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A Comparative Heuristic Optimization Approach for BESS Sizing in Nanogrids

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Abstract: This study focuses on optimizing the capacity of Battery Energy Storage System (BESS) for a nanogrid using three heuristic-based optimization algorithms: Grey Wolf Optimization (GWO), Artificial Bee Colony (ABC), and Particle Swarm Optimization (PSO). The energy management of the nanogrid is modeled in Python using a rule-based approach to minimize energy imports from the grid, followed by the application of these heuristic algorithms to determine the optimal BESS capacity. Simulations conducted as a part of this study revealed the performance characteristics of each algorithm. The GWO algorithm stabilized at 1.85 kW by the 25th iteration. In contrast, the ABC algorithm achieved a rapid increase, reaching 2.14 kW by the 10th iteration and maintaining this level thereafter. The PSO algorithm exhibited a more stable and consistent trajectory, maintaining a capacity of approximately 1.52 kW. The findings highlight the distinct advantages offered by each algorithm in nanogrid energy management. While GWO and ABC excelled in fast convergence and broad search capabilities, PSO demonstrates a more consistent and stable solution. In addressing the complex energy management challenges posed by BESS capacity optimization, the performance of each algorithm is evaluated and compared to determine the most efficient strategy for managing energy storage systems.

KeyWords: Nanogrid, heuristic optimization, bess capacity optimization

Nanoşebekelerde BESS Boyutlandırması için Karşılaştırmalı Sezgisel Optimizasyon Yaklaşımı

Öz: Bu çalışma, bir nanoşebeke sisteminde Bataryalı Enerji Depolama Sistemi (BESS) kapasitesinin optimizasyonunu üç farklı sezgisel algoritma (Gri Kurt Optimizasyonu-GWO, Yapay Arı Kolonisi-ABC ve Parçacık Sürü Optimizasyonu-PSO) kullanarak incelemektedir. Python'da kural tabanlı bir enerji yönetim modeli geliştirilerek şebekeden elektrik enerjisi alımını minimize etmek amaçlanmış ve her algoritmanın performansı karşılaştırmalı olarak analiz edilmiştir. Simülasyon sonuçlarına göre GWO algoritması 25. iterasyonda 1.85 kW'da kararlılığa ulaşırken, ABC algoritması 10. iterasyonda 2.14 kW'a hızla ulaşmış ve bu performansı sürdürmüştür. PSO ise yaklaşık 1.52 kW ile optimal sonucu üretmiştir. Çalışma, GWO ve ABC'nin hızlı yakınsama ve geniş arama yetenekleriyle öne çıktığını, PSO'nun ise daha tutarlı çözümler sunduğunu ortaya koyarak nanoşebeke enerji yönetiminde algoritma seçimine yönelik kritik bilgiler sunmaktadır. BESS kapasite optimizasyonunun karmaşıklığı dikkate alındığında, bu araştırma enerji depolama sistemlerinin verimli yönetimi için optimal stratejilerin belirlenmesine önemli katkı sağlamaktadır.

Anahtar kelimeler: Nanoşebeke, sezgisel optimizasyon, bess kapasite optimizasyonu

1. Introduction

The traditional power grid, designed for alternating current (AC) transmission, faces significant challenges due to the extensive distances between power generation facilities and end-users. Among the most critical issues are energy losses caused by transmission line resistance, which substantially reduce overall efficiency. Despite advancements in technology, the construction, maintenance, and upgrading of transmission and distribution infrastructure remain resource-intensive and costly. Additionally, the grid's ability to adapt to rapid fluctuations in energy demand is limited, often resulting in imbalances between supply and demand. The centralized structure is highly susceptible to widespread outages during faults or natural disasters, while long-distance transmission exacerbates issues such as load imbalances and frequency instability, compromising overall reliability. The grid also relies on a complex infrastructure of transformers, poles, circuit breakers, and other components, which further constrains its sustainability, stability, and resilience. Moreover, fossil-fuel-based power plants significantly contribute to climate change through greenhouse gas emissions, and the inefficiencies inherent in long-distance transmission amplify active power losses. Despite ongoing technological progress, the traditional power grid is

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increasingly constrained by its technical, economic, and environmental limitations. [1-6]. To mitigate the shortcomings of centralized power grids, alternative configurations like microgrids (MGs) and nanogrids (NGs) have been introduced. Nanogrids are small-scale energy systems capable of generating electricity in the kilowatt (kW) range, often located close to or at the point of consumption. Originally envisioned as compact, independent systems utilizing renewable resources, NGs have proven to be a valuable addition to addressing the weaknesses of conventional grid infrastructures. These systems prioritize distributed energy generation, tapping into renewable sources such as solar and wind power to deliver cost-effective and environmentally friendly alternatives to traditional energy production. Additionally, NGs incorporate technologies like cogeneration and microturbines, making them well-equipped to fulfill the electricity demands of industrial and commercial applications. By decentralizing energy generation and supply, NGs improve efficiency, resilience, and sustainability, positioning them as integral components of future energy systems. [7-12]

2. Literature Review

The existing interconnected grid faces numerous challenges, including efficiency losses during long-distance energy transmission, high infrastructure costs, and imbalances between supply and demand. To overcome these limitations, distributed energy generation systems, such as NG, have emerged as a promising alternative. By integrating renewable energy sources and energy storage solutions, NGs provide more flexible and sustainable energy management at a localized level. Figure 1 illustrates the keywords associated with studies on nanogrids available in the WOS database, showcasing their interrelationships.

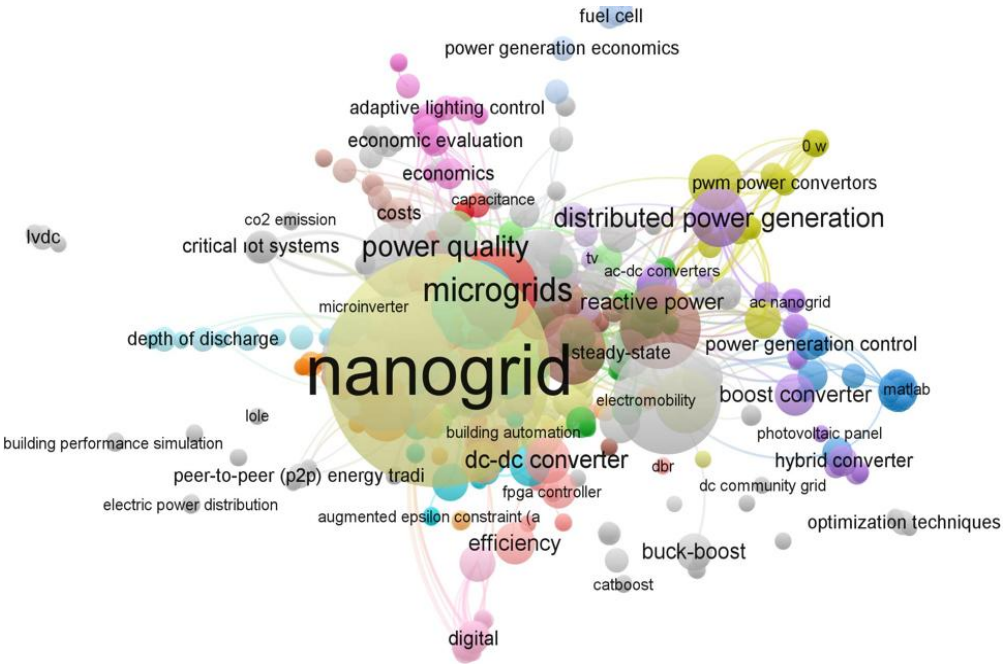

Figure 1. The distribution and intensity of keywords in publications based on the Web of Science (WoS) database [13].

