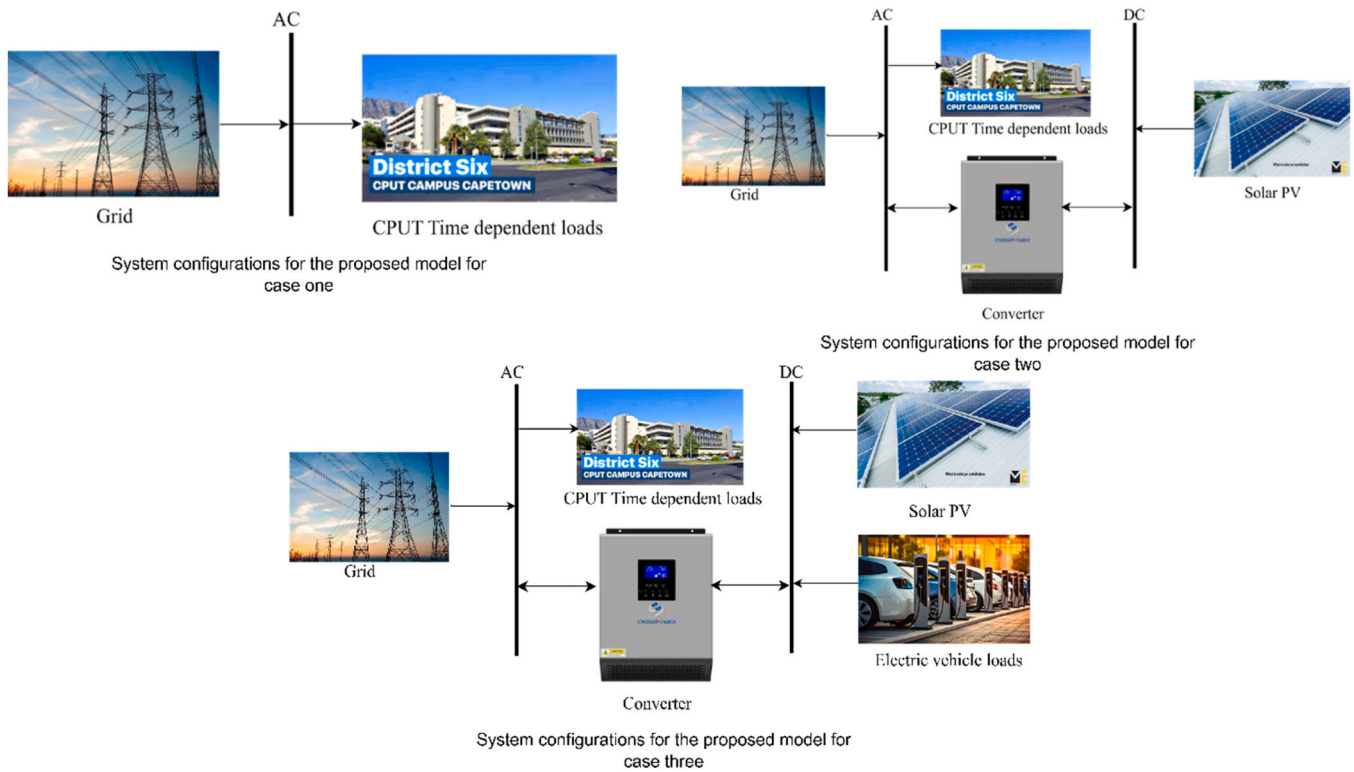


Fig. 5. System configurations for the proposed model for case one to case three.

and high-voltage equipment overloading, which can compromise power quality. Using the HOMER Pro platform, the research models and optimizes BESS integration with EV and solar PV configurations, considering different battery storage systems and accounting for various geographical and meteorological factors. Various system configurations are analyzed to assess their impacts on power losses and voltage deviations. This evaluation is conducted through the following case studies:

Case One. : Grid (Eskom Power) with Time-Dependent Loads

Case Two. : Grid (Eskom Power), Solar PVs, and Time-Dependent Loads

Case Three. : Grid (Eskom Power), Solar PVs, EVs, and Time-Dependent Loads

Case Four. : Case Three with Li-ion BESS

Case Five. : Case Three with Surrette BESS

Case Six. : Case Three with Trojan BESS

In case one scenario, the system relies solely on the grid (Eskom Power) to supply energy to time-dependent loads on the 30-bus South Africa distribution network. This case establishes the baseline for evaluating the grid's performance without renewable energy, EV integration, or energy storage, as can be seen in Fig. 3. Case two integrates solar PV systems with the grid to supply energy to the same time-dependent loads, as presented in Fig. 5. This case evaluates the impact of renewable energy integration (solar PVs) on grid performance, energy costs, and losses. The case three scenario incorporates Electric Vehicles (EVs) alongside solar PV systems and the grid to meet the time-dependent loads as shown in Fig. 5. It analyses the combined impact of EV integration and solar PV generation on the distribution network.

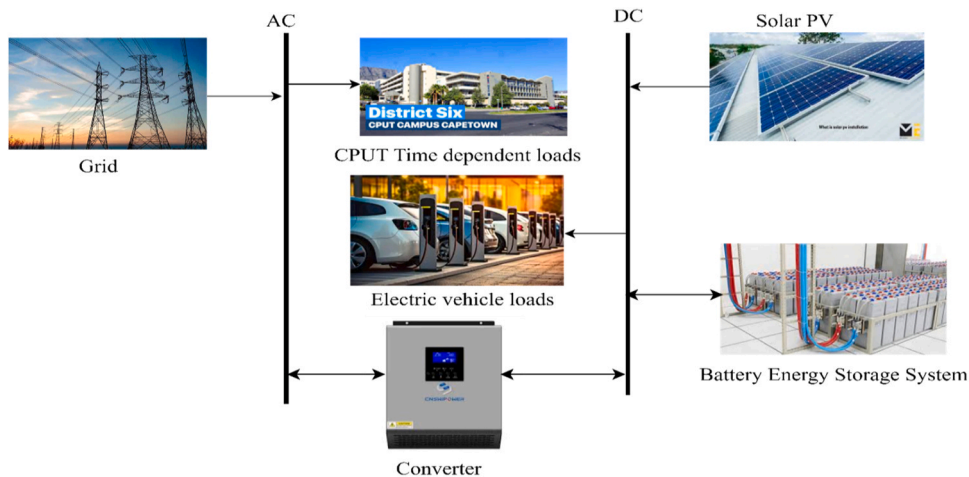


Fig. 6. System configurations for the proposed model with energy storage.

In case four, a Lithium-ion BESS is added to the grid, solar PVs, and EV-integrated network, as shown in Fig. 6. The characteristics of lithium-ion batteries make them well-suited for grid-connected, renewable energy-based power systems. Li-ion batteries offer a high efficiency of approximately 95 %, a depth of discharge of up to 90 %, and maintain optimal performance within an adequate temperature. They typically support 3000 to 5000 charge-discharge cycles and have a projected lifespan of up to 20 years (Al-Ghussain et al., 2023). This study will use energy storage from Li-ion to mitigate the challenges of EV integration and stabilize the grid. The battery energy storage will balance supply and demand by storing excess solar energy and discharging during peak periods.

Case five replaces the Lithium-ion BESS in Case Four with a Surrette Battery Energy Storage System. This case study evaluates the performance of Surrette BESS for energy storage and grid stabilization in the same configuration. The Surrette 6CS25P battery is used as the energy storage device in this study. This battery system is known for its reliability, safety, and energy efficiency. It effectively stores excess energy generated from RE sources, thereby improving self-consumption and reducing dependence on the grid. Additionally, Surrette batteries offer extended lifespans when operated at lower depths of discharge (DoD) (Chong et al., 2013). In case six, a Trojan BESS replaces the energy storage in Case Four and Case Five. Trojan batteries are service-free and are well-suited for demanding RE applications due to their higher power output. Known for their reliable performance, strong durability, and long service life, they incorporate key design features that offer notable advantages over other battery types. These batteries provide a round-trip efficiency of approximately 80 %, support maximum charging and discharging currents of 185 A and 300 A respectively, and allow a maximum charging rate of 1 A per Ah of capacity (https://www.trojanbattery.com/pdf/SAGM_06_220_IEC_61427_FINAL.pdf, 2025). This study analyses the performance and cost-effectiveness of Trojan BESS within the same configuration.

5. Results and discussion

This study will discuss the simulated results in three key categories: the impacts of integrating photovoltaic (PV) systems, electric vehicles (EVs), and battery energy storage systems (BESS) in both the real-world 30-bus South Africa distribution network and 49-bus distribution network of Baghdad City, Iraq; the optimal placement of BESS within the network; and the economic analysis of various BESS configurations on the distribution network systems.

5.1. Impacts of PV, EVs and BESS integration on a distribution network

The simulation results demonstrated a consistent trend in active power losses and voltage magnitudes throughout the 24-hour load profile analysis across all scenarios. During periods of low load, power losses were minimal, resulting in maximum voltage magnitudes. Conversely, active power losses were significantly higher during peak load periods, accompanied by a reduction in voltage magnitudes as shown in Table 1. This pattern was consistently observed across all cases studied.

Table 1
Summary of the active power loss and voltage profile for the 30-bus DN system.

