Investigating The Effects of Energy Storage Systems on The Optimal Management of a Microgrid Including Renewable Energies

Neda Shahnejat[1], Shahram Karimi[1,*], and Hamdi Abdi[1]

[1] *Department of Electrical Engineering, Razi University, Kermanshah, Iran*
**Corresponding author: shahramkarimi@razi.ac.ir*

Manuscript received 6 March, 2025; revised 2 July, 2025; accepted 7 August, 2025. Paper no. JEMT-2503-1543.

In off-grid microgrids, the lack of connection to the national electricity grid presents a significant challenge for establishing stable and self-sustaining renewable energy systems. In such microgrids, especially those relying entirely on renewable sources, energy storage systems are not optional components but essential elements for ensuring stability, managing generation uncertainty, and improving overall efficiency. This paper presents a techno-economic optimization framework to determine the optimal combination of wind and solar power capacities, supported by lithium-ion battery storage, in an off-grid microgrid. The proposed model accounts for hourly variations in weather and load, as well as functional, technical, and land-use constraints. A linear programming approach is used, and the War Strategy Optimization (WSO) algorithm is applied to solve the problem. To assess its effectiveness, the results are compared with those obtained using the well-established Genetic Algorithm (GA), under identical simulation conditions. The framework also evaluates installation cost, system capacity, land usage, operational expenses, and key economic indicators such as Levelized Cost of Energy (LCOE) and Present Cost (PC). A sensitivity analysis is conducted to examine the effects of demand and storage cost on system performance. According to the results, the optimal configuration includes 2200 kW of wind, 1125 kW of solar PV, and 6359 kWh of battery capacity. This setup yields a total present cost of €31.6 million and an LCOE of 1.5567 €/kWh. In comparison with GA, WSO achieves a lower optimal cost (23.7 M€ vs. 26.3 M€), reduced battery capacity (6359 kWh vs. 7325 kWh), and improved economic performance, although it requires more execution time (58 seconds vs. 30 seconds). These results demonstrate the effectiveness of WSO in optimizing off-grid renewable microgrids, offering a competitive alternative to conventional methods in both technical design and economic performance.

Keywords: *Optimization, Microgrid, Renewable energy, Storage system management, Meta-heuristic algorithms.*

http://dx.doi.org/10.22109/jemt.2025.510952.1543

1. Introduction

To address growing global concerns regarding environmental challenges, grid operators and planners are increasingly integrating renewable energy sources (RESs), which emit significantly fewer pollutants than traditional fossil fuel-based plants. One effective approach for implementing RESs is through the use of microgrids, which can operate in both grid-connected and islanded modes. Microgrids offer various advantages, including reduced environmental pollution, technical benefits such as lower power losses and improved voltage profiles, and economic advantages resulting from the use of RESs with minimal operational costs[1]. However, the inherent stochastic nature of RESs, such as wind turbines and photovoltaic (PV) systems, presents a major operational challenge. To manage this issue, the deployment of controllable resources and energy storage systems (ESSs) is essential for ensuring reliable and cost-effective microgrid operation. In addition to economic considerations, minimizing environmental impacts remains a key priority in microgrid design and management[2, 3]. Therefore, energy storage technologies play a critical role in reducing both operational costs and emissions, while enhancing system flexibility and adaptability[4, 5]. An effective solution for improving the flexibility of off-grid microgrids is the integration of localized energy storage, primarily in the form of batteries[6]. Battery systems increase the share of RES utilization and help reduce carbon emissions. Nevertheless, determining the optimal configuration of RES and ESS capacities remains a complex task due to multiple technical, economic, and environmental constraints. Numerous studies have investigated the optimal sizing and configuration of microgrid components to maximize the penetration of RESs. For instance, the intelligent golden jackal optimization (GJO) algorithm was proposed in [7] for energy management in hybrid microgrids, considering power balance and generation capacity constraints. The objective was to minimize operating costs and improve overall system performance. In [8], an integer linear programming (ILP) model was developed for the optimal design of a microgrid operating in both islanded and grid-connected modes. The study focused on minimizing total investment and operational costs while optimizing the hourly scheduling of microgrid assets throughout the project lifecycle. Similarly, a short-term seasonal optimization model was introduced in [9] for PV-based microgrids incorporating energy storage. The study analyzed the effects of climate variability on optimal daily energy scheduling using the converged barnacles mating optimizer (CBMO) method. The work in [10] examined battery sizing and cost analysis for stand-alone microgrids using the particle swarm optimization (PSO) algorithm to minimize the net present value (NPV). Given the fluctuations in energy production from PV and wind sources, these variations can reduce battery lifespan. Since batteries are among the most expensive components in a microgrid and frequent replacements lead to higher operational costs, the study proposed a capacity optimization framework that accounts for battery lifetime. In [11], Gholami et al. applied the firefly algorithm to enhance microgrid reliability by identifying the optimal type and capacity of battery energy storage systems. Reference [12] proposed a framework for designing a standalone hybrid system that includes solar panels, wind turbines, battery storage, and diesel generators. The aim was to minimize electricity costs and ensure sustainable energy access in remote rural areas. The study employed the smell-based fish search (SFS), symbiotic organisms search (SOS), and PSO methods to compare their effectiveness in meeting power demand at the lowest cost. The integration of RESs and ESSs into active distribution networks (ADNs) was also addressed in [13]. The study used clustering algorithms, including an improved k-means method with graph partitioning and the Silhouette technique, to divide the network into multiple microgrids. Multi-objective optimization was then carried out to determine the best RES and ESS capacities, with criteria such as reliability, total cost, and excess power. The Pareto-fuzzy (IPF) method was introduced as an effective tool for identifying optimal solutions. Some previous studies have included fossil fuel-based generators as backup sources, which results in carbon emissions and environmental degradation. In [14], the interior-point method was used to determine optimal power capacities. Although this method offers certain advantages, its application to large-scale problems involves extensive matrix operations, which increase memory requirements and computational complexity. Consequently, optimization time increases and convergence speed decreases.

1.1. Microgrid Overview

Microgrids are localized power systems operating within defined electrical boundaries and functioning as a single controllable entity in relation to the main grid. In microgrid design, flexible thermal power units, primarily diesel generators, are often employed. However, due to high fuel costs, carbon emissions, and low efficiency, diesel generators are typically operated only under specific conditions [15]. To reduce reliance on diesel-based power in microgrid development, two alternatives have been proposed [14]: (1) integrating renewable energy sources while utilizing thermal units solely as backup during resource shortages, or (2) fully replacing thermal generation with variable renewable sources supported by energy storage systems. In the present study, a microgrid configuration comprising PV solar arrays, wind turbines, and a lithium-ion battery is considered. This setup is designed to evaluate an energy capacity planning algorithm and assess the economic feasibility of a fully renewable, off-grid microgrid. The capacities of system components serve as decision variables in the optimization process. Fig. 1 presents the structure of the proposed microgrid, in which solar and wind sources supply electricity, and the battery maintains the energy balance between supply and demand. Lithium-ion batteries are selected as the primary energy storage technology due to their low self-discharge, fast response, and high cycling efficiency[16-19]. Among various energy storage options, they offer favorable performance, cost-effectiveness, and storage duration, making them suitable for long-duration storage in off-grid renewable microgrids.

