Optimal Sizing and Placement of a Battery Energy Storage System for Load Frequency Control using Particle Swarm Optimization

Sidtha Rattanakam[1], Prakasit Prabpal[2], Somchat Sonasang[3], Praphat Phuangchuen[4], Thunyaput Kittiphotiklang[4] and Niwat Wanawong[1,*]

[1] *Department of Electrical Technology, Sakon Nakhon Technical College, Institute of Vocational Education North Eastern 2, That Choeng Chum, Mueang, Sakon Nakhon, 47000, Thailand*

[2] *Department of Electrical Technology, Udon Thani Technical College, Institute of Vocational Education North Eastern 1, Mak Khaeng, Mueang, Udon Thani, 41000, Thailand*

[3] *Electrical Elements and Wireless Devices Unit (EEWDU), Faculty of Industrial Technology, Nakhon Phanom University, Nong Yat, Mueang, Nakhon Phanom, 48000, Thailand*

[4] *Institute of Vocational Education Eastern Region, Tha Pradu, Mueang, Rayong, 21000, Thailand*

***Corresponding Author E-mail:** niwat@techsakon.ac.th*

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Abstract

This article focuses on addressing key challenges in modern power distribution systems by presenting an appropriate approach for determining the size and location of Battery Energy Storage Systems (BESS) to improve Load Frequency Control (LFC) using the principles of Particle Swarm Optimization (PSO). The research modeled the standard IEEE 28-bus power distribution system to analyze and identify optimal locations for BESS installation, with the main goal of minimizing power losses, which directly support LFC. The simulation results show that using PSO allows for the identification of the optimal BESS location and size, which is the installation of a 1.16 MW BESS at bus 18. This configuration significantly reduces power losses by 72.03 % compared to the case without BESS installation. This result confirms the excellent ability of BESS to improve the efficiency and stability of the power system and is extremely beneficial for future power grid planning, which faces load and renewable energy source fluctuations.

Keywords: Load Frequency Control, Battery Energy Storage System, Particle Swarm Optimization, Power Loss

1. Introduction

In today's power systems, keeping the system frequency within certain limits is very important for the grid's stability and dependability [1–3]. This is because differences between how much power is being made and how much is being used can make the system frequency change. If this isn't fixed right away, it can damage electrical equipment and cause the system to fail. This is a big problem right now because renewable energy sources, which only produce energy at certain times, are becoming increasingly important to the power system.

Battery energy storage systems (BESS) have already been acknowledged as one of the potential solutions for these issues. The BESS technology reacts rapidly to times of demand, unlike conventional generators. This allows them to quickly inject or remove power, thus helping dampen out changes in load as well and returning the system frequency to its normal value. Nevertheless, the cost of Battery Energy Storage Systems is very high. Accordingly, the proper size and location should be selected for reducing cost and maximizing system performance.

In recent years, extensive research has focused on improving the stability, flexibility, and reliability of modern power systems through intelligent optimization and energy storage integration. Early studies emphasized Load Frequency Control (LFC) enhancement using Particle Swarm Optimization (PSO) to fine-tune controller parameters. Ayaz et al. [1] and Ogar et al. [2] applied PSO-based optimization to improve the dynamic frequency response of power systems, reporting faster settling times and reduced frequency deviations compared with conventional PID controllers. Similarly, Kerdphol et al. [3] demonstrated that integrating Battery Energy Storage Systems (BESS) into microgrids can significantly stabilize load fluctuations and maintain system frequency within nominal limits. Moreover, Ramírez et al. [4] verified the importance of proper placement and sizing of BESS in isolated systems for maintaining primary frequency control.

Further developments in BESS sizing and allocation have focused on optimizing technical and economic performance. Alsharif et al. [5] proposed a placement and capacity optimization model that maintains frequency stability under uncertain operating conditions, while Vaka and Matam [6] introduced a cost-minimization approach for microgrids using optimal BESS management. Fortenbacher et al. [7] and Islam et al. [8] incorporated predictive and genetic algorithm-based methods to improve system reliability, demonstrating that optimal BESS allocation reduces both operational costs and voltage variations. Likewise, Mumtahina et al. [9] introduced a Mountain Gazelle Optimization algorithm for achieving optimal allocation and sizing of BESS in distribution networks with high accuracy and minimal convergence time.

