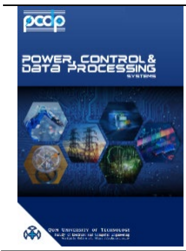
DOI: 10.30511/pcdp.2025.2075347.1053 - ISSN: 3060-8376 - Vol 3(2), 2026



POWER, CONTROL AND DATA PROCESSING SYSTEMS

Available Online at: https://pcdp.qut.ac.ir/

Strategic Deployment of Energy Storage Systems in Microgrids for Enhancing the Resilience of Distribution Systems

ARTICLE INFO

Article Type
Original Research

Authors
Mehrdad Pourali Sharami[1]
Abdolmajid Dejamkhooy[2]
Majid Hosseinpour[3]

[1] Faculty of Engineering, University of Mohaghegh Ardabili, Ardabil, Iran.,mehrdadpsh371@gmail.com
[2] Faculty of Engineering, University of Mohaghegh Ardabili, Ardabil, Iran,, majiddejam@uma.ac.ir
[3] Faculty of Engineering, University of Mohaghegh Ardabili, Ardabil, Iran,., hoseinpour.majid@uma.ac.ir

**** Correspondence***
Address: Faculty of Engineering, University of Mohaghegh Ardabili, Daneshghah Boulevard, Ardabil, Iran
Phone: -
Fax: -
mehrdadpsh371@gmail.com

Article History
Received: October 22, 2025
Accepted: December 19, 2025
ePublished: June 01, 2026

ABSTRACT

In recent years, environmental concerns and the depletion of fossil fuels have drawn significant attention to renewable energy resources, particularly wind turbines and solar energy, among power system operators and designers. However, the installation and commissioning costs of solar, wind, and other renewable-based generation systems are, on average, higher than those of conventional fossil-fuel power plants. Moreover, the expansion of grid infrastructure and the deployment of energy storage systems impose additional expenses. Another major challenge arises from integrating renewable energy sources into existing distribution networks. This process often requires infrastructure upgrades, modifications to load management systems, and the establishment of communication with smart devices within the grid. Consequently, electrical energy storage systems (EESS) are increasingly employed as complementary resources. In the presence of grid-connected storage units, energy exchange between the power grid and storage systems can be managed in a way that significantly enhances the resilience of the grid against unpredictable events. the problem of optimal placement and sizing of electrical energy storage systems in smart power networks involves numerous technical and economic challenges, while also contributing to enhanced grid resilience. Accordingly, the objective function of this study is formulated to account for both the design and operational costs of storage systems, while explicitly considering resilience indices as a key performance measure.

Keywords: Energy Storage Systems, Resilience, Flexible Distribution Networks, Renewable Energy Sources

1 Introduction

With the exponential growth of global energy consumption, along with the economic and environmental concerns associated with fossil fuels, increasing attention has been directed toward renewable energy sources as clean and sustainable alternatives [1]. Although the penetration of renewable energy resources into electrical distribution networks offers significant benefits, these systems still face several challenges and drawbacks. One of the key disadvantages of renewable energy integration is the intermittency of power generation [2]. Therefore, it is essential to develop battery energy storage systems (BESS) and load management schemes to mitigate the fluctuations in renewable energy generation. in addition to generation variability, the increasing penetration of renewable resources may lead to instability in power distribution networks [3].

Renewable energy sources such as solar and wind power are inherently variable and can produce sudden changes in output. These fluctuations can cause voltage and frequency instabilities in the network [4]. To effectively manage these issues, smart grid control and management systems are required, along with greater flexibility in power distribution networks. while the integration of renewable energy resources into distribution systems brings numerous advantages, it also introduces challenges that necessitate the development of advanced technologies, regulatory frameworks, and appropriate standards to ensure optimal management and enhance grid resilience [5].

Among these challenges, the resilience of distribution networks in the presence of renewable energy sources has emerged as a critical topic due to its economic and social significance within the power industry [6]. distribution system resilience refers to the ability of the electrical grid to withstand low-probability but high-impact disturbances [7]. A resilient network ensures stable and continuous power supply under such conditions. One of the key technologies that play a vital role in improving the resilience of distribution systems is the electrical energy storage system (EESS), which exists in various scales and applications [8].

In recent years, electrical energy storage systems have experienced remarkable growth in both grid-scale and microgrid applications. This expansion has been driven primarily by the need to enhance the integration of renewable energy sources into power systems. Due to their fast response times and controllable characteristics, energy storage systems are essential for the seamless integration of renewables, supporting various functions such as peak shaving, frequency regulation, voltage control, and compensating for the variability of wind and photovoltaic generation. However, given the presence of multiple uncertainties including variable renewable generation, fluctuating demand, and the integration of storage systems the operation and coordination of such networks remain challenging, posing risks to grid flexibility [9].

Several studies have documented the use of energy storage devices in microgrids for various purposes. For instance, reference [10] provides a comprehensive review of the diverse approaches employed in the design of storage devices for microgrids. The authors of [11] propose an ideal framework for the design of storage systems and microgrids with a particular focus on ensuring system flexibility and security. However, this work focuses solely on reliability indices in microgrid design, without addressing the economic and technical aspects of the system. Reference [12] discusses the implementation of multiple interconnected microgrids using a minimum cut set approach. However, this study overlooks environmental and technical factors such as system losses and voltage characteristics.