Parameters	Case One	Case two	Case three	Case four	Case five	Case six
Max power losses (MW)	0.038440	0.038430	0.038500	0.06666	0.06720	0.06685
Min power losses (MW)	0.038410	0.038410	0.038420	0.06582	0.06624	0.06750
Total power losses (MW)	0.922212	0.922109	0.922666	1.590579	1.60228	1.60558
Max voltage (pu)	0.9991	0.9991	0.9991	0.9991	0.9926	0.9926
Min voltage (pu)	0.9988	0.9988	0.9988	0.9988	0.9765	0.9765

- **Case one:** The simulation results indicated that the highest power loss, 0.03844 MW, occurred at 12:00:00, while the lowest power loss, 0.03841 MW, was observed at 04:00:00. Additionally, the maximum voltage deviation of 0.9991 pu occurred at 03:00:00, and the minimum deviation of 0.9988 pu was recorded at 13:00:00. Fig. 7 to Fig. 9 illustrate the load profiles, voltage deviations, and active power loss patterns.
- **Case two:** Photovoltaic (PV) systems were integrated into the network in the second case study. The simulation results demonstrated that the integration of PVs had minimal impact on both power losses and voltage deviations, as summarized in Table 1 and Figs. 7 to 9.
- **Case three:** The third scenario examined the effect of EVs on a distribution network with time-dependent loads. Nine EVs were connected to the network, with scheduled charging occurring during the off-peak period of the load profile. The simulation results indicated that the integration of EVs significantly impacted both the active power losses and the voltage profile. As a result, the maximum and total active power losses increased by over 24 % and 18.8 %, respectively. Additionally, the minimum bus voltage dropped from 0.9991 pu to 0.9988 pu. The plots illustrating the voltage profile and active power losses are provided in Figs. 7 and 9.
- **Case four:** This scenario examines the impact of integrating Li-ion BESS at buses HIGH TECH HV and SUB 3 on power losses and the voltage deviation of the system profile. The simulation results, as shown in Table 4, indicate that integrating BESS at these locations reduced the maximum and minimum power losses to 0.0666 MW and 0.06582, respectively, while the voltage values remained unchanged.
- **Case five:** This scenario examines the impact of integrating Surrette BESS at buses HIGH TECH HV and SUB 3 on power losses and the voltage deviation of the system profile. The simulation results, as shown in Table 4, indicate that integrating BESS at these locations shows the maximum and minimum power losses at 0.06720 MW and 0.06624 MW, respectively, while the voltage values range from 0.9926 pu and 0.9765 pu respectively.
- **Case six:** This scenario examines the impact of integrating Trojan BESS at buses HIGH TECH HV and SUB 3 on power losses and the voltage deviation of the system profile. The simulation results, as shown in Table 4, indicate that integrating BESS at these locations shows the maximum and minimum power losses at 0.06685 MW and 0.06750 MW, respectively, while the voltage values remained unchanged.

5.2. Optimal Placement of Battery Energy Storage System

The optimal placement of BESS in the test systems was determined using the objective function defined in Eq. (2). The optimization aimed to identify the bus location that minimizes overall system costs arising from active power losses and voltage deviations upon BESS integration. Four optimization algorithms were employed, utilizing all necessary input data to solve the objective function. The results are summarized in Tables 2 and 3, while the corresponding convergence plots are illustrated in Fig. 10.

The simulation results in Table 2 indicate that the minimum system cost—considering both power losses and voltage deviations was

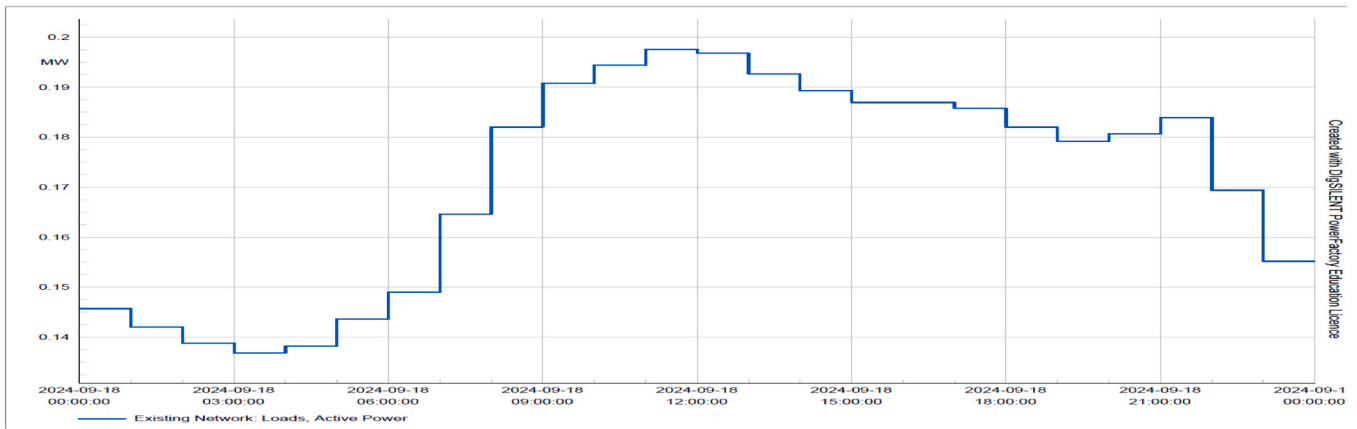


Fig. 7. Load profile of the distribution Network showing peak and off-peak loads for case one.

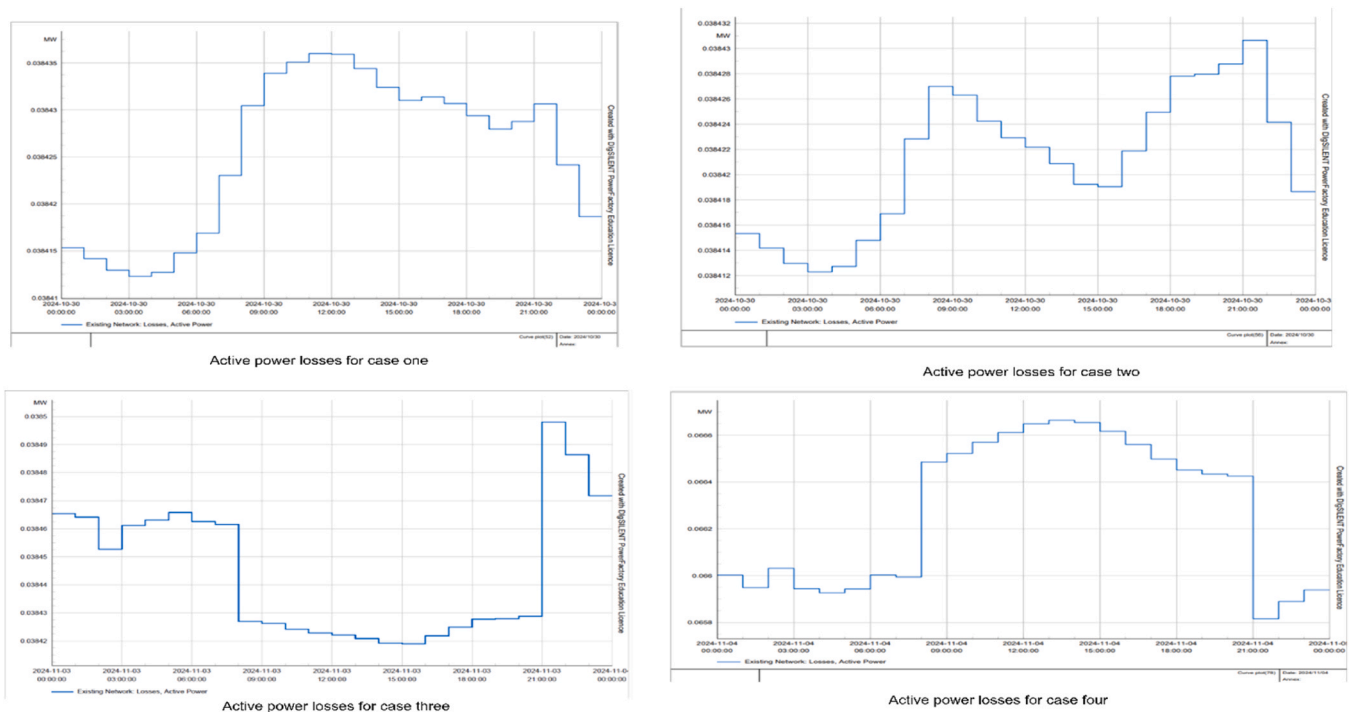


Fig. 8. Active power losses in the DN for case studies.

achieved when the BESS is placed at bus STN CNT in the 30-bus network. In contrast, bus SUB 3 yields the highest system cost, making it the least favorable location for BESS integration. Therefore, bus STN CNT is identified as the optimal placement for minimizing losses and improving voltage stability in the 30-bus system. Likewise, for the 49-bus network (Table 3), placing the BESS at bus 10 results in a system cost of \$614.13, which is more than twice the cost incurred when BESS is placed at bus 22 (\$270.28). Hence, bus 22 is determined to be the optimal BESS location for the 49-bus system. The convergence plot corresponding to the 49-bus optimization is shown on Fig. 10.

The effects of optimal BESS placement on voltage magnitude and power losses are clearly evident in the larger 49-bus test system. The corresponding simulation results are presented in Table 4 and Table 5.

As shown in Table 4, prior to placing the BESS at the optimal location (bus 22), eight out of the 49 buses in the network recorded voltage magnitudes outside the acceptable range of 0.95 pu to 1.05 pu. These violations can be seen in the second column. However, after installing the BESS at bus 22, the voltage levels were significantly improved and

brought within the acceptable limits, as indicated in column 3 in Table 4. In contrast, placing the BESS at a non-optimal location (bus 10) led to continued violations of voltage limits. A comparative analysis of the voltage magnitudes at these critical buses under different network conditions is illustrated in Fig. 11.

From Table 5, it is shown that placing the BESS at the optimal location significantly influences the reduction of active power losses. The integration of the BESS at the optimal bus (bus 22) results in a 33.33 % decrease in active power losses. In contrast, placing the BESS at a non-optimal location (bus 10) leads to a 100 % increase in losses, highlighting the importance of strategic placement for effective system performance.