There is a wide range of studies in the literature focused on BESS sizing. Battery energy storage systems play a crucial role in enhancing energy systems by addressing renewable energy variability, improving grid stability, and optimizing energy management. Recent research has proposed various optimization methodologies for determining the optimal BESS capacity under different technical and economic constraints. A life cycle cost (LCC) based framework was developed in [14], providing a comprehensive approach to BESS sizing by including installation, maintenance, decommissioning, and disposal costs over the system lifetime. In [15], mixed-integer linear programming (MILP) was employed to optimize BESS sizing under different electricity market mechanisms and ownership structures, maximizing the net present value of investments while accounting for multiple market uncertainties. BESS sizing within microgrid environments has also been a major research area. For instance, [16]

proposed a security constrained optimal power flow (SCOPF) based model that integrates PV generation and BESS operation under stochastic forecasting errors, enabling cost minimization and improved reliability. Similarly, [18] developed a frequency stability constrained BESS sizing model, formulated as a MILP and solved via Benders decomposition, which ensures compliance with dynamic criteria such as frequency, RoCoF, and steady-state frequency limits. In the residential sector, [17] presented a MILP-based PV–BESS optimization model for households equipped with home energy management systems (HEMS). The model incorporates day-ahead load scheduling, PV tilt angle optimization, and battery degradation to maximize the net present value under dynamic economic conditions. Specialized applications of BESS have also been widely studied. In [19], a power-smoothing-oriented BESS sizing methodology was proposed for PV plants, accounting for mission profiles, irradiance variability, temperature effects, and oversizing factors to optimize both performance and lifetime. Likewise, [20] developed a robust MILP-based optimization model for extreme fast-charging stations (XFCS), considering demand and solar generation uncertainties, utility tariffs, and degradation dynamics to minimize annualized total cost. Smart microgrids with high PV penetration have been addressed in [21], which proposed a two-layer strategy integrating virtual energy storage systems (VESS) and Markowitz risk assessment to minimize costs and optimize dispatch while maintaining stability under PV and load uncertainties. In a recent contribution, [22] presented a comprehensive optimization model for BESS sizing integrated with customer PV installations and domestic load profiles. The study emphasized the importance of coupling linear programming with heuristic scheduling to minimize grid dependence and enhance the cost-effectiveness of nZEBs under varying seasonal electricity pricing scenarios. Industrial applications were explored in [23], where a BESS sizing approach for facilities participating in real-time pricing (RTP) demand response utilized k-means clustering to reduce scenarios and maximize industrial profits under stochastic electricity pricing. Lastly, [24] investigated optimal BESS sizing and operation in peer-to-peer (P2P) energy sharing networks, highlighting the economic benefits of user-owned BESS systems for maximizing net present value, particularly in campus buildings. These studies collectively highlight the advancements in BESS sizing methodologies across various contexts, from residential and industrial applications to microgrids and peer-to-peer energy networks. They emphasize the importance of integrating technical, economic, and environmental factors to optimize BESS deployment effectively.

2.1. Motivation and research gap

Despite the growing interest in battery capacity optimization, many studies have focused on single optimization algorithms or traditional techniques, with comparatively limited efforts devoted to systematic comparisons of metaheuristic methods. In particular, the application of PSO, GWO, and ABC algorithms to BESS capacity optimization has received little attention, especially in the context of nanogrid studies. While Turan et al. [25] quantified the techno-economic feasibility of nanogrids across Türkiye using HOMER (Hybrid Optimization of Multiple Energy Resources) Grid, the present study focuses on the operational optimization of battery energy storage within such systems through heuristic and meta-heuristic algorithms. To address this gap, this research conducts a comparative assessment of these algorithms, analyzing their convergence behaviors, stability, and efficiency. The results aim to provide practical insights for selecting suitable optimization techniques in complex energy management problems and to motivate further exploration of hybrid or tailored algorithmic solutions. Among various metaheuristic approaches, PSO, GWO, and ABC were selected because they represent three complementary search philosophies such as swarm intelligence, leadership hierarchy, and collective foraging which offer a balanced trade-off between exploration and exploitation with relatively few control parameters. Other algorithms such as Genetic Algorithm (GA), Differential Evolution (DE), and Ant Colony Optimization (ACO) were excluded at this stage due to their heavier parameter tuning requirements, sensitivity to problem-specific settings, and higher computational complexity, which are reserved for future comparative extensions of this research.

2.1.1. Highlights

This study makes the following contributions:

- Provides one of the few comparative analyses of PSO, GWO, and ABC algorithms for BESS capacity optimization in nanogrid applications.
- Offers novel insights into the convergence characteristics and search strategies of three metaheuristic algorithms.
- Demonstrates PSO’s consistent performance with balanced and stable optimization outcomes.

- Shows that GWO and ABC achieve rapid convergence and competitive capacity values.
- Contributes to the methodological basis for algorithm selection in complex energy management scenarios.

3. BESS Capacıty Optımızatıon Of A Nanogrıd Usıng GWO, ABC, And PSO Algorıthms

In this study, PSO, GWO, and ABC were selected as representative metaheuristic algorithms owing to their complementary search strategies, proven efficiency in continuous optimization problems, and relatively low parameter tuning requirements. Although other approaches such as Genetic Algorithm (GA), Differential Evolution (DE), and Ant Colony Optimization (ACO) have been widely applied in energy-related optimization tasks, their extensive parameterization and problem-dependent sensitivity may limit their robustness in BESS sizing applications. By contrast, PSO, GWO, and ABC provide a well-balanced trade-off between exploration and exploitation, making them particularly suitable for the nonlinear and high-dimensional search spaces of energy storage optimization. Moreover, these algorithms have been frequently benchmarked in recent studies, offering a reliable basis for comparative analysis in nanogrid applications.

NGs are innovative energy production and distribution infrastructures that enable the optimization of generation, storage, and consumption systems at a local level. With the integration of renewable energy sources, energy storage systems have become critical to ensuring production continuity, balancing generation and consumption, and minimizing reliance on the main grid. Precise sizing of BESS is therefore essential to optimize energy costs and reduce grid dependency. Accordingly, the selected algorithms are employed in this study to determine the optimal BESS capacity within a nanogrid environment.