In power microgrids, enhancing the efficiency and profitability of infrastructure requires the design of flexible and resilient transmission systems. The optimization framework must conduct feasibility studies and assess the economic viability of establishing new power plants [20]. This study presents a techno-economic optimization framework for determining optimal capacity in off-grid microgrids that rely exclusively on renewable energy sources, including solar and wind power, to meet load demand at minimal Present Cost (PC). The framework includes a long-term performance evaluation of battery energy storage system (BESS). The proposed model applies the War Strategy Optimization (WSO) algorithm in MATLAB to minimize the objective function. WSO is a recent metaheuristic algorithm known for maintaining a dynamic balance between exploration and exploitation, thereby improving convergence speed and solution quality. Although WSO has shown promising capabilities, its application in the context of renewable energy systems remains largely unexplored. This study applies WSO to optimize the configuration of photovoltaic arrays, wind turbines, and BESS under realistic and time-varying scenarios. The model incorporates hourly variations in load demand and renewable generation. The performance of WSO is benchmarked against the Genetic Algorithm (GA), a widely recognized method in energy optimization. Results indicate that WSO outperforms GA in terms of total cost, storage sizing, and economic indicators such as PC and Levelized Cost of Energy (LCOE). While the computational time of WSO is slightly higher, this is offset by its improved solution quality and consistency. Unlike previous studies that primarily relied on traditional optimization techniques such as GA, PSO, or Grey Wolf Optimizer (GWO), this research is among the first to implement the WSO algorithm for renewable microgrid planning. The novelty of this work lies not only in applying WSO to this complex domain but also in demonstrating its effectiveness in solving high-dimensional, nonlinear, and constrained techno-economic problems. Additionally, WSO exhibits superior adaptability under real-time operational dynamics including fluctuations in renewable generation and load profiles, where conventional algorithms often struggle. These findings present WSO as a novel, scalable, and economically efficient alternative for future research on resilient and optimized renewable energy systems. The main objectives of this study are as follows:

- To perform a comprehensive techno-economic assessment of optimal sizing for hybrid renewable energy sources (solar and wind) and storage systems, considering investment, maintenance, operational constraints, and battery limitations.
- To apply multi-objective optimization techniques for determining the optimal configuration of the hybrid renewable energy system and storage.
- To theoretically determine the backup energy storage capacity required to ensure 100% renewable energy supply.
- To evaluate the techno-economic performance of energy storage systems, including lithium-ion batteries.
- To analyze the feasibility of achieving a fully renewable power microgrid compared to a conventional fossil-fuel-based system.

The remainder of this paper is organized as follows: Section 2 describes the proposed methodology. Section 3 introduces and explains the optimization algorithm. Section 4 presents the case study and the parameters used to solve the problem. Section 5 discusses the simulation results and their implications. Finally, Section 6 concludes the paper with a summary of the key findings.

2. Methodology

In the proposed method, the optimal capacity measurement model of the microgrid is broken down into three key elements:

- Renewable energy generation characteristics
- Energy storage management
- Feasibility analysis

2.1. Optimal Sizing of Renewable Energy Based on a Techno-Economic Model for a Microgrid

The key inputs and outputs of the proposed methodology are shown in Fig. 2, Inputs include theoretical electricity generation profiles (wind and solar), energy storage characteristics, and capital and operational costs of generation units. The optimization model identifies the optimal combination of renewable energy capacities that satisfies the total electricity demand while minimizing the PC and considering spatial constraints. After optimization, the outputs include the time-dependent generation strategy, optimal generation and storage capacities, the LCOE, the PC of the microgrid, and the occupied land area. The methodologies used for each component of the techno-economic model are described in Sections 2.1.1–2.1.4.

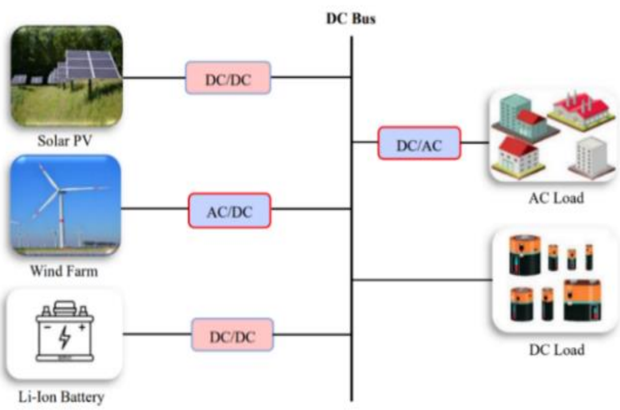

Fig. 1. Diagrammatic configuration of the Off-grid microgrid network

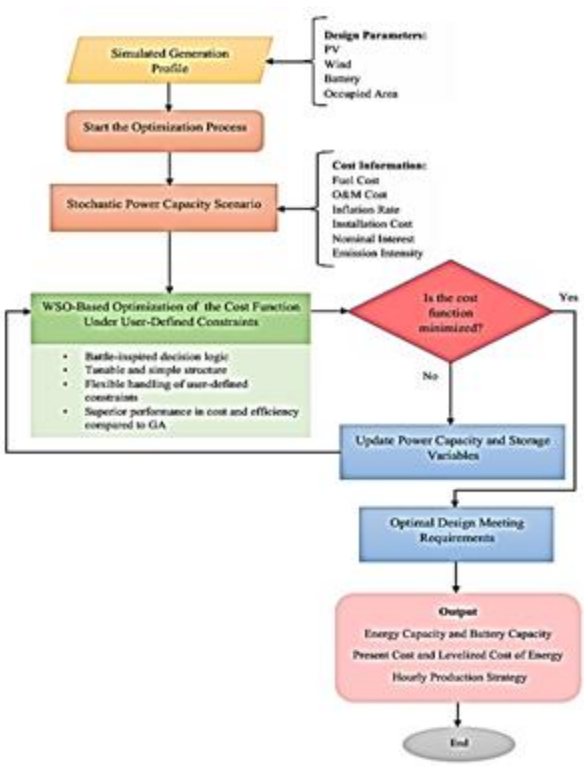

Fig. 2. Proposed flowchart for optimizing the capacity of the renewable power microgrid

2.1.1. Capacity Factor of Wind and Solar Resources

In this study, the efficiency values (Rp), also called capacity factors, for wind and solar resources are calculated using Equations (1) and (2), respectively. These values represent the ratio of the actual annual energy production to the theoretical maximum possible generation over one year. The wind and solar generation profiles, denoted as Wg and Sg represent the hourly energy generation per unit of installed capacity (kWh/kWp) throughout the year. Cap_{Wind} and Cap_{PV} denote the installed capacities of the wind and solar systems in kilowatts (kW). The denominator in each equation consists of the installed capacity multiplied by the total number of hours in a year (8760 hours), which represents the maximum possible energy output assuming continuous full-capacity operation. Since the normalized energy production (in kWh per kWp) is divided by the product of installed capacity (kW) and total hours (h), the result is a dimensionless ratio. Multiplying this ratio by 100 expresses (Rp) as a percentage. This method is widely accepted and commonly used in renewable energy performance analysis.

$$(\%)Rp_{wind} = \frac{\sum_{h=1}^{h=8760} W_g}{Cap_{Wind} \times 8760} \times 100 \tag{1}$$

$$(\%)Rp_{PV} = \frac{\sum_{h=1}^{h=8760} S_g}{Cap_{PV} \times 8760} \times 100 \tag{2}$$

According to our calculations, the resulting capacity factors are 28% for wind and 16% for solar resources, indicating the effective utilization of the installed renewable energy systems over the course of a year. The daily production profiles are illustrated in Figures 3 and 4.