Fig. 11 compares voltage magnitudes across eight critical buses under three network conditions: without BESS, with BESS at the optimal location (bus 22), and with BESS at a non-optimal location (bus 10). Without BESS, several buses, particularly Bus 20 to Bus 25—exhibit voltage levels below the acceptable threshold of 0.95 pu, indicating undervoltage issues. With BESS installed at the optimal location (bus

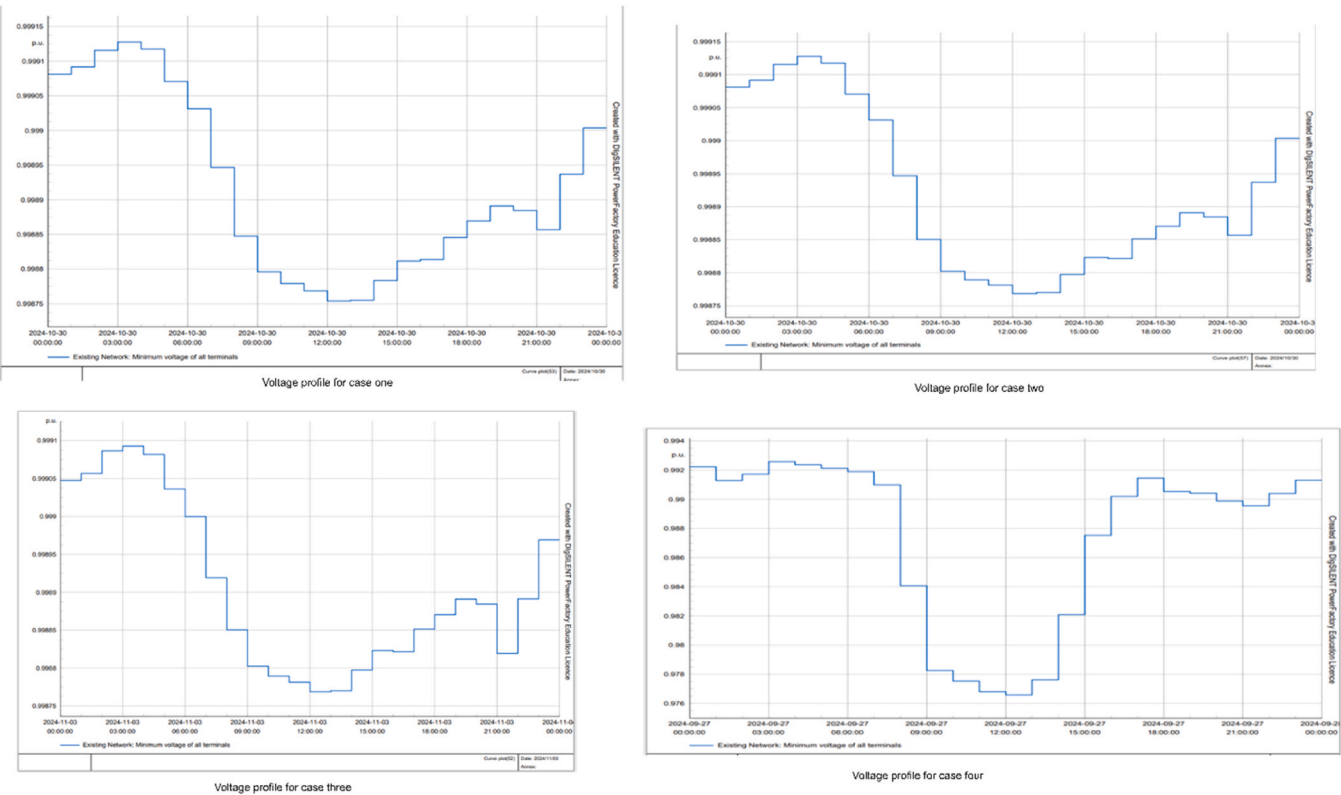


Fig. 9. Voltage profiles in the DN for case studies.

Table 2 System costs due to power losses and voltage deviation for 30-bus system.					
Bus name	System costs (\$)	Remarks	Bus name	System costs (\$)	Remarks
Chem Eng	6.127	Optimal system cost	NT LV	6.1987	The Worst system cost
STN CNT	6.12465		SCLV	6.13962	
R1 LV	6.19698		S1LV2	6.20024	
S4 LV	6.14618		ABC Bld	6.12559	
RES_1	6.12678	Optimal system cost	Eskom	6.12654	The Worst system cost
SUB 4	6.12596		CE LV	6.1953	
ELEC Eng	6.1252		S3 LV	6.12788	
Major SH	6.12559		MSH LV	6.14711	
Food Tech	6.12682	Optimal system cost	EELV	6.13694	The Worst system cost
CPUT	6.12649		R2LV	6.14733	
New Tech	6.12722		SUB 3	10.1719	
FT LV	6.15129		SUB 2	8.6058	
ABC LV1	6.14666	Optimal system cost	RES 2	8.8771	The Worst system cost
ABC LV2	6.13951		S2LV	6.15081	
FT LV	6.15129				

22), all buses show improved voltage profiles, with values mostly close to or exceeding 0.95 pu. In contrast, placing the BESS at the non-optimal location results in limited voltage improvement, with some buses still below acceptable levels. This analysis confirms that optimal siting of BESS significantly enhances voltage regulation and power quality in the distribution network.

The simulated results from Table 3 indicate a trade-off between BESS size, power losses, and voltage deviation. Larger BESS size (high λ_{BESS})

Table 3 System costs due to power losses and voltage deviation for 49-bus system.					
Bus number	System costs (\$) (using PSO)	Remarks	Bus number	System costs (\$) (using PSO)	Remarks
1	425.87	The Worst system cost	33	497.76	Near-worst system cost
10	614.13		34	554.55	
11	412.37		35	384.01	
12	412.39		36	383.99	
13	412.43	Optimal system cost	37	383.96	Optimal system cost
14	440.84		38	355.65	
15	469.24		39	409.26	
16	469.25		40	384.01	
17	383.97	Optimal system cost	41	384.02	Optimal system cost
18	355.55		42	355.6	
19	327.14		43	327.19	
20	298.72		44	327.22	
21	278.78	Optimal system cost	45	384.03	Optimal system cost
22	270.28		46	412.43	
23	279.29		47	412.41	
24	298.69		48	412.4	
25	327.1	Optimal system cost	2	412.07	Optimal system cost
26	412.34		3	412.02	
27	412.42		4	412.06	
28	412.52		5	412.07	
29	440.93	Optimal system cost	6	412.08	Optimal system cost
30	469.34		7	452.47	
31	469.35		8	533.29	
32	497.75		9	573.7	

improve voltage stability but increase power losses, while smaller sizes (low λ_{BESS}) reduce losses but lead to more significant voltage deviations. An optimal performance range lies in mid-range λ_{BESS} values (1.4–1.0), which balance reasonable power losses and voltage regulation. This suggests that a moderate BESS size is most efficient for maintaining

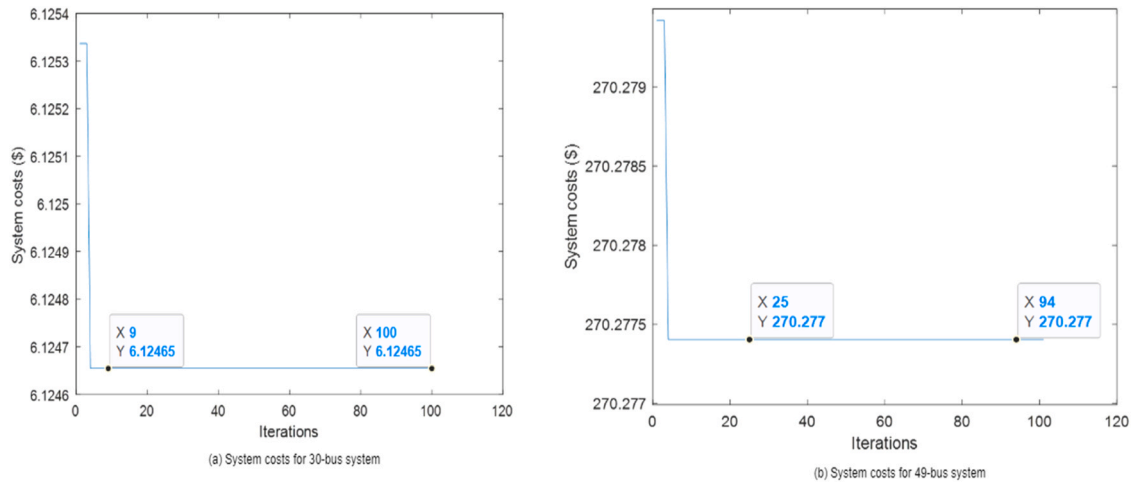


Fig. 10. Convergence plot for the minimum system costs.

Table 4

Voltage profile analysis for the 49-bus network system.

Critical buses	Voltage magnitude (network without BESS) (pu)	Voltage magnitude (network with BESS at optimal location of bus 22) (pu)	Voltage magnitude (network with BESS at non-optimal location of bus 10) (pu)
Bus 8	1.076	0.956	1.076
Bus 9	1.086	0.956	1.086
Bus 20	0.940	0.990	0.941
Bus 21	0.930	0.990	0.927
Bus 22	0.900	1.000	0.902
Bus 23	0.900	1.000	0.901
Bus 24	0.890	0.990	0.890
Bus25	0.880	0.990	0.886

Table 5

Analysis of power losses for the 49-bus network system.

Network conditions	Power losses (MW)
Distribution network without BESS	1.5
BESS at the optimal location	
Bus 22	1.00
Selected non-optimal locations	
Bus 10	2.0
Bus39	1.70
Bus48	1.50
Bus9	1.90
Bus 18	1.30

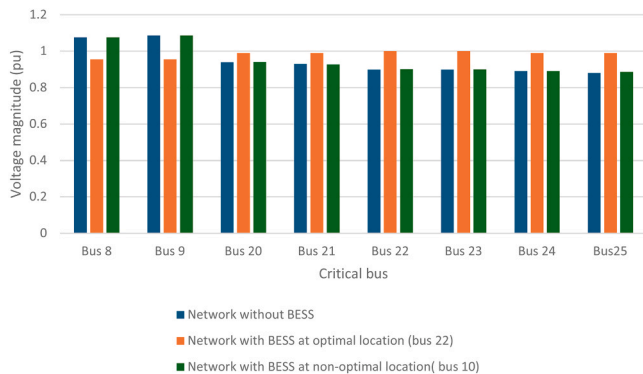


Fig. 11. Comparison of voltage magnitudes for different network conditions.

system stability and minimizing losses.

The analysis in Table 4, Fig. 10 shows that as the BESS multiplier (λ_{BESS}) and corresponding BESS size decrease, the system experiences a slight improvement in power losses but a marginal increase in voltage deviation. Larger BESS sizes ($\lambda_{BESS} = 1.93333$, 0.29 MW) have slightly higher power losses (1.000166 pu) and the minor voltage deviation (0.000993 pu). Smaller BESS sizes ($\lambda_{BESS} = 0.06667$, 0.01 MW) result in the lowest power losses (0.999963 pu) but the most significant voltage deviation (0.001092 pu).

The multi-objective functions for the optimal sizing of BESS in the two test systems are formulated. Using MATLAB regression scripts from Eqs. (15) to (18), the datasets from Tables 6 and 7 (for the 30-bus network) and Table 8 (for the 49-bus network) are utilized to develop mathematical models that capture the relationship between the BESS multiplier (λ_{BESS}), power losses (P_L) and voltage deviation (V_D). The resulting formulations are presented in Eqs. (22) and (23) for the 30-bus network, and Eqs. (24) and (25) for the 49-bus network. The corresponding plot functions are illustrated in Figs. 12 and 13.

