Design and optimization of a hybrid energy storage system using the Dandelion Optimization Algorithm in islanded rural DC microgrids

İzviye Fatımanur Tepe
Department of Electrical and Electronics Engineering
Grad. Sch. of Natural and Applied Sci.,
Gazi University,
Ankara, Türkiye
23833004003@gazi.edu.tr

Oğuz Taşdemir
Department of Electricity and Electronics, Faculty of Engineering and Architecture,
Kırşehir Ahi Evran University
Kırşehir, Türkiye
oguz.tasdemir@ahievran.edu.tr

Erdal Irmak
Department of Electrical and Electronics Engineering
Faculty of Technology,
Gazi University
Ankara, Türkiye
erdal@gazi.edu.tr

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***Abstract*— The prevalence of microgrid systems has increased in recent years, with the objective of providing solutions to the global energy demand and to support the electrification of rural areas. These systems, which are generally based on renewable resources, suffer from stability problems due to the variability of resources. Energy storage systems are critical to overcoming this problem. However, batteries are limited due to performance loss over time and high maintenance costs. Therefore, Hybrid Energy Storage Systems (HESS) supported by supercapacitors come to the forefront. In this study, a solar and wind powered HESS for a rural island microgrid is designed and cost and sizing optimization is performed using the Dandelion Optimization Algorithm. Simulation results show that HESS reduces costs, increases system performance and improves energy efficiency.**

Keywords—hybrid energy storage system (HESS), cost optimization, dandelion optimization algorithm, rural microgrid

I. INTRODUCTION

The increasing demand for energy, combined with environmental concerns and fossil fuel depletion, has resulted in a shift towards renewable and distributed energy systems. Microgrids have emerged as a promising solution for rural and remote areas where extending the main utility grid is not feasible. These small-scale energy systems can operate independently or in conjunction with the main grid, and they provide a platform for the integration of renewable energy sources like solar and wind power. This enables sustainable and decentralized electrification, supporting the energy transition and acting as a strategic tool for rural electrification. Many people in developing countries lack reliable electricity access, and extending the central grid to these areas is hindered by high costs and difficult geography. Microgrids offer flexible and cost-effective solutions, utilizing local energy sources and contributing to health, education, and economic development. Therefore, the adoption of microgrids in rural areas is both a technical requirement and a social and economic necessity. [1]. Although the use of renewable-based microgrids offers many advantages, some challenges arise due to the intermittent and stochastic nature of resources such as solar and wind energy. These challenges include voltage and frequency instability, energy mismatch and reliability concerns in islanded operating modes [2,3]. Energy storage systems (ESS) are used to solve these problems. While batteries are the most widely used technology due to high energy density and scalability, relying solely on batteries can bring limitations such as additional performance degradation and high lifecycle costs [4,5]. Therefore, hybrid energy storage systems (HESS) have been developed [6-8]. By combining batteries with supercapacitors, HESS can manage transient power demands, extend the lifetime of batteries and improve system response. This integration offers a more robust and economical energy storage solution, especially for remote microgrid applications [6,7]. Determining the optimal configuration and control of hybrid energy storage systems utilizing renewable energy sources (RES) is a task that considers many important factors such as cost, efficiency, lifetime and system stability. However, conventional optimization methods are often inadequate to deal with such complex and nonlinear problems. Recent research use metaheuristic algorithms as a solution to this problem [9-11]. In this study, a HESS is designed and optimized for a rural islanded microgrid powered by solar and wind energy. The proposed system aims to enhance energy security and reduce operational costs in a region with limited access to electricity. A Dandelion Optimization Algorithm (DO) is employed to optimize the size and operational strategy of the HESS under varying generation and load scenarios. The simulation results demonstrate that the integrated system enhances the performance and reliability of the microgrid, as well as significantly improving energy efficiency and reduces the total cost of ownership. The outcomes of this study provide a compelling case for the deployment of DO-optimized HESS architectures in decentralized, renewable-based microgrids. This paper is divided into the following sections: Section 2 presents a summary of the current literature on the rural microgrid concept and hybrid energy storage structures. In the third section, the conceptual background of the main elements considered in the study is discussed. Section four details the proposed microgrid structure, system components and problem definition. In the fifth section, simulation scenarios and parameters are presented, and the performance of the model is evaluated. Finally, the sixth and last section of the paper summarizes the findings, interprets the results and discusses future work.

II. BRIEF OVERVIEW OF RELATED LITERATURE

The integration of RES into standalone microgrids presents major challenges due to their inherently intermittent and unpredictable nature. To address these fluctuations in power generation, HESS has been widely adopted. By combining the high energy density of lithium-ion batteries with the high-power density of supercapacitors, HESS architectures are able to enhance system responsiveness, extend battery lifetime, and improve overall efficiency. Numerous studies have highlighted the benefits of HESS.