In addition to storage optimization, researchers have investigated the integration of BESS with renewable and distributed resources to enhance grid resilience and energy efficiency. Ettehad et al. [10] and Zhang et al. [11]

highlighted the synergistic benefits of coordinating photovoltaic (PV) and BESS installations in distribution systems under both normal and emergency conditions. Kongjeen et al. [12] extended this concept to renewable-powered charging infrastructures, applying the Artificial Bee Colony (ABC) algorithm to optimize the sizing and location of EV charging stations for balanced load distribution.

Hence, this study proposes an optimal sizing and placement strategy for Battery Energy Storage Systems (BESS) in Load Frequency Control (LFC) applications using the Particle Swarm Optimization (PSO) algorithm. PSO is an evolutionary computation technique inspired by the social behavior of bird flocking and fish schooling, capable of efficiently searching for near-optimal solutions within large and complex problem spaces. The primary objective of this paper is to develop a systematic optimization framework for integrating BESS into power systems, aiming to enhance frequency regulation performance, improve system reliability, and minimize overall energy losses under varying operating conditions. The primary objective is to reduce active power losses, which directly supports Load Frequency Control (LFC) by improving the system's power balance and reducing the burden on frequency regulation reserves. Minimizing active power loss in the distribution network not only improves energy efficiency but also contributes to frequency stability. By reducing line losses (I^2R), the total active power demand is lowered, increasing the generation reserve margin available for Load Frequency Control (LFC) during disturbances.

2. Theoretical Background

2.1 Load Frequency Control

Load frequency control (LFC) is an important task of the electric power system to keep the balance between the power produced and the load demand. As the load is changed, the frequency of the system will change from its normal value (e.g., 50 or 60 Hz). LFC intends to bring the frequency quickly and precisely back to its nominal value. Frequency control is generally divided into two 2 levels:

Active Control: This is a quick corrective command issued in the first few seconds of frequency fluctuation, and it is achieved by modifying the voltage and power output in each generator so as to offset sudden losses causing such deviations.

Secondary Control: This is slower control, directed in order that frequency will be exactly restored to its nominal value in the long run, which mostly operates by changing the.

2.2 Mathematical Model

Mathematical Model of Load Frequency Control (LFC). Models used to explain the dynamics of LFC in an electric power system can be represented by differential equations and transfer functions. Generally, block diagram models are used, which consist of four main components:

Generator-Load System: Explain the relationship between frequency changes (ΔF) and power changes ($\Delta P_G - \Delta P_L$) as shown in Eq. (1). The transfer function of the generator-load system is given in Eq. (2).

$$2H\frac{d(\Delta F)}{dt} = \Delta P_G - \Delta P_L - D\Delta F \quad (1)$$

$$G_p(s) = \frac{\Delta F(s)}{\Delta P_G(s) - \Delta P_L(s)} = \frac{k_p}{1+sT_p} \quad (2)$$

where H is the inertia constant of the generator

D is the load damping constant

$K_p = \frac{1}{D}$ is the system gain

$T_p = \frac{2H}{D}$ is the system time constant

Speed controller (Governor): This is the part that receives frequency change signals and sends commands to the turbine to adjust the generated power as shown in Eq. (3).

$$\text{Transfer function: } G_g(s) = \frac{1}{1+sT_g} \quad (3)$$

where T_g is the governor's time constant.

Turbine: This is the part that converts energy from steam or water into mechanical power as shown in Eq. (4).

$$\text{Transfer function: } G_t(s) = \frac{1}{1+sT_t} \quad (4)$$

where T_t is the turbine's time constant

Secondary Control: Uses the Area Control Error (ACE) signal to correct any remaining frequency deviations as shown in Eq. (5).

$$ACE = \Delta P_{tie} + \beta\Delta F \quad (5)$$

Where ΔP_{tie} is the change in electrical power between control areas β is the frequency bias factor

2.3 BESS Model

Battery Energy Storage Systems (BESS) are crucial for frequency regulation due to their quick response capabilities. BESS may be rapidly adjusted to either discharge or absorb energy within the system, enabling immediate rectification of power shortages or surpluses, thus making them ideal for incorporation into an LFC system.