Multi-objective function using the 30-bus network.

$$V_D = 0.0011 - 0.0001\lambda_{BESS} + 0.0000\lambda_{BESS}^2 + 0.0000\lambda_{BESS}^3 \quad (22)$$

$$P_L = 1.0000 - 0.0006\lambda_{BESS} + 0.0003\lambda_{BESS}^2 + 0.0001\lambda_{BESS}^3 \quad (23)$$

Multi-objective function using the 49-bus network.

Table 6

Simulated results for load flow.

BESS multiplier (λ_{BESS})	BESS size (MW)	Power losses (pu)	Voltage Deviation (pu)
1.93333	0.29	1.000166	0.000993
1.8	0.27	1.00072	0.000999
1.66667	0.25	0.999986	0.001005
1.53333	0.23	0.999917	0.001011
1.4	0.21	0.999859	0.001018
1.26667	0.19	0.999814	0.001024
1.13333	0.17	0.999782	0.001031
1	0.15	0.999757	0.001039
0.86667	0.13	0.999754	0.001046
0.73333	0.11	0.999758	0.001053
0.6	0.09	0.99977	0.001063
0.46667	0.07	0.999799	0.001068
0.33333	0.05	0.999843	0.001076
0.2	0.03	0.999898	0.001084
0.06667	0.01	0.999963	0.001092

Table 7
Load flow with power losses and voltage deviation.

BESS multiplier (λ_{BESS})	BESS size (MW)	Power losses (pu)	Voltage Deviation (pu)
1.93333	0.29	1.000166	0.000993
1.8	0.27	1.00072	0.000999
1.66667	0.25	0.999986	0.001005
1.53333	0.23	0.999917	0.001011
1.4	0.21	0.999859	0.001018
1.26667	0.19	0.999814	0.001024
1.13333	0.17	0.999782	0.001031
1	0.15	0.999757	0.001039
0.86667	0.13	0.999754	0.001046
0.73333	0.11	0.999758	0.001053
0.6	0.09	0.99977	0.001063
0.46667	0.07	0.999799	0.001068
0.33333	0.05	0.999843	0.001076
0.2	0.03	0.999898	0.001084
0.06667	0.01	0.999963	0.001092

Table 8
Simulation data for regression analysis implementation for 49-bus network.

BESS multiplier	BESS capacity (MW)	Power losses (MW)	Power losses (pu)	Average voltage deviation (pu)
0.10	0.70	1.40	0.93333	0.03592
0.20	1.40	1.30	0.86667	0.03546
0.30	2.10	1.20	0.80000	0.03396
0.40	2.80	1.10	0.73333	0.03250
0.50	3.50	1.10	0.73333	0.03106
0.60	4.20	1.00	0.66667	0.02974
0.70	4.90	1.00	0.66667	0.02842
0.80	5.60	1.00	0.66667	0.02714
0.90	6.30	1.00	0.66667	0.02590
0.95	6.65	1.00	0.66667	0.02522
1.10	7.70	1.00	0.66667	0.02442
1.20	8.40	1.10	0.73333	0.02444
1.30	9.10	1.10	0.73333	0.02520
1.40	9.80	1.10	0.73333	0.02594
1.50	10.50	1.20	0.80000	0.02676
1.60	11.20	1.20	0.80000	0.02762
1.70	11.90	1.30	0.86667	0.02850
1.80	12.60	1.40	0.93333	0.02932
1.90	13.30	1.50	1.00000	0.03026
1.95	13.65	1.50	1.00000	0.03072

$$V_D = 0.0389 - 0.0196\lambda_{BESS} + 0.0049\lambda_{BESS}^2 + 0.0016\lambda_{BESS}^3 \tag{24}$$

$$P_L = 1.0089 - 0.8640\lambda_{BESS} + 0.6011\lambda_{BESS}^2 - 0.0814\lambda_{BESS}^3 \tag{25}$$

5.3. Simulation results from metaheuristic optimization algorithms

Four metaheuristic optimization algorithms are employed to solve the multi-objective functions developed. The objective is to determine the optimal BESS multiplier that minimizes power losses and, subsequently, voltage deviation. The algorithms used include Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Deep Sleep Optimizer (DSO), and Grey Wolf Optimizer (GWO). The optimal solutions obtained from these algorithms are compared to identify the most effective BESS multiplier and, by extension, the optimal BESS capacity for reducing active power losses and mitigating voltage deviations. A summary of the optimal Pareto front solutions from the four algorithms is provided in Table 7 for the 30-bus network and Table 8 for the 49-bus network. The corresponding Pareto front plots are illustrated in Figs. 11 to 15. Selected samples of Pareto front solutions are presented in Tables 9 to 12, with the optimal parameters clearly highlighted.

The results from Table 11 indicate that the optimal BESS multiplier (λ_{BESS}) values range from 0.9481 to 1.9333, representing a variety of battery sizes required for different optimization scenarios. Most solutions fall between 1.0 and 1.9, suggesting a preference for medium to large storage capacities in the majority of cases. Smaller multipliers, like 0.9481, are suitable for scenarios with lower storage needs, while larger values, such as 1.9333, are optimal for situations requiring higher energy storage to manage system demands effectively. The diversity of these values underscores the adaptability of BESS sizing to meet specific operational and performance objectives.

The results from Table 12 show minimal voltage deviation, ranging between 0.0009 pu and 0.0010 pu, indicating a well-regulated voltage profile across all scenarios. Power losses are also consistently close to 1.0 pu, with slight variations from 0.9998 pu to 1.0001 pu. This demonstrates efficient system performance with minimal energy loss. The uniformity of these values suggests that the BESS configurations effectively maintain system stability and efficiency under varying operational conditions. Table 13

The selection of the best optimal solution among the four algorithms is guided primarily by the consistency of the results across all methods. Since the voltage deviation values in all Pareto front results fall within acceptable limits, the next priority is given to the algorithm that yields the lowest active power losses. In cases where all algorithms produce identical values for both power losses and voltage deviation, preference is then given to the algorithm that generates the lowest and most reliable

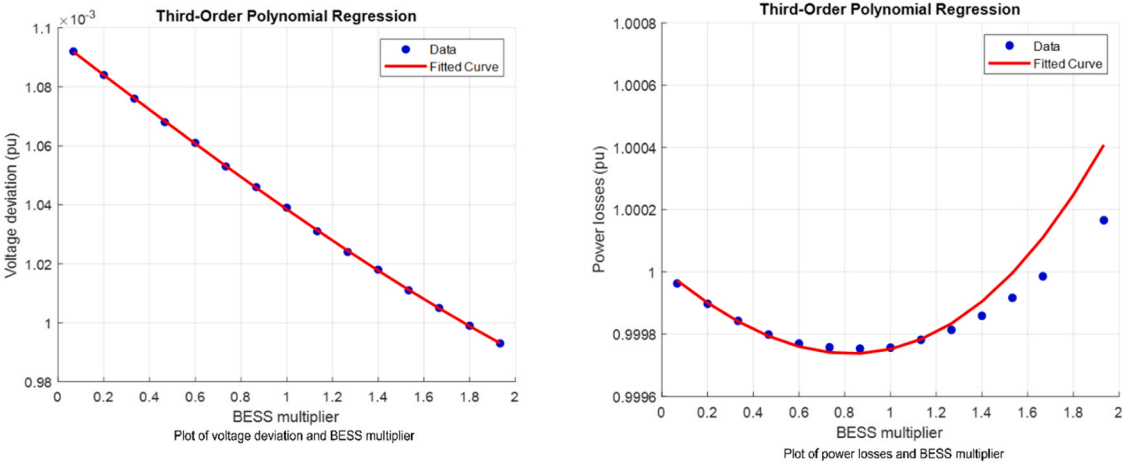


Fig. 12. Plot of voltage deviation and power losses against BESS multiplier for 30-bus system.

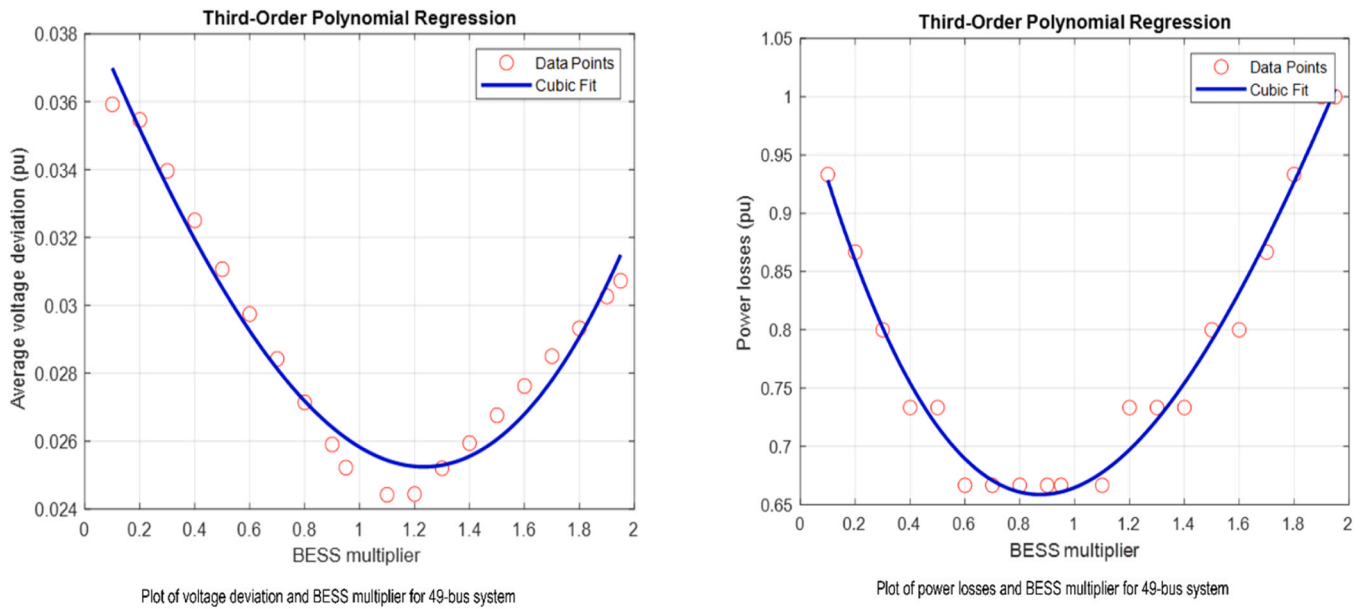


Fig. 13. Plot of voltage deviation and power losses against BESS multiplier for 49-bus system.