Ganege and Chandima [12] investigated a solar system that integrates battery and pumped hydro storage in Sri Lanka. Li et al. [13] and Zhang et al. [14] analyzed HESS configurations in small-scale microgrids, optimizing battery and supercapacitor (SC) capacities based on system dynamics. A shift toward life cycle cost (LCC) analysis has also emerged, as evidenced by the works of Roy et al. [15], Jain et al. [16], and Lu and Wang [17]. These researchers modeled degradation effects and incorporated them into optimization frameworks. In a similar line of research, Zhou and Sun [18] employed a SAPSO algorithm for HESS sizing within an LCC context, while Seixas et al. [19] utilized PSO to optimize fuzzy logic control for battery longevity in transportation systems.

Recent contributions have demonstrated the practical benefits of HESS integration in various domains. Chen et al. [20] implemented HESS in railway systems, thereby achieving a 39% cost reduction. Javed et al. [21, 22] proposed a fuzzy logic-based energy management system for rural HESS applications. Adaptive fuzzy controllers were developed by Sinha and Bajpai [23] for standalone DC microgrids. In their seminal work, Premadasa and Chandima [24] introduced a multi-objective cost function that accounts for two key factors: unused PV generation and unmet demand. Karunanithi et al. [25] focused on MPPT-integrated HESS in residential PV systems, and Gugulothu et al. [26] proposed an SOC-based energy management strategy, which was later validated under various scenarios by Krishan and Suhag [27]. Meanwhile, Faria et al. [28, 29] developed SOC-based and ANN-enhanced controllers to improve SC utilization.

Li et al. [30] optimized HESS sizing under varying PV load profiles, while Chong et al. [31] presented an adaptive algorithm to minimize transient battery stress. Aktaş et al. [32] experimentally validated a dynamic energy management approach using a laboratory-scale HESS model. Even though a considerable body of research has examined the cost and control optimization of hybrid energy storage systems, many of these studies have relied on fixed capacity assumptions or conventional metaheuristic techniques. The employment of bio-inspired algorithms within this specific context remains limited. The DO is a promising solution that strikes a balance between exploration and exploitation. However, its application to HESS sizing and cost problems in islanded microgrid settings remains unexplored.

The objective of this study is to address this knowledge gap by proposing a DO-based cost minimization framework for HESS sizing in an off-grid PV-wind microgrid. In contrast to numerous extant studies, the proposed method incorporates a battery sizing approach constrained by daily net energy balance and SOC boundary analysis. Instead of implementing dynamic constraints within the optimization loop, pre-simulation is utilized to ascertain the minimum technically feasible battery capacity that satisfies SOC limits. The integration of technical boundaries into the sizing model is a realistic approach that strengthens the reliability and economic relevance of the results.

The remainder of this paper is organized as follows: Section II reviews related literature, Section III presents the conceptual background, Section IV outlines the proposed system and methodology, Section V discusses simulation results and cost analysis, and Section VI concludes the study with key findings and future directions.

III. Conceptual Background

A. Islanded Rural Microgrids

Despite advancements in modern energy sources, many individuals in rural regions continue to struggle to access essential energy services due to challenges such as limited resources and distribution gaps, leading to energy deprivation. This lack of energy access hinders efforts in improving quality of life, reducing poverty, and promoting sustainable development. The focus on rural electrification underscores the link between efficient energy use and poverty alleviation, yet progress remains slow due to obstacles like high costs, infrastructure deficiencies, and technical complexities. Alternative approaches, such as distributed energy generation and microgrids, show promise in addressing rural electrification challenges. Specifically, rural microgrids, powered by RES, offer a decentralized and reliable energy supply to remote communities with limited access to the main electricity grid, gaining popularity as sustainable power solutions for underserved areas.

Islanded microgrids, particularly in rural regions, offer a sustainable and practical solution for providing electricity where grid expansion is not economically viable or technically feasible. These systems are defined as decentralized energy systems that function independently from the central utility grid. Their importance lies in promoting energy access, resilience, and independence for remote communities often lacking reliable infrastructure. Relying on localized renewable energy generation and energy storage systems, rural microgrids not only reduce fossil fuel dependency but also support socio-economic development through decentralized electrification strategies. In such configurations, all energy generation, regulation, and balancing must be achieved locally, without external support. Therefore, effective energy management is paramount to ensuring that supply meets demand on an hourly or even sub-hourly basis.

As illustrated in Figure 1, the primary energy sources are typically photovoltaic (PV) panels and wind turbines. However, due to their weather-dependent and intermittent nature, these sources introduce generation uncertainty and require robust management strategies to handle surplus and deficit conditions. To mitigate these fluctuations, ESS are employed to absorb surplus energy during periods of excess generation and release it when generation falls below consumption. This stabilizes power delivery, minimizes reliance on fossil backup sources, and improves power quality. Hence, the appropriate integration and sizing of ESS components are crucial for the operational success of islanded microgrids.

Fig. 1. An example of an islanded rural microgrid [1].