In [13], the enhancement of distribution network resilience through the optimal sizing and allocation of energy storage systems is investigated, based on the optimal power management of renewable sources and net load balancing within the grid. Reference [14] also examines the improvement of distribution system resilience using energy storage systems, introducing a multi-objective optimization approach combined with data envelopment analysis to determine the optimal placement and capacity of storage units. Similarly, references [15] and [16] address resilience enhancement through optimal placement and sizing of storage systems within power grids. In [17], the focus is on the planning of a hybrid renewable energy system consisting of wind turbines and bioenergy units, as well as both stationary (e.g., batteries) and mobile (e.g., electric vehicles) energy storage systems. Reference [18] focuses on energy management in flexible, grid-connected energy hubs that integrate electrical and thermal networks, where renewable energy sources and storage devices are coordinated through a hub structure. In [19], storage systems are utilized to enhance flexibility within energy hubs, with the main objective of conserving groundwater resources. Meanwhile, [20] presents simulations of renewable energy and storage integration for smart grid development.

In contrast to the above studies, the present research not only considers renewable energy integration and storage applications but also incorporates optimal placement and capacity sizing of energy storage systems, taking into account design and operational costs, as well as grid resilience under severe contingencies and load recovery prioritization. While previous studies have discussed the design and operation of storage systems in microgrids from different perspectives, the strategic utilization of energy storage systems as backup resources in microgrids, considering economic, technical, and flexibility factors, remains a complex issue highly dependent on unpredictable parameters. The primary objective of this study is to develop an optimal and strategic framework for the deployment of energy storage systems to enhance the resilience of distribution networks based on microgrid architectures.

In general, the main innovations of this dissertation compared to previous studies are as follows:

- Providing a comprehensive and accurate model for the optimal placement of electrical energy storage systems, taking into account various distributed generation sources.
- Employing new and precise indices to evaluate the resilience of power networks against different types of disturbances.
- Considering different network loads and prioritizing them to enable effective power system restoration.

The remainder of this paper is organized as follows: Section ٢ presents the modeling and problem formulation. Section ٣ describes the simulation and optimization process. Section ٤ discusses the results and analysis of the proposed model. Finally, Section ٥ provides the conclusion and future research directions.

2 Modeling and Problem Formulation

The main objective of this paper is to determine the optimal location and capacity of electrical energy storage systems, considering both economic costs and the resilience of the power network. To this end, a multi-objective modeling approach has been employed to solve the proposed problem. Equation (1) defines the economic objective function of the problem. It consists of four main components: the first two represent the investment and operational costs of the batteries; the third component denotes the cost of network losses; and the last part specifies the additional cost (Penalty Cost) or the nonlinear cost. The detailed calculations for each part of the objective functions are presented in Equations (2) to (10).

$$F(1) = \sum_{i=1}^{N_{\mathrm{ESS}}} \psi_i \times IC_i^{ESS} + \sum_{t=1}^{T} \sum_{i=1}^{N_{\mathrm{ESS}}} \xi_{i,t} \times OC_i^{ESS} + \sum_{t=1}^{T} \sum_{l=1}^{N_t} P_{l,t}^{loss} \times LC + \sum_{t=1}^{T} \sum_{i=1}^{N_{\mathrm{ESS}}} \phi_{i,t} \times \exp\left(\beta \times P_{i,t}^{ESS}\right) \tag{1}$$

$$IC^{ESS} = \sum_{i=1}^{N_{\mathrm{ESS}}} K_i^{ESS} \times P_i^{ESS} \tag{2}$$

$$OC^{ESS} = C_G^{ESS} + C_{OS}^{ESS} + C_{ST}^{ESS} + C_{EM}^{ESS} \tag{3}$$

$$C_G^{ESS} = \left(\pi_t^e \times P_{i,t}^{\mathrm{ch}}\right) - \left(\pi_t^e \times P_{i,t}^{dis}\right) \tag{4}$$

$$C_{O\&M}^{ESS} = k_{O\&}^{ESS} \times t \times P_i^{ESS} \tag{5}$$

$$C_{SST}^{ESS} = \left[\alpha_{ST}^{ESS} + \theta_{ST}^{ESS}\left(1 - e^{-\left(\frac{t_{\mathrm{tojf}}}{\tau}\right)}\right) \times u_{i,t}\left(u_{i,t} - u_{i,t-1}\right)\right] \tag{6}$$

$$C_{EM}^{ESS} = X_{EM}^{ESS} \times P_{EM}^{ESS} \tag{7}$$

$$C_{\mathrm{cap}}^{ESS} = \frac{P_i^{ESS} \times I \times t}{P_{rate}^{ESS} \times CF_i^{ESS} \times 8760} \times \frac{j(1+j)^n}{(1+j)^n - 1} \tag{8}$$

$$C_{\mathrm{ch/dis}}^{ESS} = X_{ch/dis}^{ESS} \times P_i^{ESS} \times t + X_O^{ESS}/8760 \tag{9}$$

$$C^{\mathrm{loss}} = \sum_{t=1}^{T} \sum_{l=1}^{N_t} 3 \times k_{l,t}^{\mathrm{losS}} \times R_l \times I_{l,t}^2 \tag{10}$$