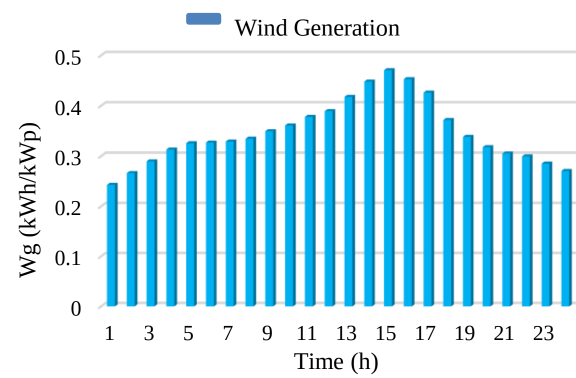

Fig. 3. Hourly wind energy output per kWP of installed capacity

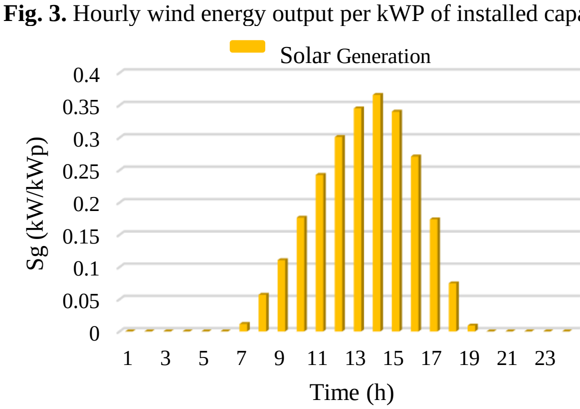

Fig. 3. Hourly solar energy output per kWP of installed capacity

2.1.2. Lithium-Ion Battery Energy Storage Management Algorithm

The performance of BESS plays a significant role in formulating the optimization model that determines optimal charge and discharge schedules. Accurate determination of the BESS status at each time step is essential. The amount of electricity available for storage is calculated using Equation (3), under the assumption that any excess energy from PV and wind sources, after meeting the load demand and accounting for system losses, is stored in the battery:

$$Elec_h = \left(Sg_h \times Cap_{PV} + Wg_h \times Cap_{Wind}\right) - LOAD_h - LOSS_h, h \in \{1, 8760\} \quad (3)$$

Where $Elec_h$ denotes the electricity available for storage in hour h; Cap_{PV} and Cap_{Wind} are the installed capacities of PV and wind systems in kilowatts (kW), respectively; Sg_h and Wg_h are the generation profiles in kWh/kWp for PV and wind; $LOAD_h$ is the electricity demand; and $LOSS_h$ accounts for power losses. The amount of energy stored in the battery is determined by (4):

$$Battstored_h = Battstored_{h-1} \times (1-\delta) + Elec_h \times \eta_{BattC}, h \in \{1, 8760\} \quad (4)$$

where δ represents the hourly energy loss rate of the battery, and η_{BattC} denotes the charging efficiency factor. The battery state of charge (SoC) is defined by (5):

$$SoC_h = \frac{\left|Battstored_{h-1} - Battstored_h\right|}{Cap_{Batt}}, h \in \{1, 8760\} \quad (5)$$

Here, Cap_{Batt} denotes the total battery capacity in kW. The amount of stored energy is limited by constraints associated with the battery's capacity, as expressed in (6):

$$SoC^{\min} \le SoC_h \le SoC^{\max}, h \in \{1, 8760\} \quad (6)$$

If the stored energy remains within the defined operational boundaries, SoC^{min} and SoC^{max}, then the curtailment is considered zero. The amount of energy charged and discharged is determined by (7) and (8), respectively:

$$Elec_h^{Char} = \max\left(Elec_h \times \eta_{BattC}, 0\right) \quad (7)$$

$$Elec_h^{DisC} = \max\left(-Elec_h \times \eta_{BattD}, 0\right) \quad (8)$$

Where η_{BattD} denotes the battry's discharge efficiency. If the battery reaches its maximum charge level, surplus renewable generation is curtailed, as defined in (9):

$$Elec_h^{Curt} = Elec_h - \left(Battstored_{h-1} - Battstored_h\right) \quad (9)$$

2.1.3. Power Capacity Formulation and Method

By formulating the theoretical framework for renewable energy generation and strategies for managing surplus and deficit loads, a combination of power capacities capable of fulfilling the overall load demand of the microgrid network can be achieved. The power capacity optimization framework includes decision variables, the objective function, and system constraints.

2.1.3.1. Formulation of the Objective Function

The objective function for the optimization problem considers the installation, operational, and maintenance costs of the microgrid. The objective function is defined as in (10):

$$Min\Big(\sum_{h=1}^{8760} Cost_{PV} \times Cap_{PV} + Sg_h \times Cap_{PV} \times O\&M_{PV} + Cost_{Batt} \times Cap_{Batt} + Cost_{Wind} \times Cap_{Wind} + Wg_h \times Cap_{Wind} \times O\&M_{Wind}\Big), h \in \{1, 8760\} \quad (10)$$

In (10), $Cost_{PV}$ denotes the installation cost of solar PV, $Cost_{Batt}$ represents the installation cost of lithium-ion batteries, and $Cost_{Wind}$ corresponds to the installation cost per kilowatt (€/kW) of wind power. Operation and maintenance (O&M) costs of the solar PV plant and wind farm, denoted as $O\&M_{PV}$ and $O\&M_{Wind}$, are expressed in €/kWh.

2.1.3.2. Constraints of Equality

Within the distributed energy system, the equality constraint ensures that the total load demand (LOAD), energy charged into the battery system ($Elec^{Char}$), distribution losses (LOSS), and spinning reserve (Spin) are equal to the total energy generated by photovoltaic systems (Sg × Cap_{PV}), wind turbines (Wg × Cap_{Wind}), and the electricity discharged from the battery ($Elec^{DisC}$). This relationship is expressed in Equation (11):

$$LOAD_h + Spin_h + Elec_h^{Char} + LOSS_h = Sg_h \times Cap_{PV} + Wg_h \times Cap_{Wind} + Elec_h^{DisC} \quad (11)$$

2.1.3.3. Constraints of Inequality

The inequality constraints in the objective function minimization ensure that the installed capacities of wind farms, PV power plants, and lithium-ion battery storage systems are non-negative. These constraints are formulated in Equations (12)–(14):

$$Cap_{PV} \ge 0 \quad (12)$$

$$Cap_{Wind} \ge 0 \quad (13)$$

$$Cap_{Bat} \ge 0 \quad (14)$$

The other inequality constraints pertain to the available area for the installation of generation plants, as expressed by Equation (15):

$$0 < \left(Cap_{PV} \times A_{PV} + Cap_{Wind} \times A_{Wind} + Cap_{Batt} \times A_{Batt}\right) < A_{Available} \quad (15)$$

In Equation (15), A_{PV}, A_{Wind}, and A_{Batt} represent the total area occupied by the installed capacities of PV power plants, wind farms, and the battery storage system, respectively, all expressed in square kilometers (km²). denotes the total available land area for installing these technologies. To ensure that the spinning reserve requirement is met during each operational hour, the combined available power from wind turbines and the energy stored in the battery must be greater than or equal to the required spinning reserve. This constraint is expressed in Equation (16):

$$\left(Wg_h \times Cap_{Wind} + Battstored_h\right) > Spin_h \quad (16)$$

In Equation (16), Wg_h refers to the wind power generation profile (kWh/kWp), and Cap_{Wind} is the installed capacity of the wind power plant (kW). $Battstored_h$ denotes the energy stored in the battery (kWh), and $Spin_h$ is the spinning reserve required (kW).