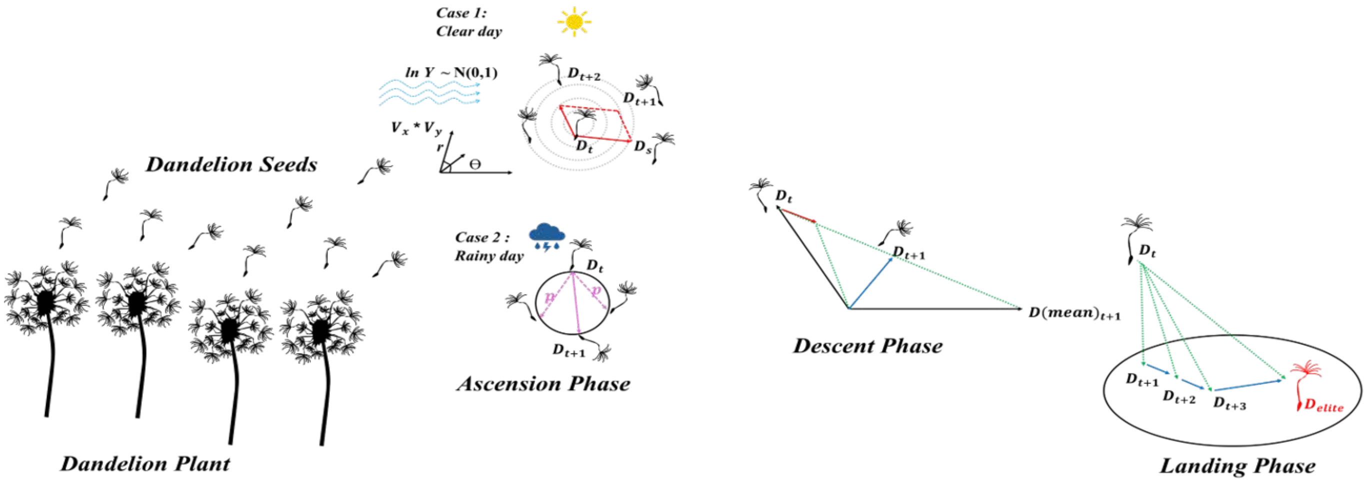

Fig. 2. Spread behavior of dandelion seeds [1].

B. Dandelion Optimization Algorithm

The Dandelion Optimization (DO) algorithm is a novel swarm intelligence-based metaheuristic proposed by Shijie Zhao [33], inspired by the natural dispersal mechanisms of biological systems of dandelion plant. As shown in Figure 2, the DO algorithm simulates the dispersal behavior of dandelion seeds carried by wind, modeling their movement and settlement processes in the environment.

This process consists of three phases reflecting the algorithm's exploration–exploitation behavior: (1) rising stage, where seeds spiral upward under drag force for global search; (2) descending stage, enabling local search through gradual settling; and (3) landing stage, where seeds disperse due to atmospheric effects, maintaining diversity and guiding convergence toward optimal solutions.

Initialization

Like other nature-inspired metaheuristic algorithms, the DO algorithm begins with a population-based initialization and proceeds through iterative evolutionary optimization. The initial population is defined mathematically as follows:

$$population = \begin{bmatrix} D_1^1 & \cdots & D_1^{Dim} \\ \vdots & \ddots & \vdots \\ D_{pop}^1 & \cdots & D_{pop}^{Dim} \end{bmatrix} \quad (1)$$

Here, pop denotes the population size and Dim the problem dimensionality. Each individual D_i is initialized within the defined lower (LB) and upper (UB) bounds, and its position is calculated as:

$$D_i = rand \times (UB - LB) + LB \quad (2)$$

$i \in \{1,2,...,pop\}$ denotes the individual index, and rand is a uniformly distributed random number in the range [0,1]. Lower and upper bounds as:

$$LB = [lb_1, ..., lb_{Dim}]\ ,\ UB = [ub_1, ..., ub_{Dim}] \quad (3)$$

During the initialization phase, the DO algorithm selects the individual with the best fitness value as the initial elite (best) solution.

This elite solution D_{elite} is identified based on the minimum value of the objective function across the initial population and is expressed as:

$$f_{best} = \min\big(f(D_i)\big) \quad (4)$$
$$D_{elite} = D\Big(find\big(f_{best} == f(D_i)\big)\Big) \quad (5)$$

Here, the find() function returns the index corresponding to the minimum objective function value in the population.

1) Rising Phase

During the rising phase, varying meteorological conditions and wind speeds determine the vertical lift height of dandelion seeds. Therefore, weather conditions are classified as either sunny or rainy, influencing the dispersal dynamics as shown in Figure 3.

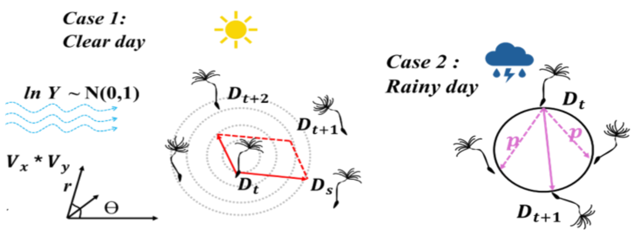

Fig. 3. Cases of ascension (rising) phase.