The second objective of the problem, which is resilience-based, is defined in equation (11), where three key indices are employed to assess system resilience in the presence of batteries. The method for calculating the resilience indices is presented in equations (12) through (18). Previous studies have mostly relied on traditional reliability indices to evaluate the resilience of power networks; however, these indices lack sufficient accuracy and capability for assessing system security under critical conditions. Conventional reliability indices such as SAIDI and SAIFI primarily focus on the number and duration of outages, without accounting for the actual lost energy, the economic impact, or the role of distributed generation (DG) and energy storage systems (ESS). In contrast, the resilience index used here evaluates system performance under fault conditions by calculating the Expected Not Supplied Energy (ENS) for each bus and incorporates economic effects through a weighting factor. This resilience index inherently considers the flexibility provided by DG and ESS, simultaneously reflecting energy losses, voltage quality, and operational costs. Therefore, it provides a more comprehensive and practical assessment of network performance under uncertain conditions and outperforms traditional indices such as SAIDI and SAIFI.

Equation (17) computes the number of network outages resulting from severe events, while equation (18) calculates the number of disconnected loads in each event. One of the most essential resilience indices at the power system level is the ENS value, which represents the average amount of energy curtailed due to the occurrence of disruptions. Clearly, the lower this value, the higher the network resilience.

$$F(2) = \omega_1 \times \frac{ENS}{ENS_{bcse}} + \omega_2 \times \frac{IEEI}{IEEI_{bcse}} + \omega_3 \times \frac{IEED}{IEED_{base}} \tag{11}$$

$$\omega_1 + \omega_2 + \omega_3 = 1 \tag{12}$$

$$ENS = \sum_{t=1}^{T} \left\{ \sum_{b}^{N_b} C_{b,t}^{II} \times \lambda_b \times IL_{b,t} \left(\sum_{ra}^{N_{ras}} P_{b,t}^{res} \times T_{b,t}^{res} + \sum_{rep}^{N_{\mathrm{rep}}} P_{b,t}^{rep} \times T_{b,t}^{rep} \right) \right\} \tag{13}$$

$$\lambda_s = \sum_{b}^{N_b} \lambda_b \tag{14}$$

$$U_s = \sum_{b=1}^{N_b} \lambda_b \times r_b^r \tag{15}$$

$$r_s = \frac{U_s}{\lambda_s} = \frac{\sum_b \lambda_b \times r_b}{\sum_b \lambda_b} \tag{16}$$

$$\mathrm{IEEI} = \frac{\sum_b SL_b \times T_b}{NI} \tag{17}$$

$$IEED = \frac{\sum_b (L_b - G_b) \times T_b}{NI} \tag{18}$$

In this study, a combined objective function is employed to solve the multi-objective problem of siting and sizing renewable energy resources and energy storage systems. The structure of the objective function is formulated as a weighted model, where in F(1) each performance component including network power losses, voltage quality, investment and operational costs and in F(2) the network resilience index, are integrated using predefined weighting coefficients. According to equation (19), the weighting coefficients are not explicitly defined, because when multiple criteria must be improved simultaneously (such as reducing losses, improving voltage quality, lowering costs, increasing resilience, etc.), no single criterion can be considered the sole basis for decision-making. In other words, this weighted objective function enables the simultaneous optimization of losses, cost, and resilience.

$$CF=\omega_1 \times F(1)+ \omega_2 \times F \tag{19}$$

To calculate the voltage profile, line currents, and active/reactive power losses of the 33-bus distribution network, the Backward–Forward load flow method is applied. The choice of this method is based on the inherent characteristics of distribution networks as well as the computational requirements of the siting and optimal sizing problem for energy storage systems (ESS) and distributed generation (DG). Medium and low-voltage distribution networks typically have radial or quasi-radial structures and exhibit high resistance-to-reactance (R/X) ratios. This attribute makes conventional load flow methods used in transmission systems such as Newton–Raphson and Gauss–Seidel, which operate based on nonlinear equations less efficient for distribution networks. Since each iteration of the optimization algorithm (GWO) requires a load flow calculation, the stability, high speed, and modeling simplicity of the Backward–Forward method enable the optimization process to be conducted with minimal computational burden and high accuracy. Moreover, this method facilitates incorporating hourly load variations, renewable generation injections, and the charging/discharging schedules of energy storage systems with minimal complexity.

The placement and design of the batteries have been carried out in accordance with various network and resource constraints. For example, the siting of energy storage systems must be performed such that different network constraints remain within their permissible limits including the voltage range of the network buses (20) and the current flow through the transmission lines (21). In addition, Equation (22) defines the network balance constraint, which ensures the dynamic stability of the system. Constraints (23) to (27) specify the allowable operating ranges of the power outputs for different sources.