2.1.4. Methodology for Feasibility Analysis

The economic feasibility is assessed by comparing the parameters of PC and LCOE. The PC value for each system is calculated using (17):

$$PC = Acs \times \frac{(i+1)^y - 1}{(i+1)^y \times i} \quad (17)$$

In Equation (17), y denotes the functional lifetime of the microgrid, and ACs represents the annualized cost of the system (€). The value of ACs is calculated using Equation (18):

$$Acs = CoM + Cc \quad (18)$$

In Equation (18), Cc denotes the annualized capital installation costs (€), while CoM represents the annualized operation and maintenance costs (€) of the system. The annual capital expenditure for system installation is calculated using Equation (19):

$$Cc = Ics \times \frac{(i+1)^y \times i}{(i+1)^y - 1} \tag{19}$$

In Equation (19), ICs denotes the installation costs of microgrid power generation units and power transmission cables. For the renewable-based local grid, the annualized CoM is calculated using Equation (20), whereas for the fossil-fuel-based local grid, it is evaluated using Equation (21):

$$\begin{aligned} CoM &= \sum_{y=1}^{y=Lifetime} \big(O\&M_{PV} \times Sg_h \times Cap_{PV} \\ &+ O\&M_{Wind} \times Wg_h \times Cap_{Wind} \\ &+ Insurance\,Cost\big) \times \frac{(i+1)^y \times i}{(i+1)^y - 1} \end{aligned} \tag{20}$$

$$\begin{aligned} CoM &= \sum_{y=1}^{y=Lifetime} \big(O\&M_{NG} \times NG_h \times Cap_{NG} + Insurance\,Cost \times Cap_{NG} \\ &+ EF_{NG} \times CarbonTax + Fc \times NG_h \times Cap_{NG}\big) \\ &\times \frac{(i+1)^y \times i}{(i+1)^y - 1} \end{aligned} \tag{21}$$

In Equation (21), CoM includes fuel costs, labor costs, insurance costs, and carbon tax. NG denotes the generation profile of the fossil-fuel-based microgrid (kW/kWp), and Cap_{NG} represents the installed capacity of fossil-based generation plants (kW). EF_{NG} refers to the average emission factor (kg CO_2/kWh) of the fossil-fuel-based microgrid, while Fc denotes the energy source cost per kilowatt-hour. The parameter i corresponds to the real annual interest rate of the network, calculated using Equation (22):

$$i = \frac{j - f}{(1 + f)} \tag{22}$$

The parameter f represents the inflation rate, while j denotes the nominal interest rate. Additionally, the LCOE is calculated using Equation (23).

$$LCOE = \frac{Acs}{\sum_{h=1}^{h=8760} LOAD_h + Elec_h^{Char}} \tag{23}$$

3. WSO Algorithm

Big data analysis faces the challenge posed by the high-dimensional nature of data sets. To address this challenge, researchers have developed a series of intelligent optimization methods specifically designed to improve big data analysis techniques. One notable method is the WSO algorithm, introduced in 2022, which demonstrates superior optimization performance compared to other computational intelligence techniques. In the WSO algorithm, each candidate solution is abstracted as a soldier navigating a battlefield that symbolizes the optimization search space. This metaphor enhances the interpretability of the algorithm by linking tactical military behaviors to metaheuristic mechanisms. The complete process of the WSO algorithm is outlined in Fig. 5 which depicts how the population of soldiers evolves over iterations through strategic interactions. The core phases include:

- Initialization: Soldiers are randomly positioned within the search space.
- Fitness Evaluation: Objective function values are computed for all soldiers.
- Weight Assignment and Ranking: Soldiers are ranked and weighted based on fitness, distinguishing elites from weaker members.
- Tactical Phase:
  – Elites execute strikes toward optimal regions.
  – Weaker soldiers adopt protective or exploratory behaviors.
- Position Updates: New positions are calculated using adaptive movement equations driven by rank, weight, and stochastic elements.
- Mutation (optional): Additional randomness is introduced to maintain population diversity and prevent convergence to local optima.
- Convergence Check: The process repeats until a termination condition is satisfied.

As illustrated in Fig. 6 each soldier performs four coordinated tactical actions:

- Movement: The soldier explores new regions of the search space, representing global exploration aimed at avoiding premature convergence.
- Strike: The soldier targets elite or high-fitness solutions, symbolizing exploitation of promising areas.
- Protection: The soldier defends favorable positions by avoiding unproductive or risky directions.
- Weight Adjustment: The soldier's weight, determined by its fitness score, modulates its future influence; stronger soldiers become leaders, while weaker ones adapt or reposition.

These four behaviors are dynamically balanced throughout the algorithm, simulating a strategic military mission with adaptive responses. Together, Figs. 5 and 6 provide a comprehensive visual representation of both the tactical mindset and the operational workflow underlying WSO. The conceptual soldier framework aligns intuitively with its mathematical modeling, thereby supporting both implementation and reproducibility [21].

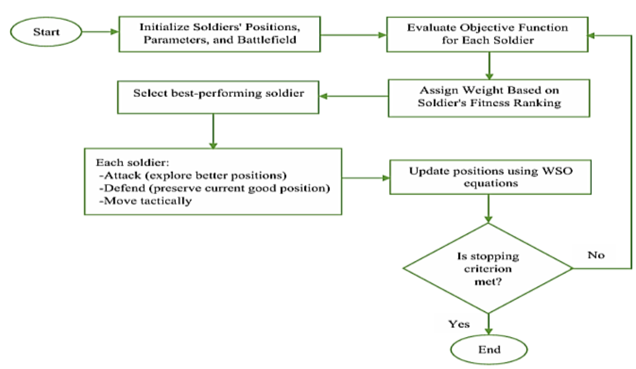

Fig. 5. Flowchart of the Operational Steps in the WSO Algorithm

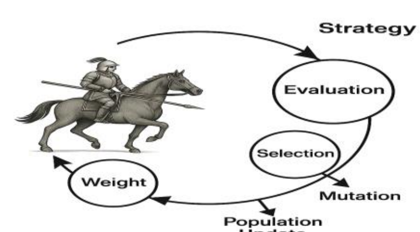

Fig. 6. Conceptual Illustration of the Soldier Agent's Tactical Behavior in the WSO Algorithm

4. Case Study

This study investigates two microgrid configurations. The first configuration includes a diesel-based generation system with a rated capacity of 536 kW. The second configuration is a hybrid renewable energy system that integrates solar PV, wind power, and lithium-ion battery storage. Both systems are evaluated under the temperate oceanic climate of Germany, classified as Cfb according to the Köppen climate classification. This climate type is characterized by mild temperatures, moderate seasonal variation, and evenly distributed precipitation throughout the year. The selected location represents typical central German conditions. To assess long-term system performance, a simulation was conducted over a 15-year period, corresponding to 131,400 operating hours. Real hourly data from the year 2018 were used for solar irradiance, wind speed, and electricity demand. These datasets were scaled to reflect seasonal and diurnal variations, ensuring realistic modeling. Additionally, a ±35% uncertainty margin was applied to the load profile to represent demand-side variability. All simulations were implemented using MATLAB R2022b and executed on a system running Windows 10, equipped with an Intel Core i3-1115G4 processor and 4 GB of RAM. This setup ensured stable and consistent computational performance for dynamic modeling and scenario analysis.