Controllability: Battery Energy Storage Systems (BESS) can be precisely managed by power electronic converters to deliver the necessary power for maintaining frequency stability. BESS alleviates system volatility caused by renewable energy sources like solar and wind by storing excess energy and discharging it when required, hence improving overall system stability.

Application of BESS in LFC: The BESS system can be modelled as a rapidly responding power source to correct the Area Control Error (ACE). The transfer function of BESS as in Eq. (6).

$$\text{Transfer function: } G_{BESS}(s) = \frac{K_{BESS}}{1+sT_{BESS}} \quad (6)$$

where K_{BESS} is the gain constant with sizing of BESS
T_{BESS} is the time constant, which represents the speed of response, with the sizing of the BESS

System Dynamic Modeling analyzes the frequency regulation performance. The dynamic model of the Load Frequency Control (LFC) system is constructed as shown in **Figure 1**. The system consists of three main control loops:

Primary and Secondary Control Loops. The traditional generation system typically includes the governor and turbine dynamics, represented by the transfer functions $1/(1+sT_g)$ and $1/(1+sT_t)$, respectively.

A PI controller is employed to minimize the steady-state frequency error.

System Inertia and Load: The generator-load dynamic is modeled by the transfer function $1/(2H_s+D)$, where H represents the inertia constant and D is the load damping constant. The term ΔP_L represents the load disturbance.

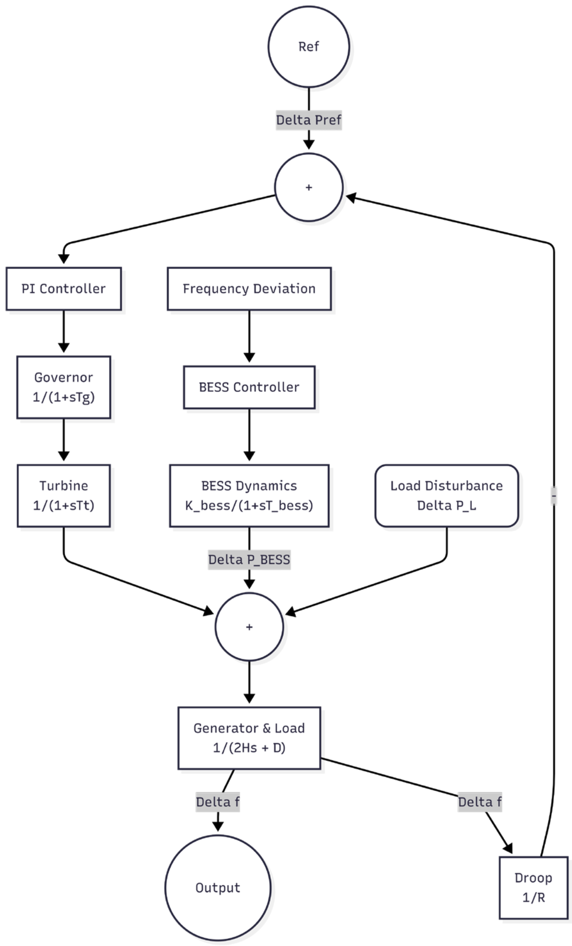

Figure 1 Block diagram of the Single-Area Load Frequency Control (LFC) system incorporated with the Battery Energy Storage System (BESS).