Case 1: Sunny Weather

Under sunny weather conditions, wind speed typically follows a Gaussian distribution, enhancing seed dispersal range. DO emphasizes global exploration via wind-induced spiral motion in this phase, simulating an ascending helical trajectory. This behavior is mathematically expressed as:

$$D_{t+1}=\{D_t+\alpha*v_x*v_y*lnY*(D_s-D_t)\ randn<1.5 \quad (6)$$

Here, D_t is the seed position at t^{th} iteration and v_x, v_y are lift coefficients controlling vertical motion. The adaptive factor α adjusts the step size, while D_s is a random position that adds stochasticity and maintains diversity.

Case 2: Other Weather conditions

Inclement weather, especially on rainy days, prevents the dandelion seeds from rising properly in the air. The mathematical expression for this situation is shown below.

$$D_{t+1} = D_t * k \tag{7}$$

Here, the parameter k is used to preserve the local search space.

2) Descending Phase

In this phase, the DO algorithm emphasizes exploration using Brownian motion to simulate seed descent. Seeds rise and fall periodically, and their movement covers a wider search space. The mean position from the ascent phase is used to stabilize the descent. This is mathematically defined as:

$$D_{t+1} = D_t - \alpha * \beta_t * \left(D_{mean\_t} - \alpha * \beta_t * D_t\right) \tag{8}$$

Here β_t is a random number and represents Brownian motion [34]. D_{mean_t} shows the average position of the population at i^{th} iteration.

3) Landing Phase

Based on the previous stages, the dandelion seed randomly chooses a landing site. As the iteration processes progress, the algorithm is expected to converge towards the global optimum solution. In order to efficiently converge towards the global optimum, search agents exploit the knowledge and experience of existing elites in order to exploit their local neighborhood. The mathematical expression of this process is given in Equation 9.

$$D_{t+1} = D_{elite} + levy(\lambda) \times \alpha \times (D_{elite} - D_t \times \delta) \tag{9}$$

Here, D_{elite} represents the optimal position of the seed, *levy(λ)* is the function of Levy flight. δ is a linear function between [0,2].

The following steps are taken for the execution of the DO algorithm [35].

- Start the optimization process by creating vector groups in the search space.
- Complete the iterative process by going through three stages: ascending stage, descending stage and descent stage, respectively.
- Rearrange the fitness function so that it is ordered from good solutions to bad solutions. In this case, the minimization problem should be considered. The solution with the lowest fitness will be considered as the elite solution.
- The optimization process will be terminated when the maximum number of iterations specified in the algorithm is reached.

C. Hybrid Energy Storage System (HESS)

RES demonstrate irregular and intermittent generation profiles, which engender challenges for supply-demand balancing in microgrids, particularly in islanding mode. ESS are of paramount importance for the purpose of storing excess generation and meeting load demands during periods of low energy production. HESS is defined as the integration of diverse storage technologies, including electrical, chemical, electromechanical, and other methodologies. The implementation of HESS offers distinct advantages over conventional storage units. Table I presents a comparison of several prominent energy storage systems based on fundamental characteristics. As illustrated in Table I, the most advantageous HESS combination is that of the battery and the supercapacitor [36]. Supercapacitors have been demonstrated to effectively manage sudden load fluctuations, while batteries offer a more stable and consistent power output, thereby extending the cycle life and reducing maintenance expenses. The integration of these technologies has been shown to enhance system stability, optimize storage unit size and cost, and improve system performance in solar and wind-based microgrids. HESS applications are pervasive in the relevant literature and offer an optimal balance between reliability and cost effectiveness in energy systems. The representative structure of the supercapacitor lithium-ion battery hybrid energy storage system under consideration in this study is illustrated in Figure 4.

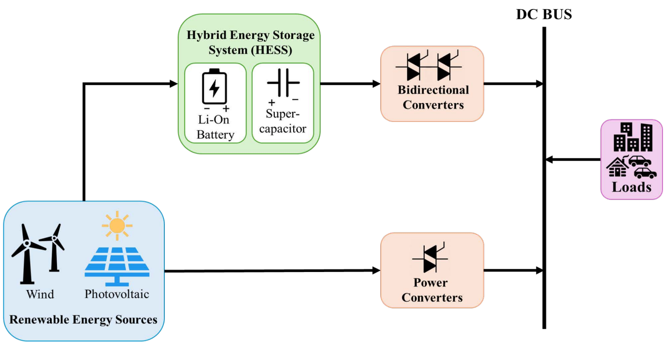

Fig. 4. Proposed HESS design structure.