4.1. Data

Hourly wind speed, solar irradiance, and electrical load data for the year 2018 were obtained from the Open Power System Data (OPSD) platform, representing a central European region with a temperate oceanic climate[22]. The region is characterized by mild temperatures and relatively uniform precipitation throughout the year. Renewable resource data were derived from weather station measurements and ERA5 reanalysis datasets, comprising 8760 hourly values. All datasets were normalized with respect to installed capacity (kWh/kWp) for consistency in performance evaluation. The mean and variance of solar irradiance were 0.16 and 0.06, respectively, while those of wind power were 0.28 and 0.04. These values reflect the temporal variability of renewable energy resources under temperate climatic conditions. The load profile was reconstructed based on a standardized medium-scale consumer demand pattern representative of the selected European context. A fixed transmission and distribution loss of 5% was assumed for all scenarios. To illustrate demand-side uncertainty, a 24-hour load curve from April 1 was selected and subjected to a ±35% variation, as depicted in Fig. 7. The technical and economic parameters used in the simulations are summarized in Tables 1–4.

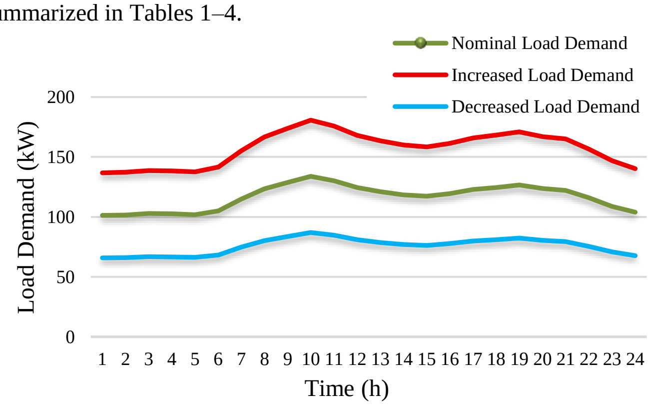

Fig. 7. Hourly Load Profile with ±35% Demand Uncertainty

4.2. Scenarios

The structure of the scenarios is illustrated in Fig. 8 and described as follows:

1. Installed Power Generation Technologies:
   (i) Scenario 1: Diesel-based microgrid
   (ii) Scenario 2: Renewable energy-based wind and solar microgrid
2. Energy Storage System:
   (i) Lithium-ion battery scenario
3. Energy Consumption Scenarios:
   (i) Scenario 1: Base load demand of the region
   (ii) Scenario 2: 35% annual reduction in load demand
   (iii) Scenario 3: 35% annual increase in load demand
4. Technology Cost Scenarios:
   (i) Scenario 1: Base installation cost
   (ii) Scenario 2: Reduced installation cost for generation technologies
   (iii) Scenario 3: Reduced installation cost for storage technologies

A total of 18 scenarios are considered, comprising 9 renewable energy-based microgrid scenarios and 9 diesel-based microgrid scenarios. The diesel-based configurations are evaluated under the assumption of no renewable generation or storage systems.

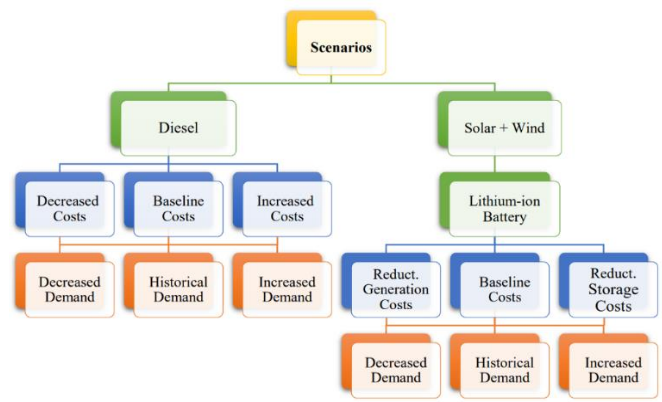

Fig. 8. Structure of the 18 Analyzed Scenarios

Table 1. Installation, operation, and maintenance costs of the renewable microgrid technologies used [23-26]

Parameters	Technology		
	Wind	Solar PV	Li-ion battery
Installation costs of the baseline (€/kW)	2000	1200	3000
Generation costs decreased (€/kW)	1500	1000	3000
Storage costs decreased (€/kW)	2000	1200	2000
Costs of O&M (€/kWh)	0.017	0.04	—
Area of occupation (m^2/kW)	2.61×10^{-4}	5.4×10^{-5}	1.7×10^{-7}

Table 2. Technical parameters of the lithium-ion battery used in the microgrid system [27]

Parameters	η_{BattC}	η_{BattD}	δ	SoC^{min}	SoC^{max}
Value	0.95	0.9	0.03	0.1	0.9

Table 3. Technical parameters of the diesel generator used in the microgrid system [28]

Technology	Installation (€/kW)			O&M (€/kWh)	Fuel (€/kWh)		
	Baseline	Decrease	Increase		Baseline	Decrease	Increase
Diesel	333	280	450	0.06	0.124	0.1	0.3