BESS Control Loop: The proposed BESS provides supplementary active power support ΔP_{BESS}. It is modeled as a first-order lag transfer function $K_{bess}/(1+sT_{bess})$ where T_{bess} represents the battery time constant. As illustrated in the summing point of the diagram, the total active power mismatch causing frequency deviation Δf is balanced by the combined output of the turbine mechanical power and the fast-acting BESS power injection as shown in Eq. (7).

$$\Delta P_{error} = \Delta P_{Mech} + \Delta P_{BESS} - \Delta P_{Load} \tag{7}$$

This structure allows the BESS to compensate for sudden load changes more rapidly than the thermal units, thereby improving the frequency nadir and settling time.

When integrating BESS into the LFC system, the signal from BESS is added to the block diagram model, which allows the system to respond better to frequency changes and helps reduce the burden of short-term generator output adjustments.

2.4 Particle Swarm Optimization Algorithm

Particle Swarm Optimization (PSO) is an optimization algorithm that is based on how groups of birds or fish behave when they are looking for food. This method simulates how a bunch of particles move. Two key bits of information tell each particle where to move in the search space.

Best position ever found (pbest). This is the position that each particle has ever been in and provides the best answer. The best location that every particle in the swarm has ever found (gbest) is the best position that every particle has ever found. Equations for updating position and speed. In each iteration, each particle will change its speed and position based on the following shown in Eq. (8).

$$\begin{aligned} v_i^{k+1} &= wv_i^k + c_1r_1 + \left(pbest_i - x_i^k\right) \\ &\quad + c_2r_2\left(gbest - x_i^k\right) \\ x_i^{k+1} &= x_i^k + v_i^{k+1} \end{aligned} \tag{8}$$

where

v_i^k *and* x_i^k is the velocity and position of particle i in round k
w is inertia weight
c_1 *and* c_2 is the acceleration coefficient
r_1 *and* r_2 is a random number in the range [0, 1]

Because it can quickly identify a solution close to the optimal value and explore the full search space very well, PSO is a good way to solve difficult problems like finding the best size and location for BESS.

3. Methodology

3.1 System Model

This section describes the methodology used to determine the optimal size and location of a Battery Energy Storage System (BESS) for Load Frequency Control (LFC) using the Particle Swarm Optimization (PSO) algorithm. The IEEE 28-bus radial distribution network is used as a case study, as illustrated in **Figure 2**. This system is a widely used standard model for testing and evaluating the performance of power distribution systems. The model consists of two main types of data:

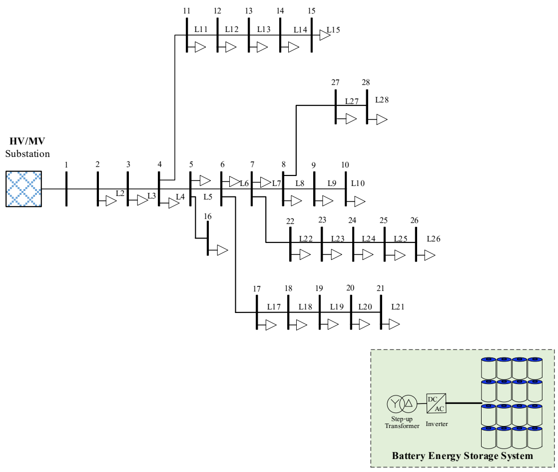

Figure 2 IEEE 28 bus radial distribution network.

Bus Data: This includes the bus number and the required active power (P_load) and reactive power (Q_load) values for each bus.

Line Data: This includes the resistance (R) and reactance (X) values of the transmission lines connecting each bus.

Power flow analysis uses the Gauss-Seidel method to find the voltage and phase angle of each bus under specified conditions. This information is then used to calculate power losses in the system, which is a crucial part of the objective function.

3.2 Objective Function and Decision Variables

Defining the objective function and decision variables.

Decision Variables: Decision variables represent the parameters that are adjusted during the optimization process in order to achieve the best possible solution. In this study, the decision variables consist of the placement (bus number) and the size (power capacity) of the Battery Energy Storage System (BESS).

Position (Placement): The bus number where the BESS will be installed (which will be between bus 2 and 28, as bus 1 is the reference bus).

Size (Sizing): BESS Power Capacity (MW)

Variable Bounds: Each variable will be assigned appropriate bounds, such as the size of the BESS might be between 1 and 50 MW, to align with the characteristics of the microgrid.