3.1. Determination of a BESS capacity with grey wolf optimization algorithm

The GWO is a metaheuristic inspired by the social hierarchy and hunting strategies of grey wolves (Canis lupus). Wolves are classified into four roles that are alpha, beta, delta, and omega. While the main hunting phases of searching, encircling, and attacking prey are mathematically modeled to guide the optimization process [26]. In this hierarchy, alphas lead decision-making, betas support them, and omegas maintain social stability. During hunting, wolves track, encircle, and ultimately attack the prey, as represented in Equations (1)–(4) [27].

$$\vec{D} = \left|\vec{C}.\vec{X}_p(t) - \vec{X}(t)\right| \quad (1)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \ \vec{A}.\vec{D} \quad (2)$$

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \ \vec{a} \quad (3)$$

$$\vec{C} = 2.\vec{r}_2 \quad (4)$$

Here, t represents the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\vec{X}_p$ represents the position vector of the prey, and $\vec{X}$ denotes the position vector of the grey wolf. The components of $\vec{a}$ decrease linearly from 2 to 0 over the iterations while $\vec{r}_2$ and $\vec{r}_1$ are random vectors in the range [0,1], enabling wolves to explore search space. Equations (1)–(4) guide wolf movement: (1–2) update positions toward the prey, (3) balances exploration and exploitation, and (4) adds randomness to avoid premature convergence [28–29]. Together, they provide a robust and adaptive search mechanism. As shown in Figure 2, alpha wolves represent the best solutions, followed by beta and delta, while the rest are classified as omega.

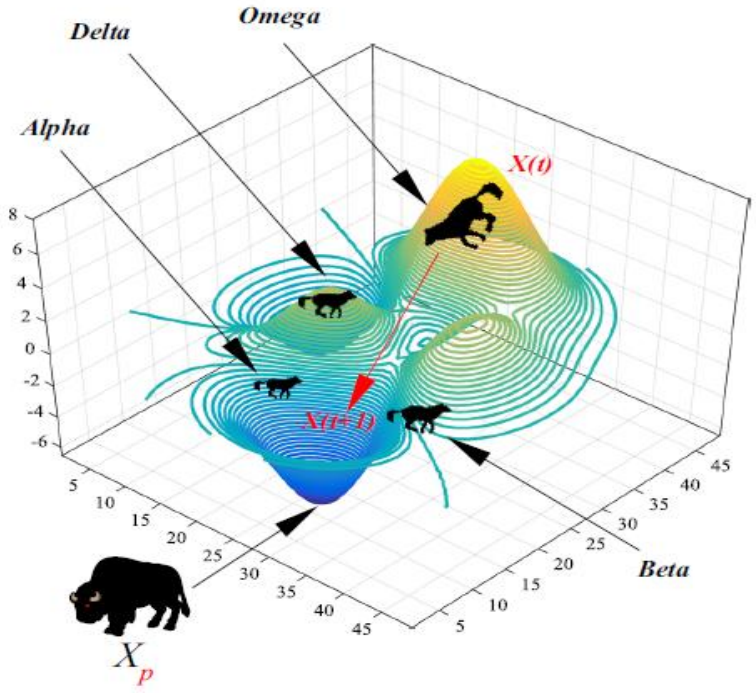

Figure 2. Positions of Alpha, Beta, and Delta wolves relative to the prey [29].

Equations (5)- (7) show that the positions of wolves within the algorithm are updated vectorially.

$$\vec{D}_\alpha = \left|\vec{C}_1\vec{X}_\alpha(t) - \vec{X}\right| \tag{5}$$

$$\vec{D}_\beta = \left|\vec{C}_2\vec{X}_\beta(t) - \vec{X}\right| \tag{6}$$

$$\vec{D}_\delta = \left|\vec{C}_3\vec{X}_\delta(t) - \vec{X}\right| \tag{7}$$

Similarly, Equations (8)- (11) provide the dynamically changing values of alpha, beta, and omega wolves at each iteration.

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1\vec{D}_\alpha \tag{8}$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2\vec{D}_\beta \tag{9}$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3\vec{D}_\delta \tag{10}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{11}$$

The mathematical formulations of the rule-based energy management system that was used before GWO, ABC, and PSO are provided in Equations (12)-(21).

$$E_t^{excess} = P_t^{generation} - P_t^{demand}, \forall t \;\; E_t^{excess} > 0, \forall t \tag{12}$$

$$E_t^{deficit} = \left|P_t^{demand} - P_t^{generation}\right|, \forall t \;\; E_t^{deficit} < 0, \forall t \tag{13}$$

$$B_t^{min} \leq B_t^{cap} \leq B_t^{max}, \forall t \tag{14}$$

$$E_t^{export} = \sum_{t=1}^{T} E_t^{excess} - \sum_{t=1}^{T} \Delta B_t^{charge} \quad (15)$$

$$E_t^{import} = \sum_{t=1}^{T} E_t^{deficit} - \sum_{t=1}^{T} \Delta B_t^{discharge} \quad (16)$$

$$OF = \min \sum_{t=1}^{T} E_t^{import} \quad (17)$$

$$B_t = B_{t-1} + \Delta B_t^{charge} - \Delta B_t^{discharge} \quad (18)$$

$$\delta_t^{charge} + \delta_t^{discharge} \leq 1 \qquad \delta_t^{charge}, \delta_t^{discharge} \in \{0,1\}, \quad \forall t \quad (19)$$

$$\Delta B_t^{charge} \leq \delta_t^{charge} . (B_t^{max} - B_t), \ \forall t \quad (20)$$

$$\Delta B_t^{discharge} \leq \delta_t^{discharge} . B_t, \ \forall t \quad (21)$$

The mathematical model used in this study incorporates a set of equations to optimize the BESS capacity for a nanogrid. These equations address energy balance, battery capacity constraints, and operational restrictions to ensure the effective management of energy production, consumption, and storage. Equation (12) defines the excess energy E_t^{excess}, which is the difference between the generated energy $P_t^{generation}$ and the demand P_t^{demand} at time t. This excess energy is only positive when generation exceeds demand. Similarly, Equation (13) determines the energy $E_t^{deficit}$, calculated as the absolute difference between demand and generation when demand surpasses generation. Battery capacity constraints are specified in Equation (14) ensuring that the battery's state of charge B_t remains within its minimum B_t^{min} and maximum B_t^{max} limits throughout the operation. Equation (15) calculates the total exported energy E_t^{export} to the grid, considering the excess energy after battery charging. Conversely, Equation (16) calculates the total imported energy E_t^{import} from the grid, accounting for the energy deficit after battery discharging. The objective function in Equation (17) aims to minimize the net energy import from the grid by balancing the imported and exported energy over the optimization period. The battery's energy balance is maintained in Equation (18), where the battery state of charge at time t is updated based on the previous state and the hourly charge ΔB_t^{charge} and discharge $\Delta B_t^{discharge}$ values. To further refine the model, binary decision variables δ_t^{charge} and $\delta_t^{discharge}$ are introduced in Equation (19), allowing only one operation (charging or discharging) at any given time. Equations (20) and (21) restrict the charging and discharging activities, ensuring that charging does not exceed the remaining battery capacity, and discharging is limited to the current state of charge.