$$V_{b,t}^{min} \leq V_{b,t} \leq V_{b,t}^{max} \tag{20}$$

$$I_{l,t} \leq I_l^{max} \tag{21}$$

$$\sum_{t=1}^{T} \sum_{i=1}^{N_{ESs}} \sum_{b=1}^{N_b} \sum_{l=1}^{N_L} P_{i,t}^{ESS} + P_{b,t}^{D} + P_{l,t}^{loss} = 0 \tag{22}$$

$$P_{ch}^{min} \leq P_{ch}^{ESS} \leq P_{ch}^{max} \tag{23}$$

$$P_{dis}^{min} \leq P_{dis}^{ESS} \leq P_{dis}^{max} \tag{24}$$

$$P_{WT}^{min} \leq P_{WT} \leq P_{WT}^{max} \tag{25}$$

$$P_{PV}^{min} \leq P_{PV} \leq P_{PV}^{max} \tag{26}$$

$$P_{CHP}^{min} \leq P_{CHP} \leq P_{CHP}^{max} \tag{27}$$

Equation (28) defines the permissible limits for the amount of energy charged into the energy storage systems, while Equation (29) specifies the amount of energy stored in the batteries at each moment. Equation (30) constrains the amount of power purchased from the grid, and Equations (31) to (36) describe the on/off scheduling constraints of the controllable units.

$$SOC^{min} \leq SOC^{ESS} \leq SOC^{max} \tag{28}$$

$$SOC^{ESS} = SOC_0^{ESS} + P_{ch}^{ESS} \times \eta_{ch}^{ESS} - P_{dis}^{ESS} \times 1/\eta_{ds}^{ESS} \tag{29}$$

$$\left| P_t^{\text{gid}} \right| \leq P^{max} \tag{30}$$

$$(T_{t-1}^{on} - MUT)(u_{t-1} - u_t) \geq 0 \tag{31}$$

$$\left(T_{t-1}^{\text{aff}} - MDT\right)(u_t - u_{t-1}) \geq 0 \tag{32}$$

$$ON_{n,t} \geq MUT_n \tag{33}$$

$$OFF_{n,t} \geq MDT_n \tag{34}$$

$$P_{nt}^{CHP} - P_{nt-1}^{CHP} \leq UR_n \tag{35}$$

$$P_{n,t-1}^{CHP} - P_{n,t}^{CHP} \leq DR_n \tag{36}$$

3 Optimization and Simulation Methods

In this study, 3 energy storage units are considered, and MATLAB software is used to simulate the proposed method.To solve the complex multi-objective optimization problem of siting and sizing distributed generation resources and energy storage systems in the distribution network, the Grey Wolf Optimizer (GWO) metaheuristic algorithm is employed. The grey wolf optimization method is a global optimization technique based on a population-based search mechanism [21]. The present problem includes discrete variables (such as determining the bus number for installing ESS units) as well as continuous variables (such as the real-power capacity of storage units), while its objective function is a combination of technical, economic, and resilience indices. Therefore, classical gradient-based or point-based methods are not capable of achieving the global optimum when faced with such a non-convex and non-differentiable search space. Moreover, the dependence of the objective function on distribution load-flow results and their dynamic variations makes derivative-sensitive methods unsuitable for this problem. A performance comparison between GWO and other commonly used metaheuristic algorithms including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), and Bat and Bee algorithms shows that GWO offers superior convergence speed, robustness in obtaining repeatable solutions, and structural simplicity. Particularly in distribution network problems, where the objective function includes nonlinear behavior associated with load flow, losses, voltage constraints, and storage power dynamics, GWO has demonstrated the ability to reach high-quality solutions without requiring complex parameter tuning.

The overall algorithm for siting energy storage systems with the objective of enhancing network resilience is presented in Figure (1). As shown in the figure, the placement of batteries is carried out in such a way that the objective functions are optimized. Two types of objective functions are considered: one cost-based and the other resilience-based. In the economic objective functions, the goal is to minimize the design and operational costs of the batteries. The second objective function is resilience-based and consists of three components used to assess the robustness and resilience of the network. the siting and sizing of batteries are performed such that maximum resilience is achieved at the minimum possible cost. Accordingly, two objective functions one for economic costs and the other for network resilience are defined and ultimately optimized using the proposed algorithm. The proposed method also incorporates energy storage management strategies. The power purchase profile in the microgrid in the presence of energy storage systems, along with the proposed resilience indices, is also evaluated in this problem. The siting and sizing of batteries for system restoration are carried out in a way that minimizes the amount of load interruption, taking into account load priority levels.

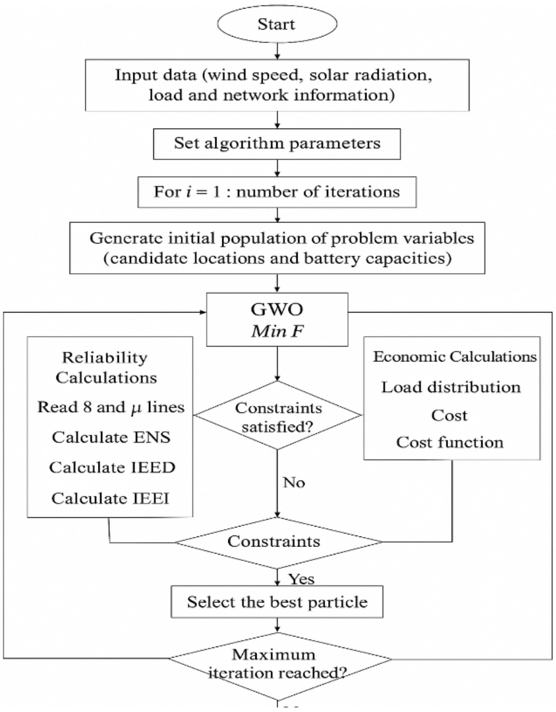


Figure 1: Flowchart of Energy Storage System Design for Economic Optimization and Network Resilience Enhancement