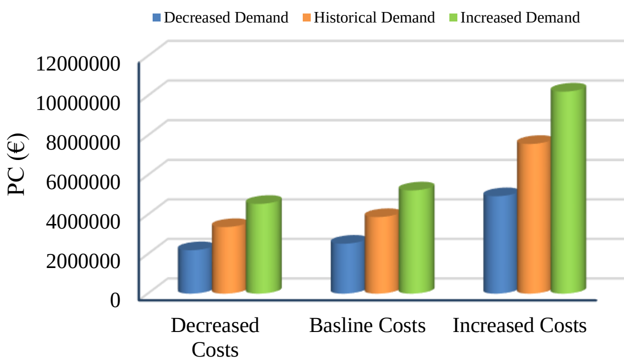

Fig. 9. PC of the diesel-based microgrid system

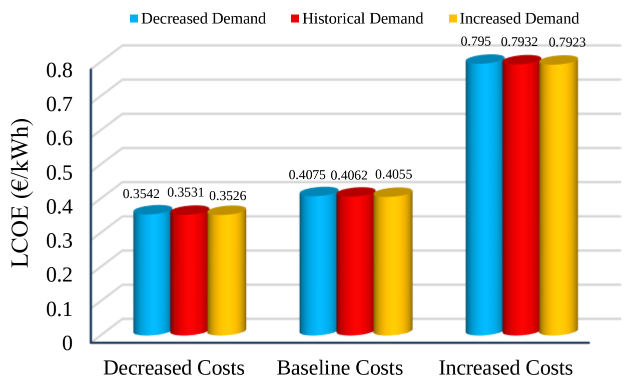

Fig. 10. LCOE of the diesel-based microgrid system

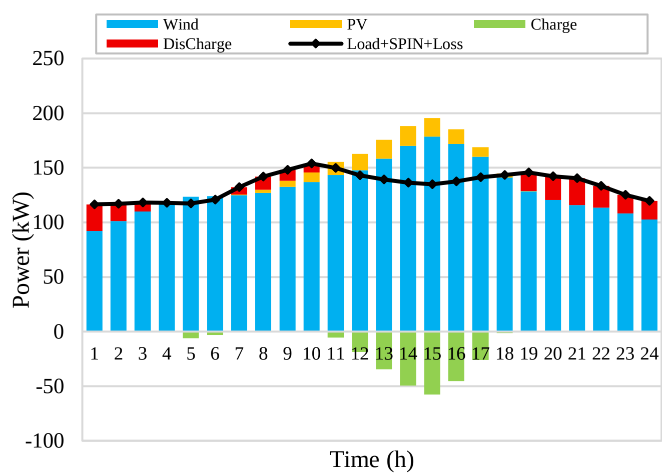

Fig. 11. Energy management in renewable microgrid

5. Simulation Results

5.1. Cost Analysis of the Diesel-Based Power System

The diesel-based microgrid, considered as the reference system for the study area, comprises only a fuel-based generator and excludes any renewable energy sources or energy storage systems. The PC and LCOE for this configuration are evaluated using (17) and (23), based on the technical and economic parameters listed in Tables 3 and 4. Fig. 9 illustrates the PC values under various scenarios characterized by differing fuel prices, installation costs, and load demand levels. As anticipated, scenarios involving higher energy demand or elevated fuel prices exhibit a substantial increase in PC, reaching up to approximately 3 million euros in the most cost-intensive cases. Conversely, the minimum PC is observed in the cost-reduction scenario, which incorporates reduced capital and operational expenditures. Fig. 10 displays the corresponding LCOE values for the same set of scenarios. The cost-reduction scenario yields the lowest average LCOE of approximately 0.2157 €/kWh, whereas the base-cost scenario results in an average LCOE of around 0.2481 €/kWh. The relatively narrow range of LCOE values suggests that variations in installation costs exert a moderate influence on LCOE when the load demand remains constant. These findings align with those reported in previous studies and substantiate the selection of the diesel-based configuration as a baseline for comparative assessments.

5.2. Renewable Energy-Based Microgrid with Battery Storage System

5.2.1. Renewable Power Microgrid Results – Installation Cost Reduction Scenario with Base Load Demand

In this section, the results of the installation cost reduction scenario under base load demand are analyzed. In this case, the microgrid is equipped solely with wind turbines, PV systems, and a lithium-ion BESS. Based on the optimization outcomes, the recommended configuration consists of 2200 kW of wind power, 1125 kW of PV capacity, and 6359 kW of lithium-ion battery capacity. The corresponding technical and economic parameters, including installation cost, rated capacity, land occupancy, O&M costs, PC and LCOE are summarized in Table 5. The PC (31.6 M€) and LCOE (1.5567 €/kWh) in this scenario are significantly higher than those of the diesel-based microgrid, which is consistent with findings reported in previous studies[33]. Fig. 11 shows the hourly load profile and the corresponding energy management strategy over a 24-hour period. During the early hours (1–3), wind generation is insufficient to meet the demand, and the battery discharges to compensate for the energy deficit. At hour 4, wind generation matches the load. In hours 5 and 6, wind output slightly exceeds the load, and the surplus energy is stored in the battery. From hours 7 to 10, solar energy becomes available, and both sources jointly contribute to supplying the load. However, the total generation remains insufficient, and the battery continues discharging. Between hours 11 and 17, the combined generation from wind and solar exceeds the demand, allowing the battery to store excess energy. At hour 18, renewable generation matches the demand, and no charging or discharging occurs. In hours 19 to 24, only wind power is available. As it is inadequate to meet the load, the battery discharges to provide the remaining energy. Fig. 12, illustrates the SoC variation of the lithium-ion battery during the same 24-hour period, reflecting the charge and discharge cycles corresponding to renewable generation and load dynamics. The SoC curve effectively demonstrates the operational role of energy storage in balancing supply and demand variability. The battery charges during daytime when solar power is available and discharges at night when generation is limited. The output power of the PV system is regulated using the maximum power point tracking (MPPT) algorithm to extract the maximum possible energy from solar irradiance. However, when the battery SoC reaches its upper threshold (e.g., SoC = 0.9) and wind generation alone is sufficient to meet the demand, the PV controller exits the MPPT mode and limits its output to fulfill only the real-time requirements, including load, reserve margin, and system losses. This operational strategy is implemented to prevent battery overcharging and to reduce energy loss caused by surplus generation.

Table 4. Input variables used in the economic feasibility assessment of the microgrid [29-32]

Parameters	Inflation rate (f) (%)	Insurance cost (%)	CarbonTax (€/kgCO_2)	Specific emissions (kgCO_2/kWh)	Nominal interest rate (i) (%)
Value	1.08	0.4% of ICs	0.041	0.765	1.3

Table 5. Results of Renewable System Sizing and Cost Estimation

Technology	Power capacity (kW)	Installation Costs (€)	O&M Costs (€/y)	Installed Area (km^2)	PC (€)	LCOE (€/kWh)
PV	1125	1,125,000	63,072	0.06	—	—
Wind	2200	3,300,000	91,734	0.574	—	—
Battery	6359	19,077,000	—	0.0011	—	—
Total	9684	23,502,000	154,806	0.6351	31,603,000	1.5567

Table 6. Performance Comparison of GA and WSO in Renewable Microgrid Optimization

Algorithm	Best Cost (M€)	PV Capacity (kW)	Wind Capacity (kW)	Battery Capacity (kW)	PC (M€)	LCOE (€/kWh)	Best Iteration	Execution Time (sec)
GA	26.3	906	2160	7325	34.3	1.5701	21	30
WSO	23.7	1125	2200	6359	31.6	1.5567	27	58

5.2.2. Overall Cost Performance of the Renewable Microgrid with Battery Storage System

This section presents the cost evaluation results of the renewable-based microgrid integrated with a lithium-ion battery. The optimization framework recommends a system configuration comprising a photovoltaic system ranging from 731 to 1519 kW, a wind farm ranging from 1400 to 2900 kW, and an energy storage system ranging from 3662 to 9022 kW, depending on cost and demand scenarios. The required land area for these configurations is 0.6351 km², which remains significantly below the total available area of the target region (5 km²). Figs. 13 and 14 depict the results for PC and LCOE, respectively, across various renewable microgrid configurations. The outcomes are categorized based on variations in installation costs, storage system costs, and consumption demand levels. As shown in Fig. 13, PC values range from approximately 10.6 M€ to 43.9 M€, depending on the scenario. The lowest PC (10.6 M€) is obtained in the case where both storage cost and load demand are reduced. In contrast, high-demand and high-cost scenarios result in significantly higher PC values. These findings indicate that PC is more sensitive to changes in load demand than to variations in installation or storage costs. Fig. 14 presents the LCOE results, which follow a trend similar to that of PC. The LCOE varies from approximately 0.8005 €/kWh to 1.6344 €/kWh across the evaluated scenarios. Scenarios characterized by lower storage costs offer more competitive energy prices. Although the renewable-based microgrid generally exhibits a higher LCOE compared to the diesel-based system (see Fig. 10), it provides long-term cost stability by eliminating fuel price volatility and reducing environmental impacts. Furthermore, from the perspectives of system reliability and investment, these scenarios entail broader implications. Lower storage costs not only improve economic performance but also enhance the operational flexibility of the microgrid by enabling better energy balancing and improving the ability to meet demand during fluctuations in generation. Likewise, reduced demand levels ease the burden on generation and storage assets, thereby increasing reserve margins and enhancing system robustness. From an investor's perspective, scenarios with lower PC and LCOE values indicate reduced financial risk due to smaller capital requirements and potentially shorter payback periods. Conversely, high-cost and high-demand scenarios entail larger investments and greater uncertainty in cost recovery, thereby increasing exposure to investment risk. These results underscore the importance of integrated planning and cost trade-off analysis in designing sustainable and economically viable microgrids. In particular, the simultaneous optimization of energy demand and component costs is essential for minimizing both total and per-unit energy costs in renewable energy systems.