TABLE I. COMPARISON OF ENERGY STORAGE TECHNOLOGIES BASED ON KEY CHARACTERISTICS

Feature	***Supercapacitor***	***Battery***	***Hydrogen***	***Compressed Air***	***Flywheel***
Power Density	High	Low	High	Low	High
Energy Density	Low	High	High	High	Moderate
Cost	Moderate	Low	Low	Low	Moderate
Response Time	Fast	Fast	Slow	Slow	Fast
Cycle Life	High	Moderate	Moderate	Moderate	High
Efficiency	Moderate	Moderate–High	Low	Moderate	High

IV. Proposed System Design and Methodology

This study presents an islanded rural DC microgrid integrating photovoltaic panels, wind turbines, and a HESS composed of a lithium-ion battery and a supercapacitor. Energy generation and consumption profiles are modelled based on 24-hour data sets and the energy needs specific to rural areas are reflected with the data obtained from literature. Figure 5, Figure 6 and Figure 7 show the daily RES generation and consumption power demand schedules respectively.

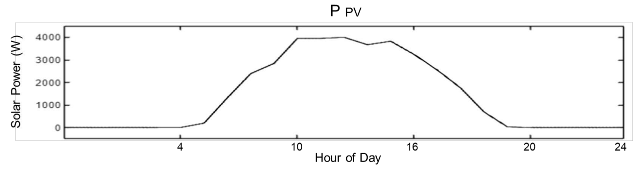

Fig. 5. Daily solar power generation profile.

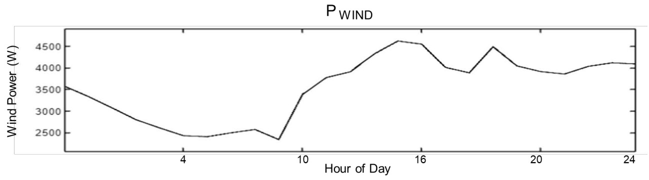

Fig. 6. Daily wind power generation profile.

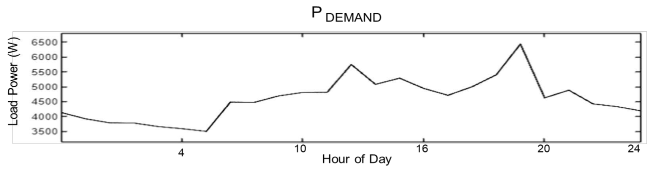

Fig. 7. Daily load profile.

The upper and lower bounds of the optimum capacity for the battery and supercapacitor are calculated based on the hourly differences between the demand power and the generated power and constitute the limitations of the dandelion algorithm. While the supercapacitor handles transient loads, the battery supports long-term demand. The block diagram of proposed system shown in Figure 8 and system parameters shown in Table II.

TABLE II. Designed System Parameters

Parameter	***Unit***	***Value***
Maximum PV power	max P_{PV}	3.8 kW
Maximum wind power	max P_{WIND}	4.5 kW
Maximum daily load power	max P_{LOAD}	6.4 kW
Optimal charging range (%)	SoC (%)	%20-%80

A. Sizing Estimation and Cost Optimization

This study proposes a comprehensive cost- and sizing-oriented optimization framework for an islanded PV–wind hybrid microgrid integrated with a HESS. Before initiating the cost optimization, lower and upper bounds for the battery and supercapacitor sizes were determined based on daily generation and load profiles. The battery size was roughly estimated according to the maximum cumulative energy deficit observed during the day, ensuring that the battery can store enough energy to cover long-duration supply gaps. Similarly, the supercapacitor's minimum required size was determined based on the highest rate of load variation, assuming it must respond to short-term high-frequency fluctuations. These sizing estimations helped define the feasible solution space for the optimization process.

The main objective of this study is to minimize the total cost of a HESS consisting of a single lithium-ion battery and a supercapacitor, while determining their optimal sizing. The objective function comprises three primary components: the initial investment cost (C_{inv}), the battery degradation cost (C_{deg}), and the operation and maintenance cost (C_{om}). The objective function is formulated as follows:

$$min\ F = C_{inv} + C_{deg} + C_{om} \tag{10}$$

Here, F is the total cost to be minimized, C_{inv} represents the initial investment cost of the battery and supercapacitor and C_{deg} is the degradation-related cost, C_{om} corresponds to the annual operation and maintenance cost. The investment cost is calculated as:

$$C_{inv} = c_{bat} \cdot E_{bat} + c_{SC} \cdot C_{total} \tag{11}$$

where c_{bat} is the unit cost of the battery (\$/Wh), E_{bat} is the battery capacity (Wh), C_{SC} is the unit cost of the supercapacitor (\$/F), and C_{total} is the total capacitance (F). The battery degradation cost is given by:

$$C_{deg} = k_{deg} \cdot DOD \cdot N_{cycle} \cdot E_{bat} \tag{12}$$

where k_{deg} is the degradation coefficient, DOD is the depth of discharge, and N_{cycle} is the number of charge/discharge cycles. It should be noted that the degradation cost is considered only for the lithium-ion battery. Supercapacitors, unlike batteries, store energy via electrostatic mechanisms and do not undergo significant aging due to chemical reactions. As demonstrated in the review by Ma et al. [37], aging in supercapacitors is negligible compared to batteries, and therefore their degradation-related cost is generally excluded from cost models in literature.