In this study, the intermittent, discontinuous, and variable nature of renewable distributed generation sources—including photovoltaic (PV) systems and wind turbines (WT)—is fully incorporated into the modeling process. To achieve this, time-series profiles of the output power of these units are used, representing variations in generation across different hours of the day. The instantaneous power of PV units depends on solar irradiance and varies during the morning, noon, and afternoon, whereas WT output is a function of wind speed and exhibits greater fluctuations. These hourly variations are directly integrated into the radial load-flow algorithm, and the voltage profile, active and reactive power losses, and DG injected power are computed independently for each hour. In addition, the network resilience index is calculated based on the amount of power that can be supplied during each hour, thereby clearly reflecting the impact of renewable generation uncertainty on the resilience index.To mitigate the inherent instability of renewable sources, an energy storage system (ESS) is employed, which compensates for PV and WT fluctuations through an appropriate charge–discharge strategy. This framework ensures that the network's required power is supplied even during low-generation periods, thereby improving voltage stability and enhancing network reliability.

4 Technical Data of the Network and the Studied System

To evaluate the performance of the proposed method, the standard IEEE 33-bus radial distribution network is used as the test system. The 33-bus power network, along with load prioritization and specified generation resources, is shown in Figure (2). This network consists of 33 buses and 32 distribution lines, and its nominal voltage level is 12.66 kV. Bus number 1 is considered the main substation (Slack Bus) and supplies the required power for the remaining buses. The network lines are modeled with series impedances, and the resistance and reactance values in per-unit are provided in Table (1).

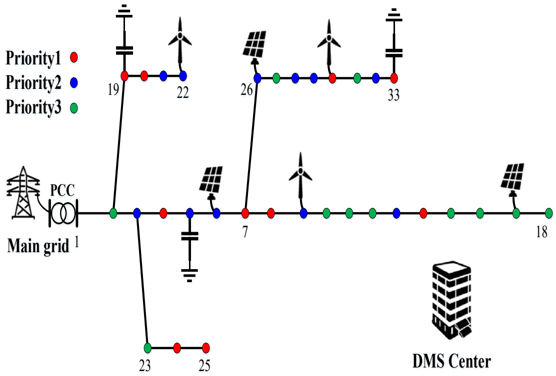


Figure 2: 33-bus network with the integration of renewable energy sources along with load prioritization

Table 1: Line impedance data of the IEEE 33-bus system

LINE	*R (p.u)*	*X (p.u)*
1–2	0.0922	0.0470
2–3	0.4930	0.2511
3–4	0.3660	0.1864
4–5	0.3811	0.1941
5–6	0.8190	0.7070
6–7	0.1872	0.6188
7–8	1.7114	1.2351
8–9	1.0300	0.7400
9–10	1.0400	0.7400
10–11	0.1966	0.0650
11–12	0.3744	0.1238
12–13	1.4680	1.1550
13–14	0.5416	0.7129
14–15	0.5910	0.5260
15–16	0.7463	0.5450
16–17	1.2880	1.7210
17–18	0.7320	0.5740
2–19	0.1640	0.1565
19–20	1.5042	1.3555
20–21	0.4095	0.4784
21–22	0.7089	0.9373

3–23	0.4512	0.3083
23–24	0.8980	0.7091
24–25	0.8960	0.7011
6–26	0.2030	0.1034
26–27	0.2842	0.1447
27–28	1.0590	0.9337
28–29	0.8042	0.7006
29–30	0.5075	0.2585
30–31	0.9744	0.9630
31–32	0.3105	0.3619
32–33	0.3410	0.5302

The network includes a total real power demand of approximately 3.7 MW and reactive demand of 2.3 MVAR. The network operates under standard operational constraints, including permissible bus voltage limits and line current limits.

$$0.95 \leq Vi \leq 1.05(pu)$$

$$I_{ij}^{max} = 300 \ \ to\, 500\ A$$

Table 2: Bus load data (P and Q in kW/kVAR)

Bus	*P (kW)*	*Q (kVAR)*
2	100	60
3	90	40
4	120	80
5	60	30
6	60	20
7	200	100
8	200	100
9	60	20
10	60	20
11	45	30
12	60	35
13	60	35
14	120	80
15	60	10
16	60	20
17	60	20
18	90	40
19	90	40
20	90	40
21	90	40
22	90	40
23	90	50
24	420	200
25	420	200
26	60	25
27	60	25
28	60	20
29	120	70
30	200	600
31	150	70
32	210	100
33	60	40

Table 3: Technical parameters of the photovoltaic units

Parameter	Value
Nominal	100–500 kW
Power factor	1 or 0.95
Efficiency	0.9
Output profile	Hourly solar irradiance data

Table 4: Technical specifications of the wind turbines

Parameter	Value
Nominal	300 kW
Cut-in wind speed	3 m/s
Rated wind speed	12 m/s
Cut-out speed	25 m/s
Power factor	0.98 lag