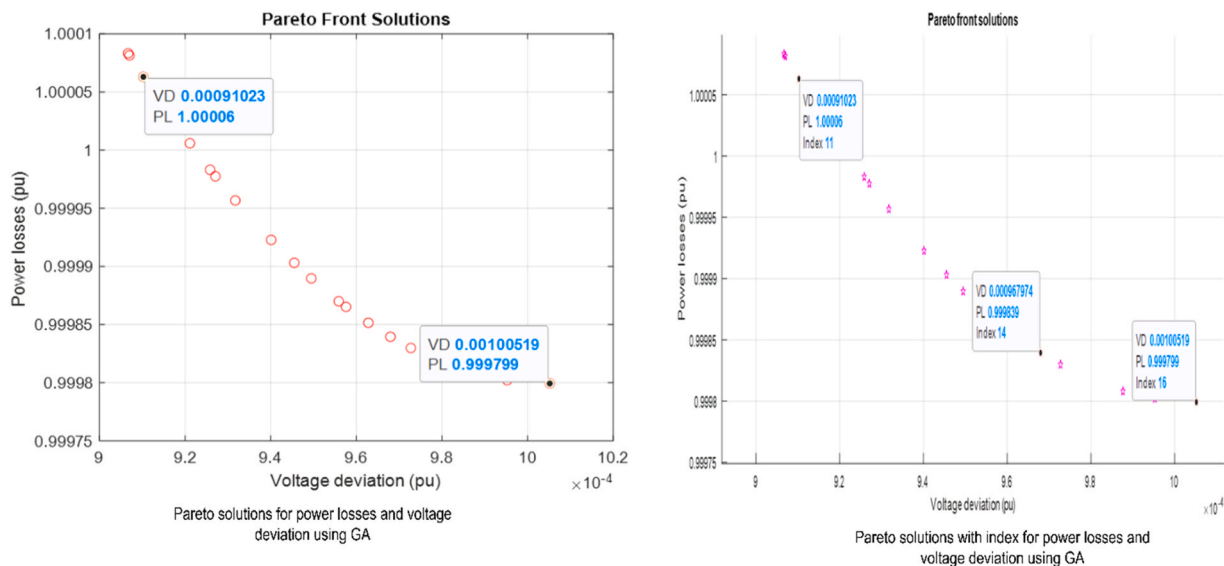


Fig. 14. Pareto solutions of power losses and voltage deviation for the GA algorithm in 30-bus system.

BESS multiplier. However, this BESS multiplier must align with the trends observed in the plots depicting the relationship between active power losses and BESS multiplier, as shown in Figs. (12b) and (13b). Based on these criteria, and referring to the optimal solutions presented in Table 7 for the 30-bus network, all four algorithms provide the same optimal values for active power losses and voltage deviation. Regarding the BESS multiplier, the results from DSO and GWO are more consistent. In contrast, the PSO-derived value of 0.7534 appears inconsistent with the observed trend in Fig. 12. Therefore, the optimal BESS multiplier is identified as 0.8266, as obtained from the DSO algorithm.

For the 49-bus test system, the optimal parameter values are presented in Table 10. As shown, all four algorithms yield identical values for voltage deviation, indicating consistency in voltage performance. While the Genetic Algorithm (GA) reports the lowest value for active power loss, it is not supported by the results of the other algorithms and is therefore considered unreliable. In terms of the BESS multiplier, the values obtained from PSO, DSO, and GWO are generally consistent, with

the DSO algorithm providing the lowest and most credible value. Consequently, the DSO algorithm is selected as the best optimal solution, with a BESS multiplier of 0.8789.

5.4. Techno-Economic analysis of various BESS configurations in distribution network system with PVS and EVs

The results demonstrated that the system configuration for the 30-bus South Africa distribution network, incorporating photovoltaic (PV) systems, electric vehicle (EV) charging infrastructure, and battery energy storage systems (BESS), can achieve a stable electricity supply while enhancing power quality and improving voltage profile conditions. The optimized system was evaluated across six different configurations to assess both the technical and economic feasibility of the proposed solution. The findings provide a comprehensive analysis of the performance of EV integration within each configuration, highlighting key technical improvements and cost-effectiveness. The detailed

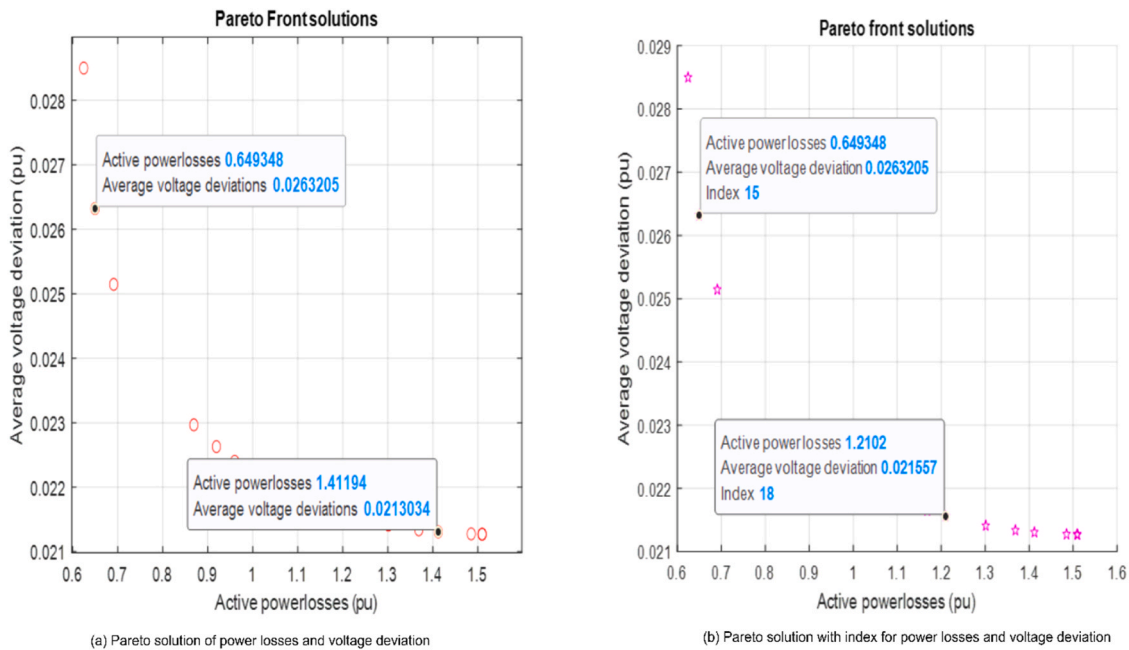


Fig. 15. Pareto solutions of power losses and voltage deviation for the GA algorithm in 49-bus system.

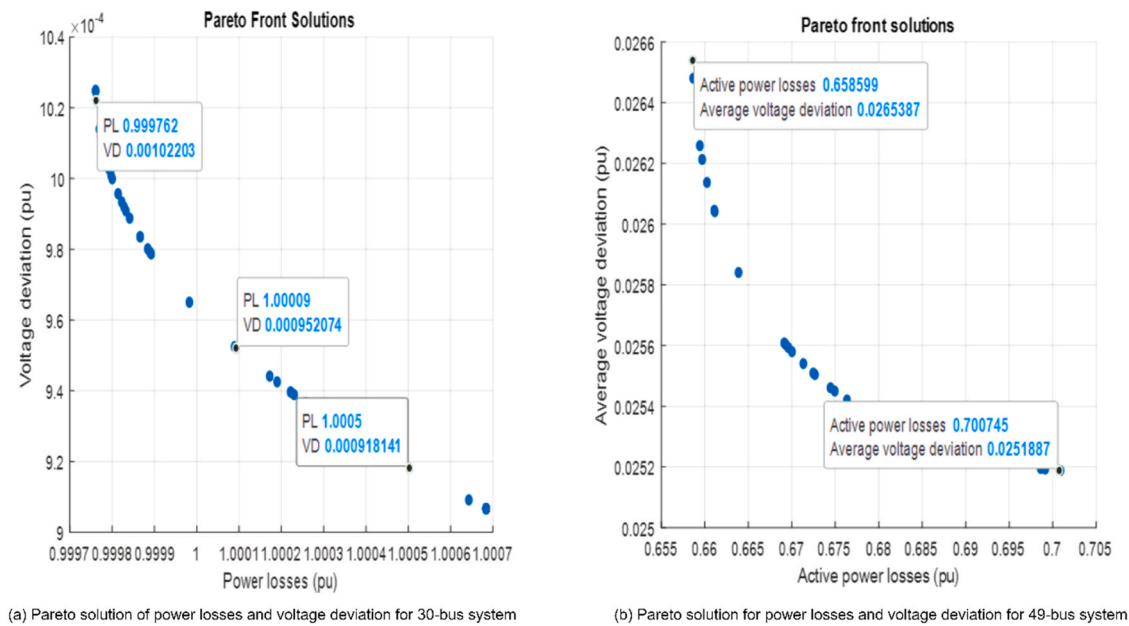


Fig. 16. Pareto solutions of power losses and voltage deviation for the PSO algorithm in 30-bus and 49-bus system.

analysis underscores the potential of the system to support efficient and reliable energy distribution.

Table 15 represents the energy purchased from the grid (Eskom Power), peak demand, and energy charges for the 30-bus South Africa distribution network annually. The monthly energy purchases fluctuate, with the lowest purchase of 137,472 kWh in February and the highest of 162,349 kWh in August. The net energy purchased is the same as the total energy purchased each month, suggesting that there is no energy generation or sales back to the grid. The peak demand varies across the months, with the highest peak demand in February and the lowest in May. These fluctuations reflect changing consumption patterns throughout the year. The energy charges correlate with the energy purchased and peak demand. The highest energy charge is observed in August, and the lowest charge is in November. There is a noticeable

increase in energy consumption during the summer months, with higher purchases in January, February, and August, possibly due to air conditioning and other cooling needs.