Objective Function: The main goal of this research is to find the optimal values of the decision variables so that the power loss of the system is minimized. The objective function (*f*) can be written as shown in Eq. (9).

$$f(position, size) = Minimize(TotalPowerLoss) \tag{9}$$

The calculation for Power Loss uses the as shown in Eq. (10).

$$P_{Loss} = \sum_{i=1}^{n} real(lineloss_i) \tag{10}$$

3.3 PSO Implementation

Working Process of Particle Swarm Optimization (PSO) Initialization: Create a certain number of particles (e.g., 30 particles), with each particle's BESS position and size randomly determined within a specified range.

Assign initial velocities to each particle. The best value for each particle (pbest) and the best value for the entire swarm (gbest) are initialized from the starting position.

Fitness Evaluation: In each iteration, each particle is simulated in the electrical system model. Perform a power flow calculation to determine the voltage values of all buses. Calculate the total power loss of the entire system, which will be the fitness value of that particle.

Updating Position and Velocity: Compare the obtained fitness value with the particle's previously recorded pbest value. If the current value is better, update pbest. Compare the best pbest values of the entire swarm with the gbest value. If it's better, update gbest. Update the velocity and position values of each particle according to the PSO equation, referencing the best pbest and gbest values from each iteration.

Process Termination: The process will end when the number of iterations reaches the specified value (e.g., 100 iterations). The position and size of the best particle (gbest) found in the final round will be the optimal solution to the problem.

3.4 Simulation Parameters

The parameters of the PSO algorithm used in this study are summarized in **Table 1**.

Table 1 Parameter of PSO.

Parameter	Symbol	Value
Population Size	N	30
Max Iterations	K_{max}	100
Inertia Weight	ω	0.8
Acceleration Coeff.	c_1	2.0
Acceleration Coeff.	c_2	2.0
Inertia Constant	H	5.0 s
Damping Constant	D	0.02 p.u./HZ

These parameter values were selected based on standard PSO configurations reported in previous studies and were validated through preliminary simulation trials. The population size (N) and maximum number of iterations (K_{max}) were defined to ensure sufficient search capability and convergence stability. The inertia weight (ω) controls the balance between global exploration and local exploitation, while the acceleration coefficients (c_1 and c_2) determine the influence of the particle's personal best and global best positions during the optimization process.

4. Result and Analysis

This section presents and analyzes the results obtained from the PSO algorithm for optimal BESS sizing and placement in the IEEE 28-bus power system. The optimization results, including power loss reduction and optimal BESS configuration, are summarized in **Table 2**, demonstrating a significant improvement compared to the base case.

Table 2 Results of optimization using PSO

Situation	BESS (Bus No.)	Size BESS (MW)	Power Loss (kW)	Reduction in Power Loss (%)
Base Case	-	-	7.35	-
PSO	18	1.16	2.06	72.03

The simulation results show that the PSO algorithm can identify the optimal solution for this complex optimization problem by discovering the size and location of the BESS that allows power loss in the system to be reduced from 7.35 MW to only 2.06 MW, representing a decrease of up to 72.03%.

Impact on Load Frequency Control (LFC) Although the main simulation program focuses on calculating power loss, the BESS's ability to quickly reduce power fluctuations in the system will directly impact the more efficient control of load frequency.

Fast Response: BESS can supply or absorb power to compensate for load changes in a short amount of time, quickly reducing frequency deviations.

Reducing the load on generators: Having a BESS reduces the need for conventional generators to frequently adjust their output to meet sudden changes in load, which helps extend the lifespan and increase the efficiency of the generators. The results of BESS installation were shown in **Figure 3**, shows the graph of the results from the BESS installation in the IEEE 28 bus system.