3.2. Determination of BESS capacity with artificial bee colony algorithm

The ABC algorithm, introduced by Karaboğa in 2005, is a metaheuristic inspired by the foraging behavior of honeybees [30]. It consists of three groups: employed bees, onlookers, and scouts. Employed bees exploit known food sources, onlookers select among them based on shared information, and scouts explore new sources when old ones are abandoned [31]. These behaviors, illustrated in Figure 3, are mathematically modeled to guide the optimization process. The search mechanism is expressed in Equations (22)–(24), where nectar sources correspond to candidate solutions and are updated based on random perturbations and the global best solution [32]. When stagnation occurs, scouts introduce new random sources, as shown in Equation (26). Together, these update rules enable the ABC algorithm to explore the solution space effectively and avoid local optima.

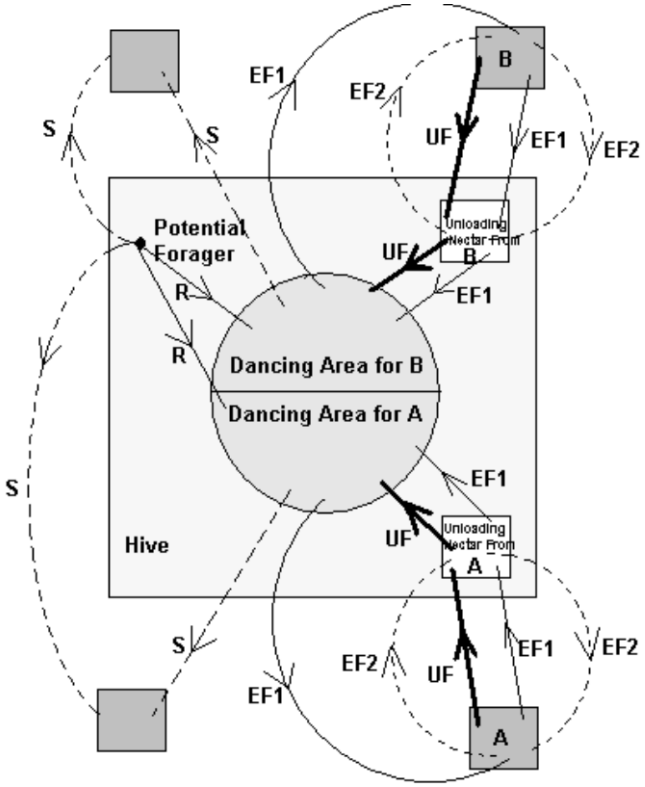

Figure 3. Illustration of bee foraging behavior in the ABC algorithm [30].

$$new_i^j = a + b\ x\ food_i^j \tag{22}$$

$$a = C_1\ x\ food_i^j + (1 - C_1) x gbest^j \tag{23}$$

$$b = \left| food_i^j - gbest^j \right| \tag{24}$$

Here, $food_i^j$ represents the nectar collected at the j. location by the i. population. $gbest$ denotes the best nectar location found by the bees currently searching. C_1 is a random number between 0 and 1. Following this, the bee colony distributes the nectar based on the information provided by the follower bees, as expressed in Equation (25).

$$new_i^j = C_1\ x\ \left(ref_{1,i} - ref_{2,i}\right) \tag{25}$$

Here, $ref_{1,i}$ and $ref_{2,i}$ represent the reference portions of nectar previously collected. If a food source falls into a local optimum, it will be abandoned. Scout bees will then search for a new food source according to Equation (22). The position of this new source is calculated using Equation (26).

$$new_i^j = rand\ (lb, ub) \tag{26}$$

Here, lb and ub represent the lower and upper bounds of the decision variables. The bees in the colony will update their fitness values and identify the most optimal food source [32–33].

3.3. Determination of BESS capacity with particle swarm optimization algorithm

PSO is a metaheuristic inspired by social behavior, designed for nonlinear function optimization. Each particle represents a candidate solution that updates its position based on its personal best ($pbest$) and the global

best ($gbest$) found so far. The velocity and position updates are defined in Equations (27)–(28), which balance exploration and exploitation through stochastic terms [34]. Owing to its simplicity and efficiency, PSO has been widely applied in diverse engineering optimization problems. By considering a population $X = \{x_1, \dots, x_i, \dots, x_n\}$ of n particles, assumed to be weightless and dimensionless, moving in a D −dimensional search space. At the $t - th$ iteration, $x_i(t) = [x_{1i}(t), x_{2i}(t), \dots x_{iD}(t)]$ represents the position of the $i - th$ particle, and $V_i(t) = [v_{i1}(t), v_{i2}(t), \dots v_{iD}(t)]$ represents its velocity. Throughout the elapsed iterations, $pbest(t) = [pbesti_{i1}(t), pbesti_{i2}(t), \dots, pbest_{iD}(t)]$ denotes the best personal position visited by particle i up to time t, while $gbest$ indicates the best global position discovered by all particles so far. At each iteration, the evolutionary process for the $i - th$ particle is formulated using Equation (27) and Equation (28) [35].

$$V_{i+1} = \omega V_i(t) + C_1\, x\, rand_1 x\, \left(pbest - X_i(t)\right) + \, C_2\, x\, \, rand_2\, x\, \left(gbest - X_i(t)\right) \tag{27}$$

$$X_{i+1} = V_{i+1} + \, X_i(t) \tag{28}$$

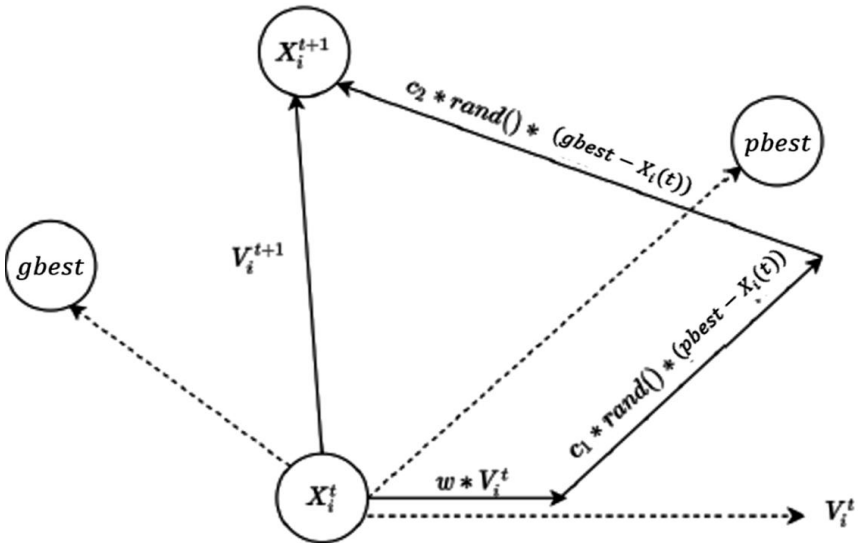

Figure 4. Particle motion inside the PSO algorithm [35].