Table 5: Technical specifications of capacitor banks for reactive power support

Parameter	Value
Rating	100–300 kVAR
Voltage	12.66 kV
Type	Fixed or switched capacitors

Table 6:Technical parameters of the ESS units considered for the three units

Parameter	Value
Energy capacity	200–600 kWh
Charge/Discharge power	50–150 kW
Charge efficiency	0.9
Discharge efficiency	0.9
Initial SoC	0.5–0.7
Minimum SoC	0.2
Maximum SoC	0.9

To provide a comprehensive evaluation of the proposed method's performance, four main scenarios are defined:
Case 1: Without any DER
Case 2: With PV and WT
Case 3: PV + WT + capacitor (Qc)
Case 4: PV + WT + Qc + ESS
These scenarios allow evaluation of system loss, voltage profile, and resilience index under different DER configurations.

Figure (3) presents the load profile of the network at different hours, which is used in the implementation of the proposed model for managing the charging and discharging of the batteries [22].

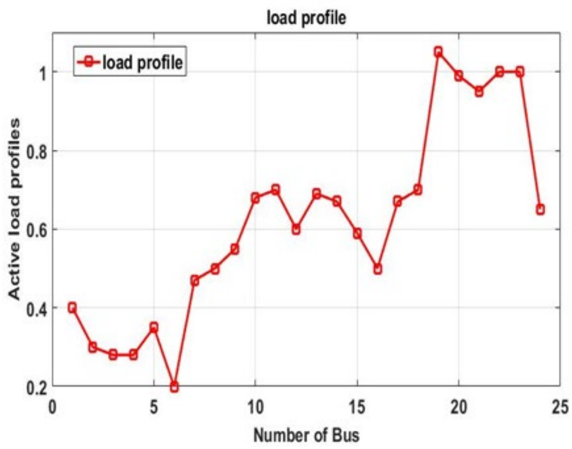


Figure 3: Daily load profile of the proposed network

5 Results of the Proposed Modeling Method

The problem of locating and determining the capacity of energy storage systems is formulated as a constrained multi-objective optimization program. In this problem, the overall objective function includes operational costs, investment and maintenance costs of the energy storage systems, as well as network resilience indices. The operational parameters and the resilience indices of the 33-bus power network are presented in Table 7.

Table 7: System simulation results before storage placement

i	Functions	Values
1	Network Active Power Losses	219.33 kW
2	Network Reactive Power Losses	168.75 kVar
3	Network Resilience Index	194.33
4	Voltage Unbalance Index	47.31%
5	Amount of Energy Not Supplied (ENS)	478.39 kWh

Now, the demand for charging the electrical energy storage systems has been calculated, and their impact on the network indices and critical components is examined. The optimization results obtained from the Grey Wolf Optimization algorithm, including the optimal location and size of the energy storage systems, are presented in Table 8.

Table 8: Technical Characteristics of the Batteries Derived from the Optimization Algorithm

Battery number	SOCmin	SOCmax	Bus Number	Capacity (Kw)
1	150	800	11	350
2	100	700	20	250
3	150	800	24	300

Table 9 presents the overall simulation results after the placement of energy storage systems. Compared to Table 7, it is evident that the results of the problem have improved significantly. For instance, the active and reactive power losses of the system have decreased by 32.87% and 42.85%, respectively, indicating a reduction in the power flow through the lines. Furthermore, the resilience index shows a 42.26% improvement, reflecting a decrease in network load interruptions and an overall increase in network resilience compared to the previous state. Finally, the amount of unserved energy with the storage systems has decreased by 222.03 kWh compared to their absence, representing a reduction of 46.58%.

Table 9: System simulation results after storage placement

i	*Functions*	*Values*
1	Network Active Power Losses	147.25 kW
2	Network Reactive Power Losses	96.25 kVar
3	Network Resilience Index	112.48
4	Voltage Unbalance Index	27.66%
5	Amount of Energy Not Supplied (ENS)	256.37 kWh

Figure 4 shows the final structure of the network with the optimal placement of energy storage systems.

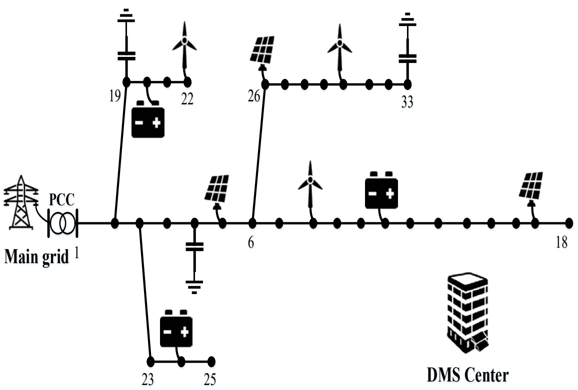


Figure 4: A 33-bus network with the optimal placement of energy resources and storage systems

To enhance resilience in the islanded mode of the system, three storage units have been allocated in the network feeders. These storage systems increase network security and resilience by charging with the excess power of the network during low-load hours and discharging during periods of network faults. Placing the storage units across different feeders reduces congestion in the main feeders and relieves the load on the primary substation.