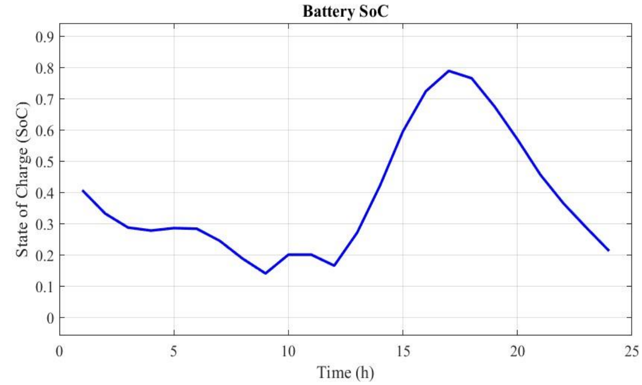

Fig. 12. Battery SoC curve for the renewable microgrid

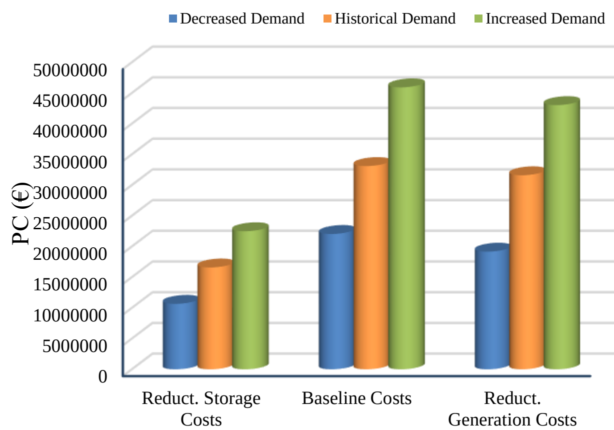

Fig. 13. PC of the renewable-based microgrid system

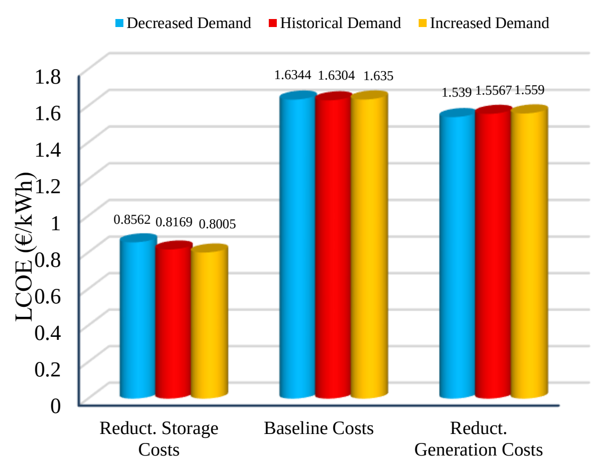

Fig. 14. LCOE of the renewable-based microgrid system

5.3 Comparative Analysis of WSO and GA

In this study, the WSO algorithm is employed as the primary method for optimizing the capacities of renewable energy sources and the storage system. To evaluate its performance, the results are compared with those of the Genetic Algorithm (GA), a widely used and well-established optimization technique. Both algorithms are executed under identical simulation settings (population size = 60, maximum generations = 200), and no convergence-based early stopping is applied. Instead, each algorithm runs until the maximum generation count is completed. The results are summarized in Table 6, which presents key performance indicators such as the optimal cost value, resource sizing, economic metrics (PC and LCOE), and execution time. As observed, WSO achieves a lower total cost (optimal cost: 23.7 M€) compared to GA (26.3 M€), reduced battery capacity (6359 kW vs. 7325 kW), and improved economic performance (lower PC and LCOE). While GA reaches its best solution at generation 21, WSO converges more gradually and achieves its optimal result at generation 27. These convergence behaviors are illustrated in Fig. 15 and Fig. 16, which depict the convergence curves of GA and WSO, respectively. The figures clearly show that WSO maintains a more consistent improvement trajectory across generations, whereas GA experiences faster early convergence but plateaus earlier. In terms of computational effort, GA completes its run in 30 seconds, while WSO requires 58 seconds. This is considered a reasonable tradeoff, given the superior solution quality provided by WSO. These findings confirm that both WSO and GA are capable of solving complex energy optimization problems. However, in this study, WSO demonstrates clear advantages in terms of solution accuracy, system design efficiency, and economic performance, making it a robust and competitive alternative.

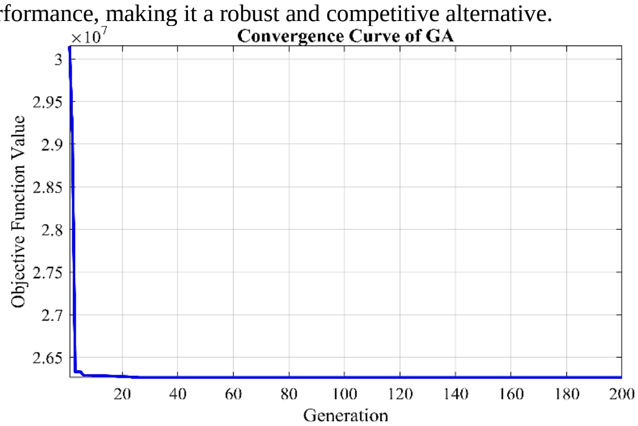

Fig. 15. Convergence curve of the GA algorithm

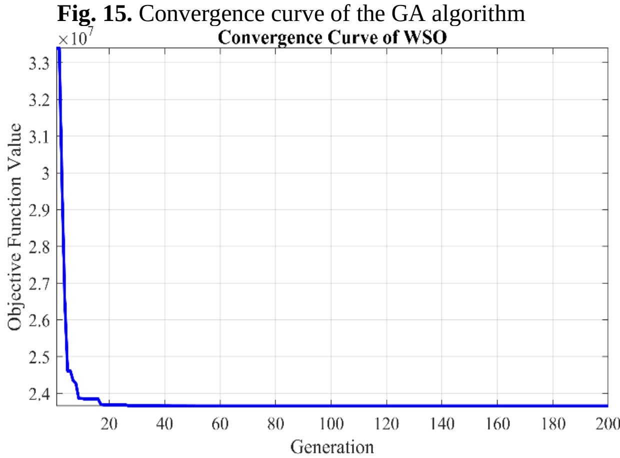

Fig. 16. Convergence curve of the WSO algorithm

6. Conclusion

Power systems are increasingly required to enhance energy efficiency, reduce operational costs, and ensure reliability and sustainability. This study presents an optimization framework to determine the optimal capacities of wind turbines, PV systems, and battery storage in an off-grid renewable microgrid under realistic and time-varying conditions. The model incorporates renewable curtailment and technical constraints to enable flexible and cost-effective energy planning. Simulation results show that battery storage integration significantly decreases reliance on fossil fuels, reduces emissions, and improves operational efficiency. Optimal configurations include PV capacities from 731 to 1519 kW, wind capacities from 1400 to 2900 kW, and battery capacities from 3662 to 9022 kW. The required land area is 0.6351 km², which is well within the available 5 km². Economic analysis indicates that the PC ranges from 10.6 to 43.9 million euros, while the LCOE varies from 0.8005 to 1.6344 euros per kilowatt-hour. Scenarios with lower storage costs and demand levels achieve better economic performance and system robustness. Two metaheuristic algorithms are used for solving the optimization problem: WSO and Genetic Algorithm GA. Under identical settings, WSO achieves lower total cost (23.7 million euros versus 26.3 million euros), smaller battery size, and better PC and LCOE values. Although WSO requires more computation time (58 seconds versus 30 seconds), its higher solution quality justifies the additional effort. In conclusion, the WSO-based framework offers a reliable and scalable solution for renewable microgrid planning. It supports strategic investment decisions and future extensions may include grid-connected applications and real-time optimization.