The determination of the optimal BESS capacity using the GWO, ABC, and PSO algorithms follows distinct methodologies inspired by their respective nature-based paradigms. In GWO, the optimization process is guided by the hierarchical structure of grey wolf packs, with alpha, beta, and delta wolves representing the best solutions and leading the search for the optimal capacity. The positions of the wolves are iteratively updated based on their proximity to the prey, simulating a balance between exploration and exploitation. For the ABC algorithm, optimization relies on the foraging behavior of bees. Employed bees evaluate specific solutions (potential capacities), onlooker bees select promising options based on fitness values, and scout bees search for new possibilities when solutions stagnate. This multi agent approach enables rapid exploration of the solution space. In the PSO algorithm, the optimal BESS capacity is determined by simulating a swarm of particles, each representing a potential solution. These particles adjust their positions iteratively based on their personal best experience and the global best solution, achieving convergence through a balanced interplay of local and global searches. The particle movement mechanism, including velocity and position updates directed toward personal best (*pbest*) and global best (*gbest*) positions, is illustrated in Figure 4. By applying these algorithms independently, the study provides a comparative analysis of their capabilities, highlighting their effectiveness in identifying suitable BESS capacities for efficient energy management. In this study, a nanogrid is modeled using the HOMER Grid software based on geographical and meteorological data. Renewable energy output is obtained as a result of this modeling. These outputs, including production and load values, are imported into a Python code via an Excel program. The photovoltaic capacity of the system simulated in HOMER is 7 kW, and the load profile is illustrated in Figure 5. This load profile and production output are also utilized in other optimization studies conducted in this research. By using codes with identical input values for production and consumption, comparisons among three nature-inspired optimization algorithms are made possible.

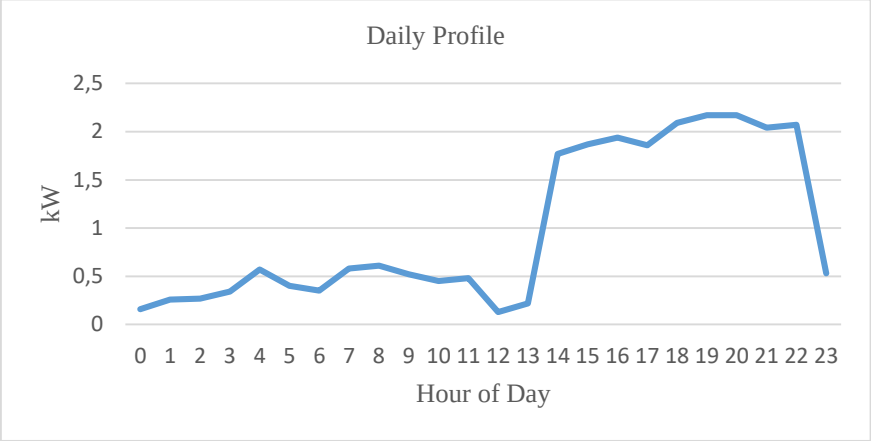

Figure 5. Load profile used in rule based energy management section.

In the figure 6 the nanogrid system manages the flow of energy between AC and DC components. On the AC side, electricity supplied by the energy provider, EPDK (Energy Market Regulatory Authority) powers a primary load with a daily energy consumption of 23.00 kWh and a peak demand of 2.81 kW. An energy converter facilitates the transition between AC and DC energy. On the DC side, energy generation is provided by the LR6-72 monocrystalline solar panel, while energy storage is managed through the LI ASM battery system. This configuration optimizes energy production and storage, reducing reliance on the grid by integrating renewable energy and storage technologies in a small-scale energy management system. In the python coding process, the optimization is run for one year, corresponding to 8,760 hours, ensuring that the program output closely approximates optimal real-world conditions. Analysis of the load demand revealed a daily electricity requirement of 23 kWh. After processing the input data, rule-based modeling is implemented for energy management, minimizing grid energy imports. Consequently, the BESS capacity is determined using the GWO-ABC and PSO algorithm. The flowchart of this study is presented in Figure 7. In the current study we proposed a methodology for optimizing the BESS capacity within a renewable energy-based nanogrid system. The process begins with input data, including meteorological parameters, load profiles, and technical specifications of the nanogrid components. These inputs are analyzed using HOMER simulation software, which provides key insights into energy production and consumption dynamics. Based on this analysis, a rule-based energy management strategy is integrated with metaheuristic optimization algorithms to achieve long-term operational efficiency.