In contrast, the energy purchased, and peak demand are relatively lower in the winter months, such as May and November, which likely correspond to reduced energy usage as temperatures are cooler. The total annual energy charge of \$480,272 is significant, indicating a steady dependency on grid energy and substantial monthly costs. The peak demand data suggests a need for efficient load management. Managing consumption during peak periods could help in reducing overall energy costs. The fluctuation in energy charges, which is highest during high-demand months, underlines the economic impact of time-dependent loads and the importance of optimizing energy use. Overall, the 30-bus South Africa distribution network's reliance on Eskom Power for

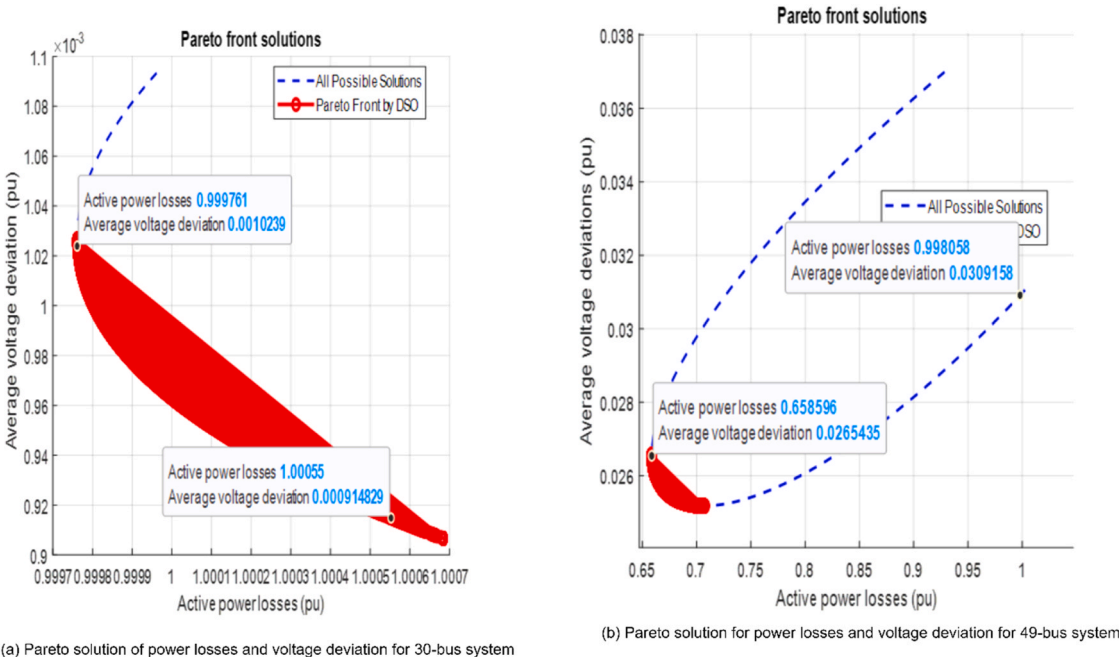


Fig. 17. Pareto solutions of power losses and voltage deviation for the DSO algorithm in 30-bus and 49-bus system.

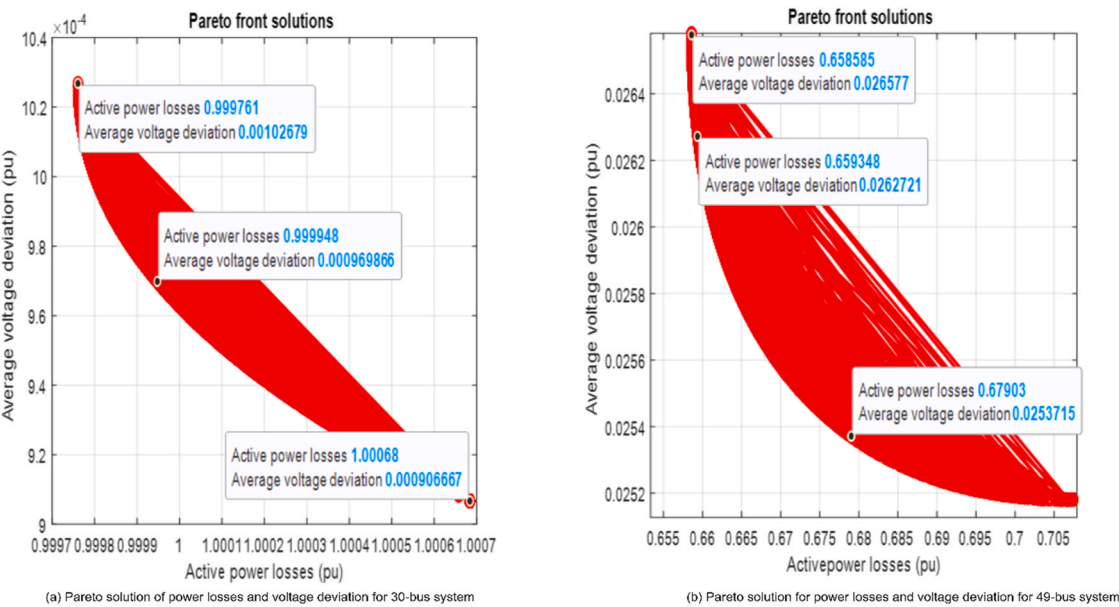


Fig. 18. Pareto solutions of power losses and voltage deviation for the GWO algorithm in 30-bus and 49-bus system.

Table 9
Comparison of optimization algorithms for optimal parameters in the 30-bus distribution network (GA, PSO, DSO, GWO).

Variables	GA	PSO	DSO	GWO
BESS multiplier (λ_{BESS})	0.9481	0.7534	0.8206	0.8226
Active power losses (pu)	0.9998	0.9998	0.9998	0.9998
Average voltage deviation (pu)	0.0010	0.0010	0.0010	0.0010

energy results in varying energy charges and peak demand throughout the year. There is potential for reducing energy costs through better load management and possible shifts to renewable energy sources, which could offset grid reliance and help mitigate peak demand costs.

Table 16 presents energy data for a system that integrates the grid

Table 10
Comparison of optimization algorithms for optimal parameters in the 49-bus distribution network (GA, PSO, DSO, GWO).

Variables	GA	PSO	DSO	GWO
BESS multiplier (λ_{BESS})	0.7436	0.8798	0.8789	0.8813
Active power losses (pu)	0.6243	0.6586	0.6586	0.6586
Average voltage deviation (pu)	0.0285	0.0265	0.0265	0.0265

(Eskom Power), solar photovoltaic (PV) systems, and time-dependent loads on the 30-bus South Africa distribution network. The total energy purchased over the year amounts to 903,962 kWh, with monthly purchases varying from 67,544 kWh in January to 86,613 kWh in June. This shows fluctuations in energy consumption, likely influenced by

Table 11
Optimal solutions for control variable, (λ_{BESS}) using GA for 30-bus system.

Index number	Optimal solutions of BESS multiplier
1	1.4413
2	1.7416
3	1.789
4	1.9303
5	1.5053
6	1.6827
7	1.1234
8	1.0475
9	1.5451
10	1.599
11	1.8977
12	1.4243
13	1.2726
14	1.3203
15	1.7294
16	0.9481
17	1.372
18	1.9333

Table 12
Optimal solutions for voltage deviation and power losses using GA for 30-bus system.

Index number	Voltage deviation (pu)	Power losses (pu)
1	0.001	0.9999
2	0.0009	1
3	0.0009	1
4	0.0009	1.0001
5	0.0009	0.9999
6	0.0009	1
7	0.001	0.9998
8	0.001	0.9998
9	0.0009	0.9999
10	0.0009	0.9999
11	0.0009	1.0001
12	0.001	0.9999
13	0.001	0.9998
14	0.001	0.9998
15	0.0009	1
16	0.001	0.9998
17	0.001	0.9999
18	0.0009	1.0001

Table 13
Optimal solutions using PSO for 30-bus system.

BESS multiplier	Power losses	Voltage deviation (pu)
1.611	1.0002	0.0009
1.933	1.0007	0.0009
0.7534	0.9998	0.001
1.8186	1.0005	0.0009
1.9333	1.0007	0.0009
0.8606	0.9998	0.001
0.9911	0.9998	0.001
0.8897	0.9998	0.001
1.9333	1.0007	0.0009
1.2133	0.9999	0.001
1.9333	1.0007	0.0009
1.3497	1	0.001
1.1651	0.9999	0.001
1.4793	1.0001	0.001
1.9333	1.0007	0.0009
1.7501	1.0004	0.0009
1.6603	1.0003	0.0009
1.6052	1.0002	0.0009
1.0805	0.9998	0.001
0.7507	0.9998	0.001
1.6618	1.0003	0.0009
0.7507	0.9998	0.001
1.6618	1.0003	0.0009

Table 14
Optimal solutions using PSO for 49-bus system.

BESS multiplier	Plosses	Vdeviation
1.0487	0.67	0.0256
1.1773	0.692	0.0252
1.1021	0.6778	0.0254
0.9275	0.6597	0.0262
1.0683	0.6727	0.0255
1.0669	0.6725	0.0255
1.1455	0.6856	0.0253
0.8879	0.6587	0.0265
0.9205	0.6594	0.0263
1.1855	0.6938	0.0252
0.9556	0.6611	0.026
1.216	0.7007	0.0252
1.183	0.6933	0.0252
1.0806	0.6745	0.0255
0.9396	0.6602	0.0261
1.2167	0.7009	0.0252
0.8798	0.6586	0.0265
1.0417	0.6691	0.0265
1.1692	0.6903	0.0252
1.2092	0.6991	0.0252
1.0929	0.6763	0.0254
1.1063	0.6785	0.0254
1.0838	0.6749	0.0255
0.992	0.6639	0.0258
1.0587	0.6713	0.0255
1.0454	0.6696	0.0256
1.043	0.6693	0.0256

Table 15
The monthly energy consumption and billing metrics for Case one.

Month	Energy Purchased (kWh)	Net Energy Purchased (kWh)	Peak Demand (kW)	Energy Charge (\$)
January	155,303	155,303	380	40,379
February	137,472	137,472	419	35,743
March	161,112	161,112	405	41,889
April	152,653	152,653	394	39,690
May	153,685	153,685	356	39,958
June	153,838	153,838	373	39,998
July	155,207	155,207	398	40,354
August	162,349	162,349	416	42,211
September	153,658	153,658	400	39,951
October	155,434	155,434	370	40,413
November	149,307	149,307	383	38,820
December	157,183	157,183	374	40,868
Annual	1847,199	1847,199	419	480,272

Table 16
The monthly energy consumption and billing metrics for Case two.