Reference

[1] T. Hai, J. Zhou and K. Muranaka, "Energy management and operational planning of renewable energy resources-based microgrid with energy saving", *Electric Power Systems Research*, vol. 214, p. 108792, 2023.

[2] A. Ghasempour, "Internet of things in smart grid: Architecture, applications, services, key technologies, and challenges", *Inventions*, vol. 4, no. 1, p. 22, 2019.

[3] A. Ghasempour and S. K. Jayaweera, "Data synchronization for throughput maximization in distributed transmit beamforming", *2017 IEEE Cognitive Communications for Aerospace Applications Workshop (CCAA)*, pp. 1-4, 2017.

[4] A. Ghasempour, "Optimum number of aggregators based on power consumption, cost, and network lifetime in advanced metering infrastructure architecture for Smart Grid Internet of Things", *2016 13th IEEE Annual Consumer Communications & Networking Conference (CCNC)*, pp. 295-296, 2016.

[5] A. Ghasempour, "Optimized advanced metering infrastructure architecture of smart grid based on total cost, energy, and delay", *2016 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)*, pp. 1-6, 2016.

[6] W. Feng, M. Jin, X. Liu, Y. Bao, C. Marnay, C. Yao, and J. Yu, "A review of microgrid development in the United States–A decade of progress on policies, demonstrations, controls, and software tools", *Applied energy*, vol. 228, pp. 1656-1668, 2018.

[7] R. P. Kumar and G. Karthikeyan, "A multi-objective optimization solution for distributed generation energy management in microgrids with hybrid energy sources and battery storage system", *Journal of Energy Storage*, vol. 75, p. 109702, 2024.

[8] A. Kazemtarghi and A. Mallik, "Techno-economic microgrid design optimization considering fuel procurement cost and battery energy storage system lifetime analysis," *Electric Power Systems Research*, vol. 235, p. 110865, 2024.

[9] M. Rawa, Y. Al-Turki, K. Sedraoui, S. Dadfar, and M. Khaki, "Optimal operation and stochastic scheduling of renewable energy of a microgrid with optimal sizing of battery energy storage considering cost reduction," *Journal of Energy Storage*, vol. 59, p. 106475, 2023.

[10] P. Wongdet, T. Boonraksa, P. Boonraksa, W. Pinthurat, B. Marungsri, and B. Hredzak, "Optimal capacity and cost analysis of battery energy storage system in standalone microgrid considering battery lifetime", *Batteries*, vol. 9, no. 2, p. 76, 2023.

[11] M. Gholami, S. A. Mousavi, and S. Muyeen, "Enhanced microgrid reliability through optimal battery energy storage system type and sizing", *IEEE Access*, vol. 11, pp. 62733-62743, 2023.

[12] B. Bacha, H. Ghodbane, H. Dahmani, A. Betka, A. Toumi, and

A. Chouder, "Optimal sizing of a hybrid microgrid system using solar, wind, diesel, and battery energy storage to alleviate energy poverty in a rural area of Biskra, Algeria", *Journal of Energy Storage,* vol. 84, p. 110651, 2024.

[13] N. N. Ibrahim, J. J. Jamian, and M. M. Rasid, "Optimal multi-objective sizing of renewable energy sources and battery energy storage systems for formation of a multi-microgrid system considering diverse load patterns", *Energy,* vol. 304, p. 131921, 2024.

[14] J. G. Gomes, H. Xu, Q. Yang, and C. Zhao, "An optimization study on a typical renewable microgrid energy system with energy storage", *Energy,* vol. 234, p. 121210, 2021.

[15] S. Y. Taya, N. E. M. Rozalia, S. R. W. Alwib, W. S. Hob, Z. A. Mananb, and J. J. Klemešc, "Design of grid-tied hybrid diesel-renewable energy systems using power pinch analysis", *CHEMICAL ENGINEERING,* vol. 78, 2020.

[16] L. M. S. De Siqueira, and W. Peng, "Control strategy to smooth wind power output using battery energy storage system: A review", *Journal of Energy Storage,* vol. 35, p. 102252, 2021.

[17] P. Blanc *et al.*, "Five steps to energy storage-Innovation Insights Brief-2020", 2020.

[18] E. Bullich-Massagué, F.-J. Cifuentes-García, I. Glenny-Crende, M. Cheah-Mañé, M. Aragüés-Peñalba, F. Díaz-González, and O. Gomis-Bellmunt, "A review of energy storage technologies for large scale photovoltaic power plants", *Applied Energy,* vol. 274, p. 115213, 2020.

[19] M. M. Rahman, A. O. Oni, E. Gemechu, and A. Kumar, "Assessment of energy storage technologies: A review", *Energy Conversion and Management,* vol. 223, p. 113295, 2020.

[20] H. Hu, S. Gong, and B. Taheri, "Energy demand forecasting using convolutional neural network and modified war strategy optimization algorithm", *Heliyon,* vol. 10, no. 6, 2024.

[21] T. S. Ayyarao *et al.*, "War strategy optimization algorithm: a new effective metaheuristic algorithm for global optimization", *Ieee Access,* vol. 10, pp. 25073-25105, 2022.

[22] F. Wiese *et al.*, "Open Power System Data–Frictionless data for electricity system modelling", *Applied Energy,* vol. 236, pp. 401-409, 2019.

[23] U. EIA, "US battery storage market trends", *Washington, DC: US EIA,* 2018.

[24] A. a. INEGI. "e2p-energias endogenas." http://e2p.inegi.up.pt/?Lang=PT. accessed: 2022.

[25] I. IRENA, "Renewable power generation costs in 2017", *Report, International Renewable Energy Agency, Abu Dhabi,* 2018.

[26] R. Shakoor, M. Y. Hassan, A. Raheem, and N. Rasheed, "Wind farm layout optimization using area dimensions and definite point selection techniques", *Renewable energy,* vol. 88, pp. 154-163, 2016.

[27] U. o. Strathclyde, "Analysis of cost reduction opportunities in the wave energy industry." http://www.esru.strath.ac.uk/EandE/Web_sites/14-15/Wave_Energy/attenuator.html. accessed: 2022.

[28] E. R. d. S. Energéticos, "Tarifas e preços para a energia elétrica e outros serviços em 2018", 2006.

[29] M. Barbaro, and R. Castro, "Design optimisation for a hybrid renewable microgrid: Application to the case of Faial island, Azores archipelago", *Renewable Energy,* vol. 151, pp. 434-445, 2020.

[30] ERSE, “Tarifas e preços para a energia elétrica em 2020”, *Entidade Reguladora dos Serviços Energéticos (ERSE),* http://refhub.elsevier.com/S0360-5442(21)01458-4/sref33. accessed: 2022.

[31] P. Luckow, E. A. Stanton, S. Fields, B. Biewald, S. Jackson, J. Fisher, and R. Wilson, "2015 carbon dioxide price forecast", *Cambridge, Massachusetts,* 2015.

[32] E. Relatório, "De gestão da electricidade dos Açores [Electricity of Azores management report]", *Angra Do Heroísmo,* 2020.

[33] C. Li, X. Ge, Y. Zheng, C. Xu, Y. Ren, C. Song, and C. Yang, "Techno-economic feasibility study of autonomous hybrid wind/PV/battery power system for a household in Urumqi, China," *Energy,* vol. 55, pp. 263-272, 2013.