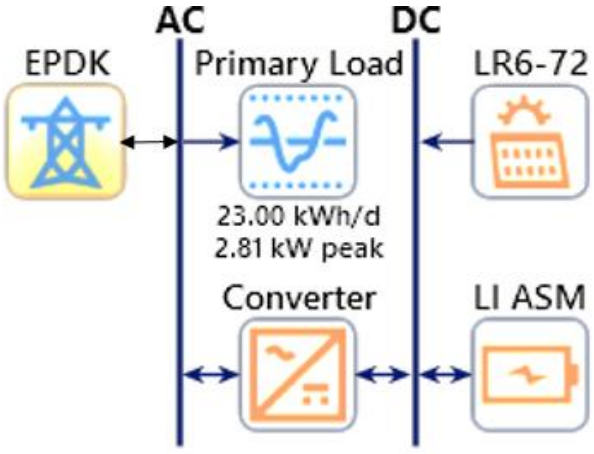

Figure 6. Nanogrid schematic of the model**.**

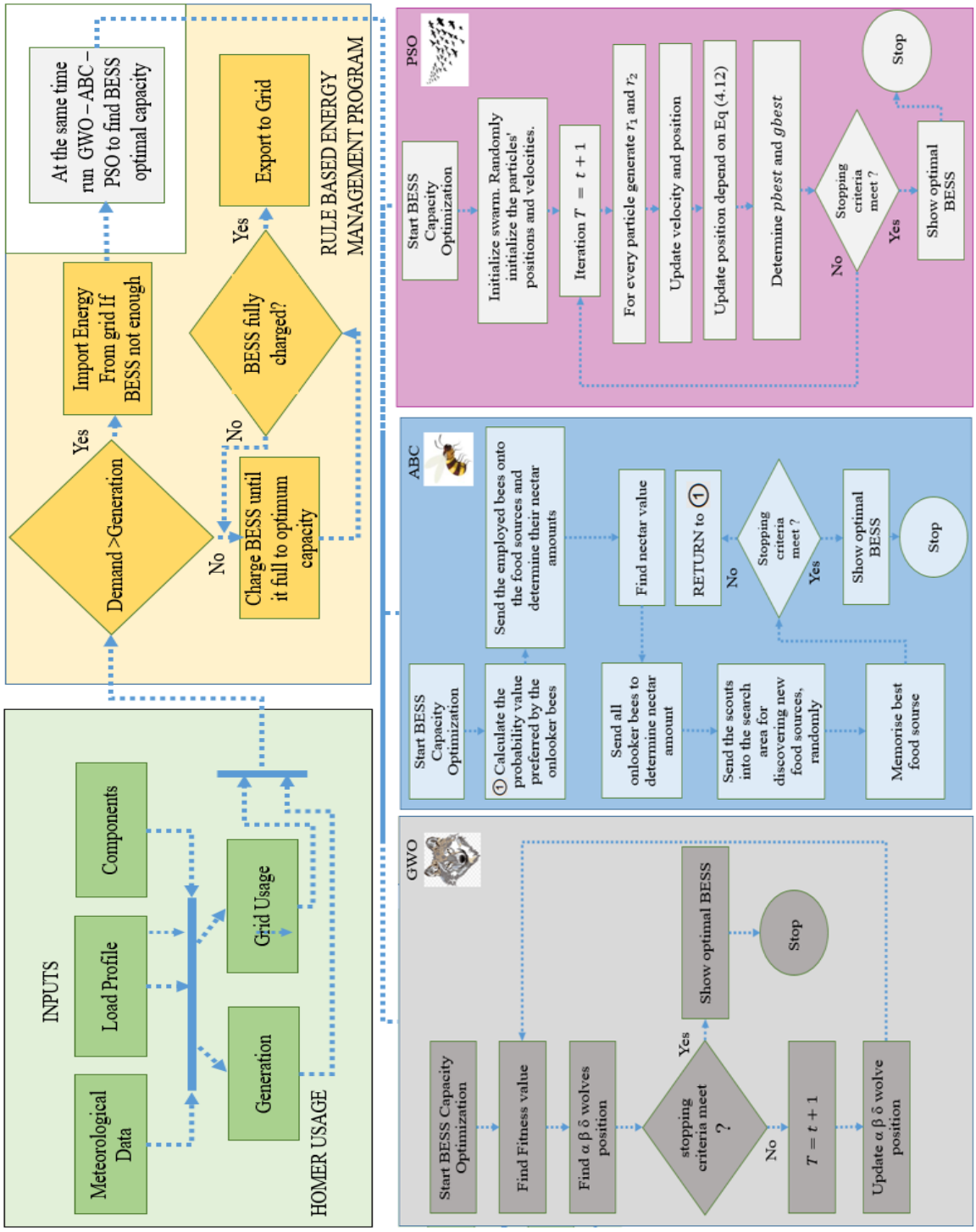

Figure 7. Flowchart of study.

The rule-based energy management system dynamically regulates energy flows within the nanogrid. When energy demand exceeds local generation, the system prioritizes discharging the BESS to meet the shortfall. If the BESS capacity is insufficient, the remaining deficit is imported from the grid. Conversely, when generation exceeds demand, the surplus energy is first directed to charge the BESS. Once the BESS is fully charged, any additional surplus is exported to the grid. This management strategy ensures an efficient balance between energy

supply and demand, minimizing reliance on external sources. This combined approach aims to minimize energy costs, enhance energy supply reliability, and optimize system performance within the nanogrid. Ultimately, the proposed methodology contributes to the technical and economic sustainability of renewable energy based nanogrids, offering a robust framework for energy management and capacity planning. In Figure 8 pseudo-codes for three algorithms are presented.

```
Start:  #Phase FOR PSO ALGORITHM
   - Initialize the positions of the particles randomly within the search space
   - Initialize the velocities of the particles randomly
   - Initialize personal best positions (pbest) and scores for each particle
   - Initialize the global best position (gbest) and score
PSO OPTIMIZATION PROCESS:
Repeat for the specified number of iterations:
   For each particle:
      - Generate random values r1 and r2 in the range [0, 1]
      - Update velocity:
        velocity[i] = (inertia_weight * velocity[i] +
                c1 * r1 * (personal_best_position[i] - current_position[i]) +
                c2 * r2 * (global_best_position - current_position[i]))
      - Update position:
        current_position[i] = current_position[i] + velocity[i]
      - Enforce boundary constraints (ensure position stays within min/max capacity):
        current_position[i] = max(min_capacity, min(max_capacity, current_position[i]))
      - Evaluate the new position (compute the objective function score)
      - If the new score is better than the personal best score:
        - Update personal best position and score
      - If the new score is better than the global best score:
        - Update global best position and score
   - Save the best score to the results list
   - Record the optimal BESS capacity for the current iteration
End:
   - Return the global best solution and its score
```

```
# Initialization Phase FOR GWO ALGORITHM
initialize_population() # Create initial positions for the wolves (Xi, i=1,2,n)
evaluate_population() # Calculate fitness for all wolves
identify_alpha_beta_delta()  # Identify alpha, beta, and delta wolves
# Main Iteration Loop
for iteration in range(max_iterations):
   update_coefficients()  # Update control parameters A and C based on
 iteration count   for each wolf in population:
      # Update position based on alpha, beta, and delta wolves
      D_alpha = calculate_distance(alpha_position, wolf_position, C_alpha)
      X1 = calculate_new_position(alpha_position, A_alpha, D_alpha)
      D_beta = calculate_distance(beta_position, wolf_position, C_beta)
      X2 = calculate_new_position(beta_position, A_beta, D_beta)
      D_delta = calculate_distance(delta_position, wolf_position, C_delta)
      X3 = calculate_new_position(delta_position, A_delta, D_delta)
      # Calculate the wolf's new position as the mean of X1, X2, and X3
      wolf_position = (X1 + X2 + X3) / 3
   # Evaluate the new positions
   evaluate_population()
   # Update alpha, beta, and delta wolves based on fitness
   identify_alpha_beta_delta()
   # Record the best score and position
   save_best_score_and_position()
# End of Iteration
return alpha_position, best_score  # Return the best solution (alpha wolf)
```

```
# Initialization Phase for ABC ALGORITHM
initialize_population()  # Create initial bee population (X_i, i=1,2,n)
reset_trial_counters()  # Set trial counters to 0 for all bees
best_score = float('inf')  # Initialize best score to infinity
best_position = None  # Initialize best position to None
define_limit()  # Set the trial limit for scout bees
# Main Iteration Loop
for iteration in range(max_iterations):
   # Employed Bees Phase
   for each bee in population:
      calculate_score(bee)  # Evaluate objective function
      if current_score < best_score:
         update_best_score_and_position()  # Update global best
         reset_trial_counter(bee)  # Reset trial counter for this bee
      else:
         increment_trial_counter(bee)
   # Onlooker Bees Phase
   for each bee in population:
      if bee_selected_by_probability():  # Based on fitness probabilities
         partner = select_random_partner()  # Select a random partner bee
         new_position = generate_new_position(bee, partner)
         new_score = calculate_score(new_position)  # Evaluate new position
         if new_score < current_score:
            update_position(bee, new_position)
   # Scout Bees Phase
   for each bee in population:
      if trial_counter_exceeds_limit(bee):  # Check if trials exceed the limit
         generate_random_position(bee)  # Assign a new random position
         reset_trial_counter(bee)  # Reset trial counter for this bee
   # Record the best score and corresponding solution
   save_best_score_and_position()
# End of Iteration
return best_position, best_score  # Output the best solution found
```

Figure 8. Pseudo-codes for three algorithms.