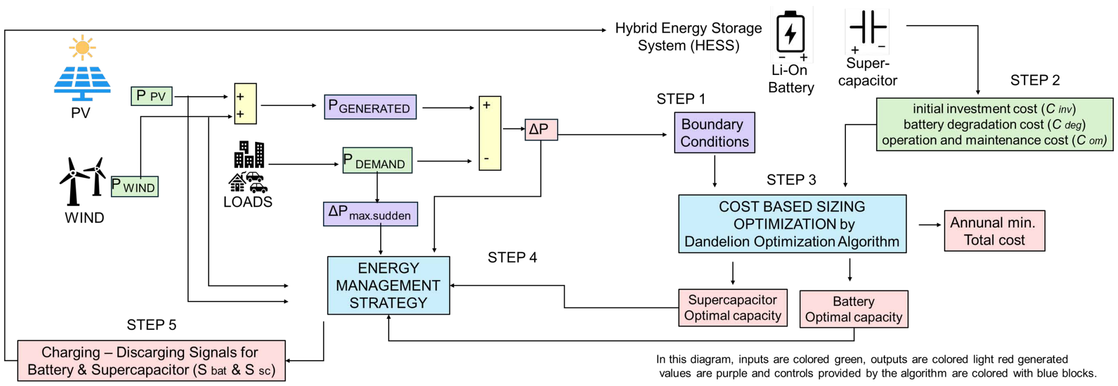

Fig. 8. Block scheme of proposed system.

Consequently, the supercapacitor is treated as a cost-effective, non-degrading component in this work, and its aging cost is not included in the objective function. Finally, the operation and maintenance cost are defined as a fixed percentage of the total investment:

$$C_{om} = \gamma \cdot C_{inv} \tag{13}$$

The operation and maintenance (O&M) cost is modeled as a fixed percentage of the initial investment cost. This study assumes a typical annual rate of 5% (i.e., γ=0.05), representing regular maintenance activities such as inspection, cleaning, and minor component replacements. In this study, the unit cost of lithium-ion batteries was taken to be \$150/kWh. This cost was determined based on recent academic literature reflecting historical trends and large-scale production forecasts. As asserted by Liu et al. the financial burden associated with lithium-ion batteries has consistently declined over the preceding decade, attaining a cost of 137 USD/kWh in 2020. This reduction can be attributed to the advancement of manufacturing methodologies and the enhancement of material efficiency [38]. Furthermore, Schmuch et al. reported that the cell-level cost of lithium-ion batteries ranges between 36–40¢/kWh, which accounts for approximately 75% of the total pack-level cost [39]. In light of these findings, this study adopts a pack-level average cost of 150 USD/kWh as a conservative and literature-supported value for system-level modeling. In addition, the unit cost of supercapacitors is considered based on recent academic literature. According to a cost analysis conducted by the University of Surrey, the production cost of non-aqueous supercapacitor devices is approximately \$2,400/kWh, which is significantly higher than that of conventional batteries [40]. This high cost is attributed to factors such as material expenses and manufacturing complexities. Nonetheless, it is imperative to acknowledge that supercapacitors boast certain advantages, including high power density and prolonged cycle life. These benefits have the potential to counterbalance their initial high costs in specific applications. The objective function of this study is to be integrated into the optimization framework and evaluated iteratively using the DO to determine the most cost-effective HESS configuration. DO simulates the seed dispersal and reproduction behavior of dandelions, striking an effective balance between local exploitation and global exploration. Its adaptive behavior allows it to dynamically tune the search space, offering faster convergence and higher-quality solutions in hybrid system design problems compared to conventional approaches like PSO or GA etc.

B. Energy Management Strategy for HESS

The proposed energy management strategy governs the coordination between the supercapacitor and the battery based on real-time power imbalance and state-of-charge (SOC) conditions. The supercapacitor is used to manage rapid load or generation changes, which appear as sudden shifts in the net power difference (ΔP). A predefined threshold (δ) is applied to detect such fast transients and activate the supercapacitor accordingly. At each time step, the net power difference ($\Delta P = P_{generation} - P_{demand}$) is calculated.

A set of decision rules is applied to determine the charging or discharging status of both storage units. The control logic can be summarized as follows:

- If $\Delta P < -\delta$ and $SOC_{SC} > 10\%$, the supercapacitor discharges to compensate for sudden load surges.
- If $\Delta P < 0$ and $SOC_{min}^{BAT} < SOC_{BAT} < SOC_{max}^{BAT}$, the battery discharges to meet long-term energy shortages.
- If $\Delta P > 0$ and $SOC_{min}^{BAT} < SOC_{BAT} < SOC_{max}^{BAT}$, the battery is charged during excess generation.
- If $\Delta P > \delta$ and $SOC_{SC} < 90\%$, the supercapacitor is charged using surplus power.