Figure 5 shows the charging and discharging schedule of the batteries in the power network. During low-load hours, when energy costs are low, the batteries are charged, and during periods of high energy costs, they discharge into the network. This strategy helps reduce the system's energy management and investment costs. Additionally, it smooths the network's load profile, which in turn improves the technical parameters of the network. From a resilience perspective, the storage systems support the distributed generation sources during network incidents, compensating for the microgrid's power shortage until normal operation is restored.

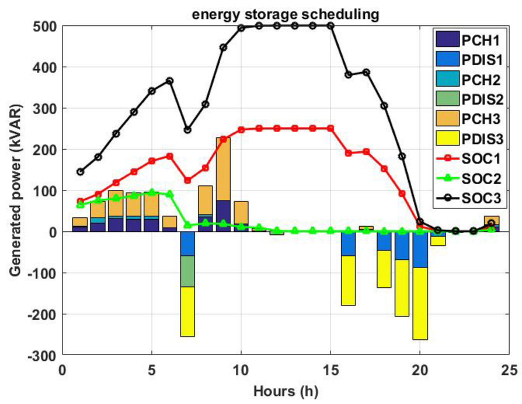


Figure 5: Battery Charging and Discharging Scheduling

The voltage profile of the network under different scenarios is shown in Figure 6.

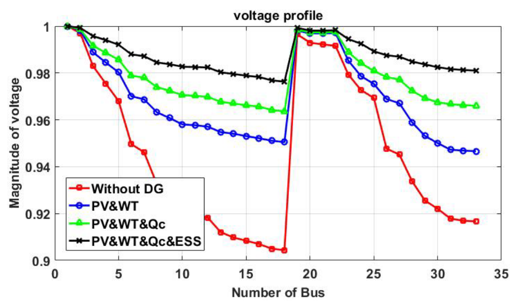


Figure 6: Analysis of the Network Voltage Profile With and Without the Presence of Energy Storage Systems

As can be seen, the use of electrical energy storage systems leads to a significant improvement in the system voltage profile. The optimal scenario occurs when all sources are present in the network. Therefore, the greater the number and diversity of sources in the network, the higher the system's power capability, while the power flow in the network feeders decreases. Consequently, not only are network losses reduced, but the voltage profile of the network is also improved. Figure 7 presents the resilience index of the power system under different scenarios.

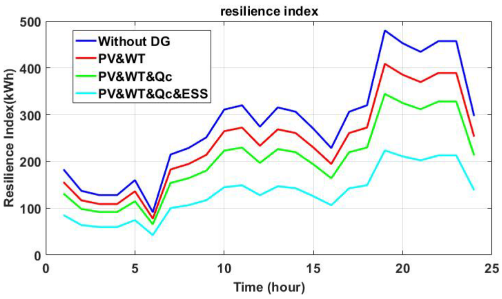


Figure 7: Assessment of Power System Resilience Index under Various Operating Conditions

6 Conclusion

The primary objective of this study was to present an optimal and strategic framework for the deployment of energy storage systems (ESSs) to enhance the resilience of distribution networks based on microgrids. In this work, network and resource data were first introduced into the algorithm as input parameters. Then, based on economic and security objectives, the optimal placement of distributed resources and energy storage units was carried out to achieve the best overall system performance.

The proposed method aimed to optimize the management of battery charging and discharging in order to improve the network's preparedness against severe disturbances. The results addressed three main objectives: minimizing design and operational costs, improving technical indices such as power loss reduction and voltage profile enhancement, and finally, providing an accurate and effective index for assessing the resilience level of the distribution network.

Disclosure of Potential Conflicts of Interest

The Authors declare that there is no conflict of interest

Reference

[1] Wang Y, Rousis AO, Strbac G. On microgrids and resilience: A comprehensive review on modeling and operational strategies. Renewable and Sustainable Energy Reviews. 2020 Dec 1;134:110313. https://doi.org/10.1016/j.rser.2020.110313

[2] Saravi VS, Kalantar M, Anvari-Moghaddam A. A cooperative resilience-oriented planning framework for integrated distribution energy systems and multi-carrier energy microgrids considering energy trading. Sustainable Cities and Society. 2024 Jan 1;100:105039. https://doi.org/10.1016/j.scs.2023.105039

[3] Xie H, Teng X, Xu Y, Wang Y. Optimal energy storage sizing for networked microgrids considering reliability and resilience. IEEE Access. 2019 Jun 14;7:86336-48. https://doi.org/10.1109/ACCESS.2019.2922994

[4] Wang, Y., A. Oulis Rousis, G. Strbac. "Resilience-driven optimal sizing and pre-positioning of mobile energy storage systems in decentralized networked microgrids." Applied Energy 305 (2022): 117921. https://doi.org/10.1016/j.apenergy.2021.117921

[5] Wang Y, Rousis AO, Strbac G. A resilience enhancement strategy for networked microgrids incorporating electricity and transport and utilizing a stochastic hierarchical control approach. Sustainable Energy, Grids and Networks. 2021 Jun 1;26:100464. https://doi.org/10.1016/j.segan.2021.100464

[6] Laaksonen H, Khajeh H, Parthasarathy C, Shafie-khah M, Hatziargyriou N. Towards flexible distribution systems: Future adaptive management schemes. Applied Sciences. 2021 Apr 20;11(8):3709. https://doi.org/10.3390/app11083709