Month	Energy Purchased (kWh)	Energy Sold (kWh)	Net Energy Purchased (kWh)	Peak Demand (kW)	Energy Charge (\$)
January	67,544	441,836	−374,292	380	−39,877
February	60,866	393,119	−332,253	360	−35,280
March	74,731	400,065	−325,334	349	−32,578
April	76,890	350,946	−274,056	381	−25,632
May	83,326	304,013	−220,687	356	−17,857
June	86,613	275,774	−189,161	360	−13,331
July	85,846	296,770	−210,924	365	−16,260
August	85,006	320,192	−235,186	347	−19,523
September	74,726	342,633	−267,908	337	−25,114
October	72,679	421,830	−349,151	319	−35,941
November	67,761	416,097	−348,337	329	−36,475
December	67,975	434,378	−366,403	348	−38,796
Annual	903,962	4397,653	−3493,691	381	−336,665

seasonal demand or system efficiency. The system sold 4397,653 kWh of energy throughout the year, indicating that solar PVs generate more energy than the system needs, particularly during periods of high sunlight. The system consistently has a negative net energy purchased value, suggesting that more energy is being sold to the grid than consumed. The annual total is −3493,691 kWh, reflecting a net-positive energy flow. The peak demand varies from a high of 380 kW in January to a low of 319 kW in October, which likely correlates with seasonal patterns in electricity usage and the solar generation capacity during those months. The energy charges (revenue from selling energy) are consistently negative, with the system generating income from selling excess energy to the grid. Over the year, the total revenue from energy charges is \$336,665. Higher energy sales, such as in January (441,836 kWh), October (421,830 kWh), and December (434,378 kWh), are likely due to periods of more substantial solar generation, supported by the time-dependent load characteristics of the network. The system operates efficiently, consistently selling more energy than it purchases, indicating a well-designed setup that utilizes solar PV to meet most of its needs, even during peak demand periods. The consistent negative energy charges reflect a revenue-generating model, where the system benefits economically by producing and selling excess energy, likely reducing operational and energy procurement costs. The variation in peak demand suggests effective load management, where the system can balance energy supply and demand by leveraging solar generation and potentially adjusting time-dependent loads to ensure stability. The total energy purchased over the year is 903,962 kWh, with total energy sold at 4397,653 kWh, generating \$336,665 in revenue. This highlights the system's positive impact on the grid, efficient energy use, and economic sustainability, driven by solar PV and optimized load management.

Table 17 involves a system that combines the Eskom Power grid, solar photovoltaic (PV) generation, electric vehicles (EVs), and time-dependent loads on the 30-bus South Africa distribution network. The system purchases energy from Eskom Power and sells energy back to the grid. In total, the system purchases 6568,772 kWh and sells 44,928,130 kWh over the year, showing a significant surplus of energy being sold back to the grid, indicating high generation and energy efficiency. The net energy purchased for the entire year is negative, meaning that the system generates more energy than it consumes, effectively making it self-sufficient and reducing dependence on grid power.

The peak demand for the system is highest in January at 3462 kW, but it generally remains consistent across the months. This indicates that the system is capable of meeting peak load demands without excessive grid reliance, likely due to the contributions of solar PV and EVs. The energy charges are consistently negative, with the system earning revenue from the energy it sells back to the grid. The energy sales are higher during the months of peak solar production, particularly from March to October. This correlates with the increased solar PV generation during sunnier months, as the system sells excess energy during these periods. The significant difference between energy purchased and energy sold, especially in the spring and summer months, suggests that the solar PV

system is a major contributor to energy generation, with the ability to produce more power than the system consumes. The inclusion of electric vehicles (EVs) suggests that the system may be using energy both for charging EVs and to support the grid, potentially contributing to the demand during higher energy use times, especially if they are charged during off-peak hours. With the net energy purchased consistently negative, the system is highly self-sufficient, relying less on Eskom Power for its energy needs. This setup helps to mitigate energy costs and reduce the environmental impact associated with grid electricity. The energy system's ability to sell large amounts of energy back to the grid makes it economically viable, generating revenue while also reducing overall energy costs for the network. This business model supports the financial sustainability of the 30-bus South Africa distribution network. Over the year, the system's energy purchases total 6568,772 kWh, while it sells 44,928,130 kWh, creating a net energy purchase of −38,359,357 kWh and energy charge revenue of approximately −\$4.13 million. This demonstrates that the integrated system of grid, solar PV, EVs, and time-dependent loads is highly efficient, profitable, and sustainable.

This analysis pertains to Table 18 integrating the Eskom power grid, solar photovoltaic (PV) systems, electric vehicles (EVs), and a lithium-ion battery energy storage system (BESS) with time-dependent loads on the 30-bus South Africa distribution network. The system consistently purchases significantly less energy from the grid compared to what is sold back, indicating a substantial surplus of energy generated by the integrated system. The net energy purchased is negative across all months, which highlights the capability of the system to generate more energy than it consumes. The peak demand of the system remains fairly constant across the year, peaking at 3462 kW in January. This suggests that while there is considerable energy storage and generation, the system can still handle high demand without relying heavily on the grid.

The energy charges remain negative throughout the year, indicating a cost-saving or revenue-generating benefit from selling excess energy back to the grid. In January, the charge is −\$458,152, which decreases during the summer months as solar generation peaks. The energy sales are consistently high, particularly in months like October and December, where the energy sold exceeds 4 million kWh. This consistent surplus shows the effectiveness of integrating solar PV with battery storage. The solar PV system generates significant energy throughout the year, while the BESS, particularly the Li-ion batteries, helps in storing energy during the day and discharging it during high demand periods or at night. This results in reduced reliance on the grid. The integration of electric vehicles (EVs) likely plays a role in absorbing surplus energy when demand from other sources is low, such as during off-peak hours, which maximizes the use of generated energy. The system is highly efficient, as it not only generates enough power to meet demand but also provides a surplus. Even in months with lower solar energy production, such as June and November, the system continues to function effectively without significantly increasing grid purchases. Over the year, the system purchases 6570,303 kWh from the grid and sells 44,828,211 kWh back to the grid. This results in a net energy purchase of −38,257,908

Table 17
The monthly energy consumption and billing metrics for Case three.

Month	Energy Purchased (kWh)	Energy Sold (kWh)	Net Energy Purchased (kWh)	Peak Demand (kW)	Energy Charge (\$)
January	480,873	4495,291	−4014,418	3462	−459,361
February	439,181	3999,189	−3560,007	3046	−405,707
March	541,594	4108,044	−3566,450	3126	−393,231
April	562,637	3586,588	−3023,951	3470	−319,971
May	610,455	3106,912	−2496,457	3193	−245,180
June	634,450	2817,131	−2182,681	3221	−201,270
July	632,338	3026,737	−2394,399	3085	−229,068
August	627,238	3295,720	−2668,482	2943	−265,362
September	543,377	3515,318	−2971,941	2969	−315,713
October	521,539	4304,621	−3783,083	2877	−424,001
November	490,524	4232,217	−3741,693	2996	−422,652
December	484,566	4440,361	−3955,795	2952	−451,260
Annual	6568,772	44,928,130	−38,359,357	3470	−4.13 M

Table 18

The monthly energy consumption and billing metrics for Case four.

Month	Energy Purchased (kWh)	Energy Sold (kWh)	Net Energy Purchased (kWh)	Peak Demand (kW)	Energy Charge (\$)
January	478,963	4533,089	−4054,126	3462	−464,771
February	437,821	4032,430	−3594,610	3046	−410,383
March	540,210	4140,950	−3600,740	3126	−397,869
April	561,182	3621,945	−3060,763	3470	−324,945
May	608,848	3144,154	−2535,306	3193	−250,439
June	632,802	2849,581	−2216,779	3221	−205,917
July	630,951	3065,107	−2434,156	3085	−234,417
August	625,895	3333,078	−2707,184	2943	−270,568
September	541,910	3550,760	−3008,850	2969	−320,702
October	519,664	4340,634	−3820,970	2877	−429,170
November	488,799	4267,152	−3778,353	2996	−427,642
December	482,746	4476,450	−3993,705	2952	−456,425
Annual	6549,792	45,355,333	−38,805,540	3470	−4.19 M

kWh, showing the high self-sufficiency of the system. The total energy charge for the year is approximately −\$4.12 million, which reflects the economic benefits of generating and selling excess energy back to the grid. The integration of solar PV, EVs, and Li-ion BESS helps reduce grid dependency and could provide financial returns, especially when energy prices are favorable.

The provided Table 19 represents the performance of a distribution network integrated with grid energy (Eskom Power), solar PV systems, electric vehicles (EVs), Surrette battery energy storage system (BESS), and time-dependent loads on the 30-bus South Africa distribution network. The energy purchased from the grid is significantly lower than the energy sold back, indicating that the system is predominantly self-sufficient and generates surplus energy. The net energy purchased is consistently negative throughout the year, which shows that the system is generating more energy than it consumes, thanks to the combined contributions of solar PVs, EVs, and Surrette BESS. The consistently high amounts of energy sold, especially in January and December, suggest that solar PV plays a major role in energy generation, with excess power being fed back into the grid. The inclusion of Surrette BESS allows for energy storage, which helps manage time-dependent loads and provides backup during periods of lower generation. This is evident in the consistent surplus in energy generation. The peak demand remains relatively stable over the year, with the highest peak observed in January at 3462 kW, indicating that the system can handle high-demand periods effectively, possibly with the help of stored energy from the BESS.

The energy charge is consistently negative throughout the year, with the highest charge recorded in January at −\$458,152. This negative charge reflects the financial benefit of selling surplus energy back to the grid, reducing the overall energy cost. The energy purchased and sold fluctuates monthly, reflecting varying demand and generation, with January, February, and December having the highest energy sold figures. This could be due to higher solar generation during sunny months or increased use of electric vehicles. Over the year, the total energy

purchased is 6570,303 kWh, while the total energy sold is 44,828,211 kWh, resulting in a negative net energy purchase of −38,257,908 kWh. This confirms the system's energy efficiency and excess generation. The negative net energy purchased and consistent surplus generation reflect a highly efficient and sustainable system. The BESS, combined with solar PVs and EVs, allows for optimized energy use, reducing reliance on grid power. The total energy charge for the year is approximately −\$4.12 million, demonstrating the system's financial viability. The ability to generate surplus energy and sell it back to the grid provides economic benefits, offsetting energy costs and potentially contributing to grid stability.