In all other conditions, both storage units remain idle. This logic enables real-time control in a DC microgrid by activating the supercapacitor for short-term rapid power fluctuations, and the battery for longer-duration energy imbalance. Since DC systems do not involve frequency regulation, decisions are based solely on power and voltage dynamics.

V. Simulation Results & Findings

The present study proposes a novel HESS optimization approach, designed to ensure both technical sustainability and reduce investment and maintenance costs. In this simulation, a 24-hour dynamic scenario was designed with time-varying load and renewable generation profiles. The supercapacitor is activated during rapid load changes, while the battery responds to sustained energy demand. Priority was given to the battery for energy storage under excess generation, and to the supercapacitor for power smoothing. Switching decisions were governed by SOC thresholds and the rate of power demand variation. To identify the optimal sizing and cost of the hybrid energy storage components, a cost minimization process was carried out using MATLAB.

The optimization aimed to minimize the total cost function defined in Eq. 10, which includes investment cost, degradation cost, and operation & maintenance cost. Prior to the optimization, the lower and upper bounds for the battery and supercapacitor capacities were determined based on daily energy generation and consumption profiles of the microgrid. The minimum battery capacity was roughly estimated from the maximum daily cumulative energy deficit, ensuring the battery could cover extended periods of energy shortage. Similarly, the minimum required capacitance for the supercapacitor was derived from the peak power variations in the load profile, assuming a short response. Once these bounds were set, a DO based MATLAB script was implemented to evaluate the total cost across different sizing configurations within the feasible region.

Figure 9 illustrates the output of the script for a selected configuration. The results indicate that investment cost increases with capacity, while degradation cost dominates over long-term operation. The optimal configuration is found at a battery capacity of 2613 Wh and a supercapacitor capacitance of 256 F.

```
----------- OPTIMAL RESULTS -----------
Population Size: 30.00
Iteration: 100.00
Optimal Battery Capacity (Wh): 2613
Optimal Supercapacitor (F): 256.9652
Minimum Total Cost: $110299.0151
```

Fig. 9. MATLAB output for cost and sizing optimization.

TABLE III. COST COMPARISON TABLE

Cases	Battery Capacity (Wh)	Supercapacitor Capacity (F)	Initial Investment Cost ($)	Battery Degradation Cost ($)	Operation & Maintenance Cost ($)	Total ESS Cost ($)
Only Battery	3000	0	1500.0	175 200.0	75.0	176 780.0
Hybrid ESS	2613	256	1357.9	152 600.0	67.895	110 300.0

*The cost breakdown represents annual estimates based on an assumed 365 charge-discharge cycles per year. The degradation cost is calculated on a yearly basis, and the investment and O&M costs are proportionally annualized. **The cost values presented in this table were determined based on assumptions derived from the methodologies and findings discussed in references [35–37].

The lower limits of the battery capacity are set at 3000 Wh, considering the energy deficit calculated from actual load and generation profiles. The upper limit is set as 10000 Wh considering the cost. The battery capacity determined in this way provides an optimized solution to provide the minimum energy required to meet the energy demand in the system and increase operational validity. The required supercapacitor size is calculated using the standard energy equation (Eq. 14) based on the transient power compensation and allowable voltage variation given in [41]. The minimum and maximum limits for SC are calculated as 100 F-300 F based on Eq. 14, again considering the cost and in order to meet the energy buffering requirements for the transient load in case of a 1-2 kW surge and to protect the battery from high-rate cycles.

$$C_{capacity} = \frac{2.P.t}{\left(V_{max}-V_{min}\right)\left(V_{max}+V_{min}\right)} \tag{14}$$

Here, P: Maximum sudden shifts in the net power difference (ΔP) according to daily data, t: the time this load will be supported , V_{max} and V_{min}: Operating voltage range of SC.

In the convergence behavior of the Dandelion Optimization Algorithm shown in Figure 10, it is seen that the total system cost continues to decrease; it is determined that the optimum configuration is reached after approximately 30 iterations.

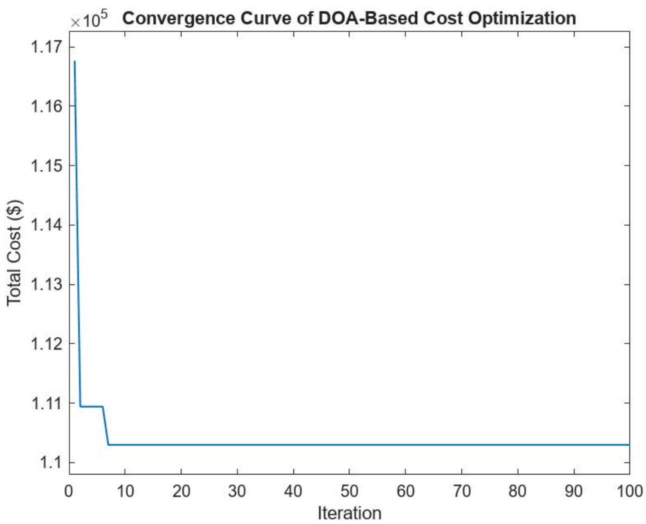

Fig. 10. The convergence curve of DO algorithm

The optimization process consistently converged to the lower bound of the search space for battery capacity. This behavior indicates that, under the current cost function formulation, minimizing the battery size yields the lowest total cost. The absence of performance penalties or energy reliability constraints in the model allows the algorithm to prefer undersized configurations.