[7] Venkateswaran, V. Balaji, Devender K. Saini, and Madhu Sharma. "Approaches for optimal planning of energy storage units in distribution network and their impacts on system resiliency." CSEE Journal of power and energy systems 6, no. 4 (2020): 816-833. https://doi.org/10.17775/CSEEJPES.2019.01280

[8] Chen, Lei, Yuqi Jiang, Shencong Zheng, Xinyi Deng, Hongkun Chen, and Md Rabiul Islam. "A two-layer optimal configuration approach of energy storage systems for resilience enhancement of active distribution networks." Applied Energy 350 (2023): 121720. https://doi.org/10.1016/j.apenergy.2023.121720

[9] Shafiei K, Zadeh SG, Hagh MT. Planning for a network system with renewable resources and battery energy storage, focused on enhancing resilience. Journal of Energy Storage. 2024 May 15;87:111339. https://ui.adsabs.harvard.edu/link_gateway/2024JEnSt..8711339S/doi:10.1016/j.est.2024.111339

[10] Ali ZM, Calasan M, Aleem SH, Jurado F, Gandoman FH. Applications of energy storage systems in enhancing energy management and access in microgrids: A review. Energies. 2023 Aug 10;16(16):5930. https://doi.org/۱۰,۳۳۹۰/en16165930

[11] Zhao, Yuxuan, Jin Lin, Yonghua Song, and Yin Xu. "A Robust Microgrid Formation Strategy for Resilience Enhancement of Hydrogen Penetrated Active Distribution Networks." IEEE Transactions on Power Systems (2023). https://doi.org/10.1109/TPWRS.2023.3305470

[12] Gharehveran SS, Zadeh SG, Rostami N. Resilience-oriented planning and pre-positioning of vehicle-mounted energy storage facilities in community microgrids. Journal of Energy Storage. 2023 Nov 15;72:108263. https://ui.adsabs.harvard.edu/link_gateway/2023JEnSt..7208263G/doi:10.1016/j.est.2023.108263

[13] Ahmadi SE, Marzband M, Ikpehai A, Abusorrah A. Optimal stochastic scheduling of plug-in electric vehicles as mobile energy storage systems for resilience enhancement of multi-agent multi-energy networked microgrids. Journal of Energy Storage. 2022 Nov 15;55:105566. https://doi.org/10.1016/B978-0-443-16086-8.00013-0

[14] Nikoobakht A, Aghaei J. Resilience promotion of active distribution grids under high penetration of renewables using flexible controllers. Energy. 2022 Oct 15;257:124754. https://doi.org/10.1016/j.energy.2022.124754

[15] Shahbazbegian V, Shafie-khah M, Laaksonen H, Strbac G, Ameli H. Resilience-oriented operation of microgrids in the presence of power-to-hydrogen systems. Applied Energy. 2023 Oct 15;348:121429. https://doi.org/10.1016/j.apenergy.2023.121429

[16] Wang Y, Rousis AO, Qiu D, Strbac G. A stochastic distributed control approach for load restoration of networked microgrids with mobile energy storage systems. International Journal of Electrical Power & Energy Systems. 2023 Jun 1;148:108999. https://doi.org/10.1016/j.ijepes.2023.108999
[17] Jokar MR, Shahmoradi S, Mohammed AH, Foong LK, Le BN, Pirouzi S. Stationary and mobile storages-based renewable off-grid system planning considering storage degradation cost based on information-gap decision theory optimization. Journal of Energy Storage. 2023 Feb 1;58:106389. https://ui.adsabs.harvard.edu/link_gateway/2023JEnSt..5806389J/doi:10.1016/j.est.2022.106389
[18] Qu Z, Xu C, Yang F, Ling F, Pirouzi S. Market clearing price-based energy management of grid-connected renewable energy hubs including flexible sources according to thermal, hydrogen, and compressed air storage systems. Journal of Energy Storage. 2023 Oct 1;69:107981. https://doi.org/10.1016/j.est.2023.107981
[19] Monemi Bidgoli M, Ghani R. Optimal Energy Management of Water-Energy Nexus in Multi-Carrier Systems Integrated with Renewable Sources. Power, Control, and Data Processing Systems. 2024 Dec 1;1(1). https://doi.org/10.30511/pcdp.2024.718536
[20] Masoudi MR, Haghighi M, Rahimipour Behbahani M. Optimal Operation of Solar Energy System integrated with Energy Storage Systems. Power, Control, and Data Processing Systems. 2024 Dec 1;1(1). https://doi.org/10.30511/pcdp.2024.718345
[21] S. Mirjalili, S. M. Mirjalili, A. Lewis. "Grey wolf optimizer." Advances in engineering software, vol. 69, pp. 46-61, 2014. https://doi.org/10.1016/j.advengsoft.2013.12.007
[22] Zheng, Yu, Yue Song, Andy Huang, and David J. Hill. "Hierarchical Optimal Allocation of Battery Energy Storage Systems for Multiple Services in Distribution Systems." IEEE Transactions on Sustainable Energy 11, no. 3 (2019): 1911-1921. https://doi.org/10.1016/j.segan.2024.101394