After defining the optimization algorithms and their pseudo-codes, their respective control parameters were configured as summarized in Table 1 to ensure uniformity and reproducibility across all simulations.

Table 1. Parameter settings of the heuristic algorithms.

Algorithm	Population Size	Maximum Iterations	Control Parameters
PSO	10	50	Inertia weight (w)=2; (cognitive) C_1=1.5; (social) C_2=2
GWO	10	50	$a \in [2,0]$; $C \in [0,2]$; α, β, δ = top 3 agents
ABC	10	50	limit = 2; $\phi \in [-1,1]$ (perturbation); onlooker selection probability p = 0.5 (approximately 1:1); scout reset & init $U[1,10]$ (capacity bounds); employed bees = 10

To ensure reproducibility, the control parameters and simulation settings of each optimization algorithm are summarized as above. These parameter values were selected based on widely adopted benchmark configurations reported in the literature to achieve a fair comparison. The same population size and iteration limits were applied across all algorithms to maintain consistency and allow a direct evaluation of convergence performance.
In optimization studies, the development and presentation of pseu-docode play a crucial role in illustrating the step-by-step logic and structure of algorithms, enabling researchers to effectively understand and replicate the methodologies [36-38]. For instance, the GWO-optimized PSO algorithm leverages GWO's global search capabilities to fine-tune PSO parameters such as inertia weight, cognitive, and social coefficients for ensuring faster and more accurate convergence. Similarly, the GWO algorithm improve diversity and avoid local optima, thereby enhancing solution quality without significantly increasing computational time. The ABC algorithm's pseudo-code, with its focus on food source exploration and exploitation, provides a clear blueprint for integrating intelligent behaviors into optimization.

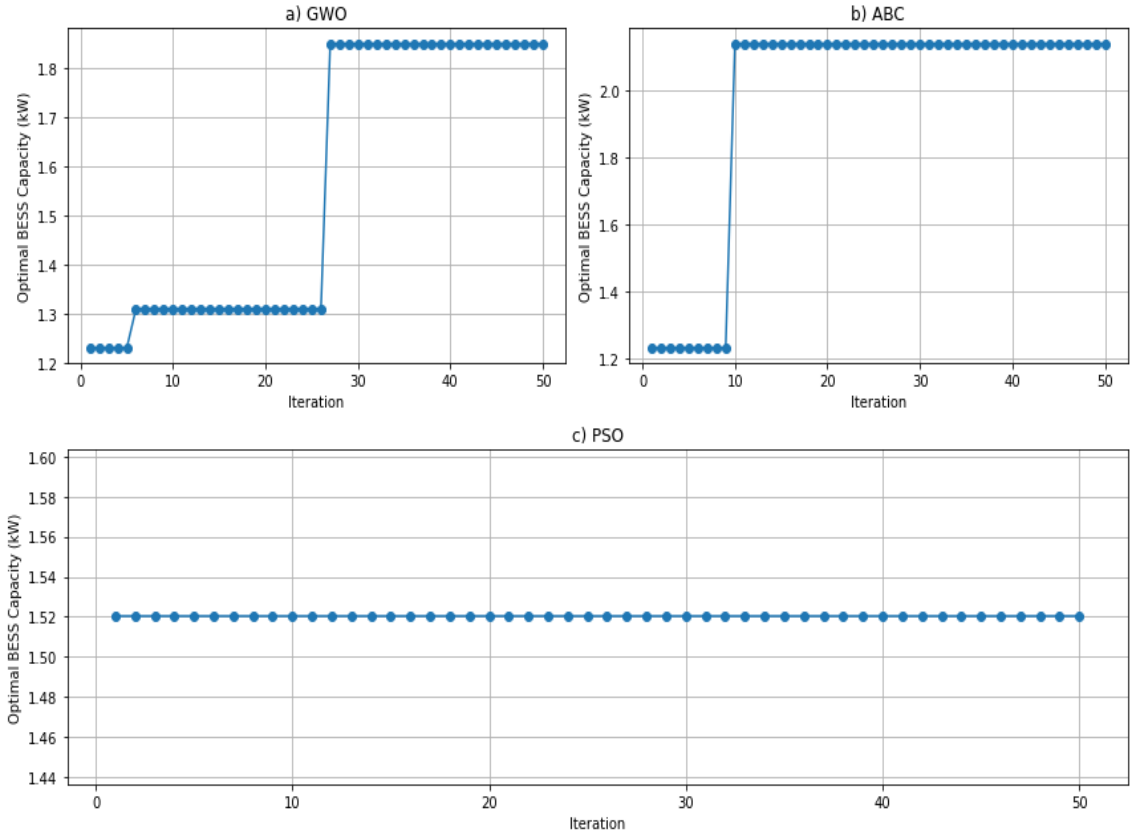

Figure 9. Optimal BESS capacity with present algorithims a) for GWO b) for ABC c) for PSO.

The analysis of optimal capacity graphs shown in Figure 9 generated by three different optimization algorithms that revealed distinct differences in their convergence behaviors and search strategies. The GWO algorithm exhibited a broad exploration phase, starting with lower capacity values and stabilizing around 1.85 kW by the 25th iteration. This behavior indicates GWO's ability to rapidly approach the optimal solution through extensive initial exploration followed by efficient exploitation. The ABC algorithm, on the other hand, demonstrated a rapid increase in capacity, rising from 1.23 kW at the 8th iteration to stabilize at 2.14 kW. ABC achieves fast convergence during the early stages but may lack refinement in its final optimization steps, leading to a less balanced solution. In contrast, the PSO algorithm presented a more stable and consistent convergence process. It maintained a steady capacity level of approximately 1.52 kW throughout the iterations, reflecting its capability to achieve a balanced and robust optimization trajectory with smaller iterative adjustments. In conclusion, while GWO and ABC algorithms demonstrated faster convergence and higher capacity solutions through broad search strategies, the PSO algorithm excelled in delivering a more stable and balanced approach to finding the optimal solution. In this study, the results of the different algorithms are collectively presented in Figure 10. In summary, GWO and ABC exhibit faster convergence, with GWO stabilizing at 1.85 kW and ABC at 2.14 kW, reflecting their distinct exploration strategies. However, PSO stands out by providing a stable and reliable solution with an optimal capacity of 1.52 kW, effectively balancing exploration and exploitation throughout the iterations.