Table III presents a comparative breakdown of the system costs between a conventional battery-only storage configuration and the DO-optimized hybrid system. The results indicate that although the hybrid configuration involves additional investment for the supercapacitor, it significantly reduces degradation cost and total cost over the system's operational life. To validate the effectiveness of the energy management strategy proposed, a 24-hour simulation was performed using MATLAB/Simulink. The simulation has been based on realistic time-series profiles for solar and wind generation as well as residential load demand. In the defined scenario, the supercapacitor was expected to handle high-rate power variations while the battery provided support for sustained energy deficits. The SOC levels of both storage units were continuously monitored. Figures 11, 12 and 13 illustrate the change in load demand, and the daily production of PV and wind resources, daily net power, the variation of the SOC of the battery and the supercapacitor respectively, over a 24-hour period. The results demonstrate that the supercapacitor effectively compensated for rapid load while the battery managed the general energy imbalance throughout the day. The initial state of charge of the battery and supercapacitor is chosen to be 60% and 70% respectively.

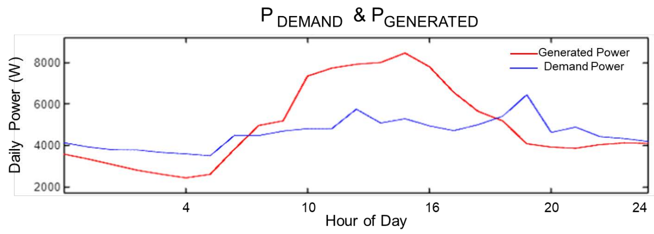

Fig. 11. Daily power demand and RES generation.

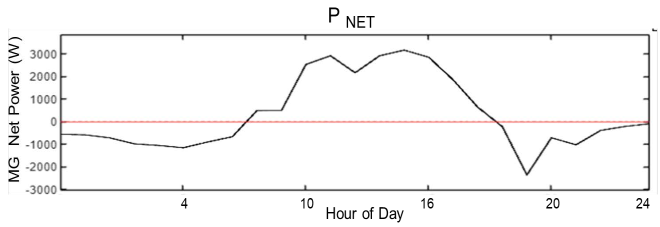

Fig. 12. Daily net power in microgrid.

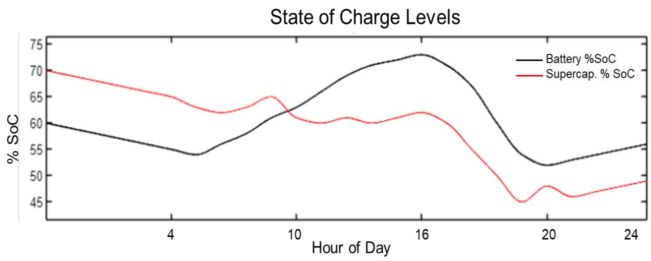

Fig. 13. %SoC levels of battery and supercapacitor under daily operation.

The simulation results demonstrate that the proposed cost-based sizing and energy management strategy provides an effective framework for hybrid energy storage operation in islanded DC microgrids. The total cost minimization process, constrained by realistic lower and upper bounds derived from daily generation–consumption profiles, enabled accurate determination of battery and supercapacitor capacities. The Dandelion Optimization Algorithm successfully identified an optimal configuration that balances investment and degradation-related costs. Additionally, the 24-hour simulation of the energy management system confirmed that the supercapacitor efficiently handled rapid power fluctuations, while the battery responded to long-term energy deficits. Throughout the operation, both storage units maintained their SOC within predefined safety limits, and power balance was achieved without overloading or under-utilizing any component. These findings validate the effectiveness of the proposed hybrid strategy in enhancing cost-efficiency, component longevity, and operational stability of DC microgrids under dynamic load and renewable generation conditions.

VI. Conclusion

In this study, a HESS has been designed and optimized for a rural islanded DC microgrid powered by solar and wind energy. The primary objective was to enhance energy reliability and reduce long-term operational costs in regions with limited or no access to the main utility grid. A cost minimization framework was developed, incorporating investment, degradation, and maintenance costs. The system parameters were constrained based on predicted daily generation and consumption profiles to ensure applicable sizing boundaries. The DO was employed to determine the optimal battery and supercapacitor capacities. Simulation results confirmed that the proposed energy management strategy efficiently coordinated the operation of both storage units: the supercapacitor responded to short-term power fluctuations, while the battery supported long-term energy imbalances. Both units maintained safe SOC levels throughout the operation.

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