Table 20 involves a distribution network with grid (Eskom Power), solar PVs, electric vehicles (EVs), Trojan Battery Energy Storage Systems (BESS), and time-dependent loads on the 30-bus South Africa distribution network. The table shows that energy purchased (kWh) is significantly lower than energy sold (kWh), indicating that the system produces more energy than it consumes, mainly due to solar PV generation and storage systems. The energy sold ranges from 3857,573 kWh (February) to 4533,089 kWh (January), showing that the system effectively utilizes its capacity to produce and export excess energy. The net energy purchased is consistently negative, meaning the energy demand from the grid is lower than the energy being generated and sold. This suggests a sustainable, net-positive energy generation system. The energy charges are negative across all months, with the highest values observed in January and December. The negative energy charge indicates that the system is self-sufficient and generating surplus revenue through energy sales. Peak demand fluctuates throughout the year, with the highest demand of 4979 kW recorded in January. Despite this, the system manages to handle the demand due to its combined generation capacity and energy storage.

The energy exports and charges tend to be higher in winter months (e.g., January and December), possibly due to greater demand for energy during these months and higher solar PV production. The integration of the Trojan BESS helps manage fluctuations in energy

Table 19

The monthly energy consumption and billing metrics for Case five.

Month	Energy Purchased (kWh)	Energy Sold (kWh)	Net Energy Purchased (kWh)	Peak Demand (kW)	Energy Charge (\$)
January	481,066	4486,380	−4005,314	3462	−458,152
February	439,284	3991,302	−3552,018	3046	−404,655
March	541,692	4100,451	−3558,759	3126	−392,219
April	562,741	3578,452	−3015,711	3470	−318,886
May	610,566	3098,119	−2487,554	3193	−244,008
June	634,605	2809,577	−2174,972	3221	−200,248
July	632,400	3017,835	−2385,435	3085	−227,894
August	627,289	3286,997	−2659,708	2943	−264,215
September	543,495	3507,121	−2963,626	2969	−314,617
October	521,734	4295,952	−3774,217	2877	−422,823
November	490,687	4224,195	−3733,507	2996	−421,567
December	484,743	4431,830	−3947,087	2952	−450,105
Annual	6570,303	44,828,211	−38,257,908	3470	−4.12 M

Table 20

The monthly energy consumption and billing metrics for Case Six.

Month	Energy Purchased (kWh)	Energy Sold (kWh)	Net Energy Purchased (kWh)	Peak Demand (kW)	Energy Charge (\$)
January	338,753	4356,904	−4018,151	4979	−478,322
February	314,707	3857,573	−3542,866	4329	−419,661
March	369,086	3927,272	−3558,186	4535	−414,583
April	369,836	3372,865	−3003,029	4791	−342,315
May	402,833	2866,782	−2463,949	4271	−267,945
June	460,347	2606,773	−2146,426	4528	−219,190
July	436,895	2791,947	−2355,052	4468	−249,360
August	419,495	3051,645	−2632,150	4530	−287,645
September	332,589	3287,422	−2954,833	4350	−340,892
October	310,705	4088,479	−3777,774	4094	−450,719
November	273,213	4015,614	−3742,401	3898	−450,994
December	259,983	4215,480	−3955,497	4271	−480,417
Annual	4288,442	42,438,758	−38,150,316	4979	−4.40 M

production from the solar PVs, ensuring that excess energy can be stored during periods of high generation and released during periods of high demand or lower generation. With a consistent net energy export, the system demonstrates high energy efficiency, as it generates significantly more energy than it purchases from the grid. The energy charge for the entire year amounts to −\$4.12 million, showing that integrating solar PVs, EVs, and BESS provides significant economic benefits by generating and selling energy. This case study reflects a sustainable energy system that successfully integrates renewable energy sources (solar PV) with energy storage (Trojan BESS) and EVs, ensuring that the network is energy-efficient and financially viable.

To compare the results for the three battery storage systems (Trojan BESS, Surrette BESS, and Li-ion BESS) based on the simulated results presented in Tables 9 to 14, we can focus on key parameters such as energy purchased, net energy purchased, peak demand, and energy charge.

- Across the three battery storage systems, the energy purchased from the grid (Eskom Power) is consistently lower for systems with battery storage than in scenarios without storage. This reduction is due to the batteries storing energy when available (e.g., from solar PVs) and discharging during high-demand periods, reducing grid dependency.
- The net energy purchased, which is the energy drawn from the grid after accounting for the energy supplied by the battery system, is lowest for the Li-ion BESS. Li-ion systems are typically more efficient, with faster charge/discharge cycles, allowing for better grid energy offset than the Trojan and Surrette systems.
- All three systems reduce peak demand, though Li-ion BESS appears to have the most significant reduction in peak demand due to its faster response times and higher efficiency in energy storage. Trojan and Surrette systems also reduce peak demand, but the impact is less pronounced than the Li-ion system.
- The energy charge is lowest for the Li-ion BESS, reflecting the ability of the system to manage energy consumption better and minimize grid purchases. Trojan and Surrette BESS systems result in slightly higher energy charges, indicating that although they reduce grid dependence, they are not as efficient at minimizing energy costs.
- The Li-ion battery storage system stands out for its higher efficiency in energy storage and discharge. This efficiency translates to a more effective reduction in energy purchased from the grid, thereby lowering energy costs.
- Li-ion BESS typically offers higher energy density, meaning more energy can be stored in a smaller space. This enables the Li-ion system to handle fluctuating demands better and maintain consistent performance across different periods of the day or year.
- Over the year, the Li-ion system leads to the lowest overall energy charges, followed by Trojan and Surrette systems. The Trojan BESS tends to balance cost and performance, while Surrette, although effective, still incurs higher costs due to its lower energy density and efficiency.

In conclusion, while all three battery storage systems reduce energy consumption and costs compared to a grid-only scenario, the Li-ion BESS is the most efficient and cost-effective option for managing energy usage in a time-dependent, renewable-integrated network.

Table 21 shows the analysis of the three battery storage systems (Li-ion, Surrette, and Trojan) based on the simulated results:

- The NPC for the Li-ion BESS is the lowest among the three, closely followed by Surrette BESS. Trojan BESS has the highest cost NPC value, reflecting its relatively expensive implementation and maintenance requirements.
- Li-ion BESS also achieves the lowest annualized cost of \$650,833, while Surrette BESS is slightly higher at \$653,787. Trojan BESS incurs a significantly higher annualized cost of \$775,540, which could be attributed to its shorter lifecycle or higher operating expenses.
- Trojan BESS demonstrates the lowest LCOE, reflecting its potential for generating net economic benefits over its lifespan. Li-ion and Surrette BESS show similar LCOEs, indicating a balanced cost-to-benefit ratio for these systems.
- Li-ion BESS strikes the best balance between initial investment, operational costs, and performance, making it the most cost-effective option. Surrette BESS provides comparable performance but with slightly higher costs, possibly due to lower energy density or efficiency.
- Li-ion batteries are known for their high energy density, long cycle life, and efficiency, which justifies their favorable NPC and annualized cost results. Typically lead-acid-based, Surrette BESS has a lower upfront cost but may incur higher operational expenses due to maintenance needs.
- Li-ion BESS offers a longer lifecycle and lower maintenance than the other two systems, contributing to its economic advantage over time. Surrette and Trojan BESS may require frequent replacements or maintenance, increasing their long-term costs.
- All three systems reduce reliance on grid power, promoting sustainability, but Li-ion BESS aligns best with long-term environmental goals due to its higher efficiency and recyclability.
- While all systems enhance energy independence and load management, Li-ion BESS stands out for its ability to handle higher peak demands and fast response times. Surrette and Trojan BESS are better suited for less demanding applications or as backup systems due to their lower performance efficiency.

6. Conclusion

The analysis of the 30-bus South African distribution network and the 49-bus distribution network of Baghdad City, Iraq, integrating solar PV systems, electric vehicles (EVs), and various battery energy storage systems (BESS), reveals significant improvements in energy efficiency and economic performance. Among the BESS technologies evaluated, systems equipped with lithium-ion (Li-ion) batteries consistently

Table 21

Economic Performance Metrics for the case studies.

System Parameters	Case one with Time-dependent load	Case two with PV	Case three with BESS	Case three with BESS (Li-ion)	Case three with BESS (Surrette)	Case three with BESS (Trojan)
Net Present Costs (\$)	6.21 M	299,412	8461,610	8413,654	8451,847	10,025,800
Annualized Costs (\$)	480,272	23,161	654,543	650,833	653,787	775,540
LCOE (\$/kWh)	0.026	0.00371	−0.011	−0.0109	−0.011	−0.0137

outperform those using Surrette and Trojan batteries. Li-ion BESS demonstrate the lowest net energy purchases, reduced peak demand, and minimized energy costs, while also generating substantial revenue from surplus energy sold back to the grid. Their superior efficiency, energy density, and extended lifecycle make Li-ion batteries the most cost-effective and sustainable choice. Although Surrette and Trojan batteries are less efficient, they still offer considerable cost savings and enhance energy independence compared to a grid-only scenario. Overall, the integration of renewable energy and storage systems highlights their potential to enhance grid stability, lower operational costs, and promote long-term sustainability. For the real-world 30-bus South African network, the PSO and GWO algorithms are preferable due to their effective utilization of BESS, achieving optimal performance with reduced storage investment. In contrast, for the larger 49-bus network, the GWO algorithm provides a more balanced and robust solution, ensuring acceptable levels of power losses and voltage quality through appropriate BESS placement. In future work, we plan to explore hybrid multi-energy systems with a stronger focus on mitigating power quality issues arising from the integration of renewable energy sources and electric vehicles.

CRedit authorship contribution statement

Senthil Krishnamurthy: Writing – review & editing, Resources, Project administration, Funding acquisition, Data curation, Conceptualization. **Prathaban Moodley:** Writing – review & editing, Project administration, Funding acquisition, Conceptualization. **Mukovhe Ratshitanga:** Visualization, Project administration, Data curation, Conceptualization. **Chukwuemeka Emmanuel Okafor:** Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation. **Saheed Lekan Gbadamosi:** Writing – original draft, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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