In the current study, the optimal sizing of BESS is explored using three heuristic optimization algorithms. Accurate BESS sizing is essential for efficient energy management in nanogrids, ensuring better utilization of renewable energy, reduced grid dependency, and minimized operational costs. The variations in convergence behaviors reflect the inherent differences in their exploration and exploitation mechanisms. While GWO and ABC demonstrate faster convergence, they may occasionally sacrifice stability in the final optimization stages. Conversely, PSO provides a more consistent and balanced optimization trajectory, though at the expense of slower convergence. These findings suggest that algorithm performance is only sometimes optimal but context-dependent, influenced by factors such as the complexity of the energy management system and the desired balance between accuracy and computational efficiency. Future work could explore hybrid approaches that combine the strengths of these algorithms, leveraging the rapid convergence of GWO and ABC with the stability of PSO to further optimize BESS sizing in nanogrids.

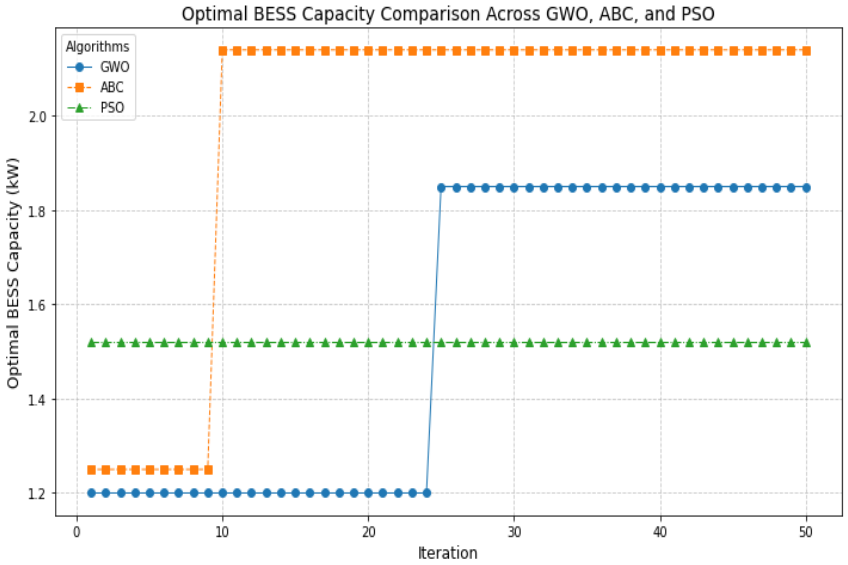

Figure 10. Optimal BESS capacity for three algorithms.

3.4. Comparative analysis of algorithm performances

To enhance the comparative assessment, additional performance indicators were introduced beyond iteration-based convergence. Table 2 summarizes the key quantitative metrics, including best fitness value, mean fitness, standard deviation, and average computation time for each algorithm. These metrics were computed based on ten

independent runs to ensure statistical consistency and to eliminate the effects of random initialization on the convergence trend.

Table 2. Performance metrics of optimization algorithms.

Algorithm	Best Fitness (kW)	Mean Fitness (kW)	Std. Dev.	Avg. Runtime (s)	Convergence Iteration
PSO	1.52	1.55	0.07	1.92	-
GWO	1.85	1.87	0.09	2.08	25
ABC	2.14	2.15	0.11	1.96	8

The results demonstrate distinct performance patterns among the three algorithms. The ABC algorithm achieved the highest optimal capacity (2.14 kW) but exhibited a relatively higher variance (Std. Dev = 0.11), indicating rapid convergence yet limited stability. Such fast convergence behavior, while beneficial for time-critical optimization problems, may lead to premature convergence in complex search spaces, a behavior similarly reported in [32, 33]. The GWO algorithm, on the other hand, reached a high optimal capacity of 1.85 kW with moderate standard deviation (0.09) and slightly longer runtime. Its hierarchical search strategy enabled balanced exploration and exploitation, allowing it to maintain robustness against local minima while efficiently approaching the global optimum. Comparable studies in [29, 36] have emphasized GWO's adaptability in nonlinear optimization problems, particularly where continuous solution refinement is required. The PSO algorithm produced the most stable and consistent results, reflected by the lowest standard deviation (0.07) and a convergence from the beginning iterations. Although its best fitness (1.52 kW) was slightly lower, PSO's repeatability and minimal oscillation between runs make it well suited for long-term nanogrid control applications that require predictable operation and robustness under varying load conditions. This stability characteristic aligns with observations in [35], where PSO demonstrated high repeatability and convergence reliability in renewable energy system optimization. The overall findings indicate that each algorithm exhibits a particular strength in addressing the BESS sizing problem within the nanogrid framework. The ABC algorithm demonstrates a clear advantage in terms of convergence speed, reaching near-optimal battery capacities in fewer iterations. GWO, in contrast, offers a broader exploration of the search space, which helps avoid premature convergence and ensures a more diverse set of candidate BESS capacities. PSO provides the most stable and repeatable optimization results, maintaining a consistent balance between exploration and exploitation across all runs.

In practical applications, the selection of an algorithm for BESS sizing should therefore depend on the intended operational goal. ABC can be advantageous when rapid computation is prioritized, such as in real-time or adaptive energy management scenarios. GWO may be more suitable for design-oriented studies where global search diversity is critical, while PSO appears most appropriate for stable long term nanogrid operation due to its robustness and reliability. From an energy management perspective, the variation in best-fitness values directly reflects the effectiveness of each algorithm in minimizing grid imports. A smaller fitness value corresponds to a reduced dependency on external power and a higher degree of local energy utilization. In this regard, PSO's lower best-fitness outcome implies a more balanced coordination between local generation, storage, and consumption, leading to an optimized BESS capacity that enhances both self-sufficiency and overall reliability of the nanogrid.

4. Conclusion

This study presents a comprehensive approach to minimizing grid energy imports by optimizing the operation of a BESS. The framework ensures a balance between energy generation and consumption by effectively managing excess and deficit energy within the system. Through precise constraints on battery capacity and dynamic energy balancing, the model prioritizes the utilization of renewable energy sources, reducing dependency on grid energy. The integration of operational constraints ensures practical feasibility by preventing simultaneous charging and discharging, while the optimization process focuses on minimizing grid import over the operational period. The application of three distinct optimization algorithms has demonstrated the efficacy of this framework in determining the optimal BESS capacity. This work underscores the potential of advanced optimization techniques to enable BESS sizing. These findings highlight that different algorithms leverage distinct search strategies to address complex problems like BESS capacity optimization. Furthermore, the results confirm that all three algorithms can be effectively employed for BESS optimization in electrical energy systems, depending on the

specific requirements of the application. GWO's capability for wide exploration makes it suitable for scenarios requiring comprehensive search across large solution spaces. ABC's rapid early convergence is beneficial for applications demanding quick solutions, while PSO's consistent and reliable performance is ideal for cases where long-term optimization quality is critical. Overall, this study underscores the adaptability and effectiveness of these algorithms in tackling complex optimization problems in energy systems. Future research could explore hybrid approaches combining the strengths of these algorithms further to enhance performance and applicability in real-world energy management scenarios.

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