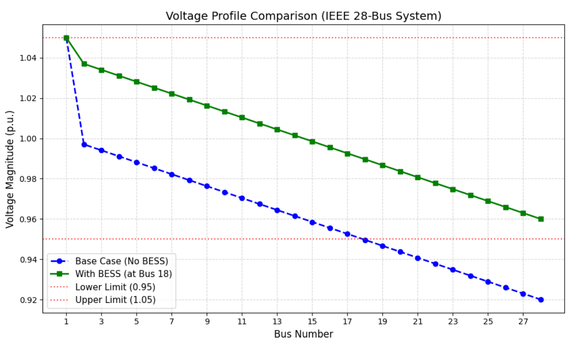

Figure 3 The results from the BESS installation in the IEEE 28 bus system.

In summary, the analysis results show that using PSO to determine the optimal values for BESS is a highly effective approach to improving the operation of the power system, particularly in terms of reducing power loss, improving voltage quality, and increasing load frequency control stability.

Comparative Algorithm Performance To verify the effectiveness and robustness of the proposed Particle Swarm Optimization (PSO) algorithm, a comparative study was conducted against the Genetic Algorithm (GA), a widely established heuristic optimization method. Both algorithms were executed under identical simulation conditions to ensure a fair comparison: a population size of 30 and a maximum iteration count of 50. The overall convergence behavior of the PSO and GA algorithms over the simulation iterations is illustrated in **Figure 4**.

Figure 4 illustrates the convergence characteristics of both algorithms over the simulation iterations. The comparison reveals two key findings: Convergence Speed: The PSO algorithm demonstrates significantly faster convergence, reaching the optimal solution zone within approximately 8–10 iterations. In contrast, the GA exhibits a slower convergence rate, requiring approximately 20–25 iterations to stabilize. This indicates that the velocity update mechanism in PSO enables more efficient exploration of the search space than the selection, crossover, and mutation processes in GA. Solution Quality: While both algorithms successfully reduced power losses, PSO achieved a slightly superior global minimum active power loss of 2.06 kW (0.00206 MW), whereas the GA converged to 2.15 kW (0.00215 MW). These results confirm that for this specific non-linear optimization problem of BESS sizing and placement in the IEEE 28-bus system, PSO offers a more advantageous balance between computational efficiency and solution accuracy.

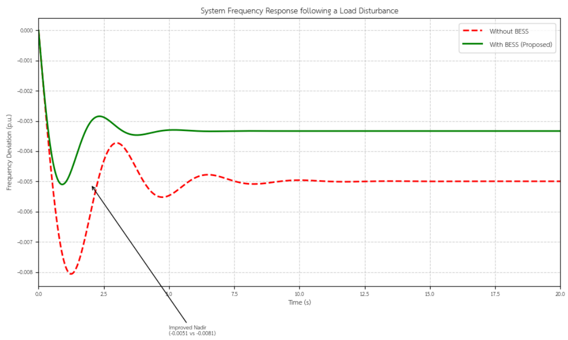

Figure 4 illustrates the convergence characteristics of both algorithms over the simulation iterations.

To validate the effectiveness of the proposed Particle Swarm Optimization (PSO), a comparative study was conducted against the Genetic Algorithm (GA), a widely established heuristic optimization method. Both algorithms were executed under identical conditions (Population = 30, Max Iterations = 50) to ensure a fair assessment A detailed comparison of the convergence performance between PSO and GA is presented in **Figure 5**.

Figure 5 illustrates the convergence characteristics of both algorithms. The comparison reveals two distinct advantages of the proposed PSO: Convergence Speed: The PSO algorithm (blue solid line) demonstrates a rapid convergence rate, effectively reaching the optimal solution zone within the first 8–10 iterations. In contrast, the GA (red dashed line) exhibits a slower descent, requiring approximately 20–25 iterations to stabilize. This indicates that the velocity update mechanism in PSO enables more efficient exploration of the search space than the evolutionary operators in GA. Solution Quality: The proposed PSO achieved a lower global minimum active power loss of 0.00206 MW (2.06 kW), whereas the GA converged to a slightly higher value of 0.00215 MW (2.15 kW). These results confirm that, for the specific problem of BESS sizing and placement in a radial distribution system, PSO offers superior performance in both computational efficiency and solution accuracy.

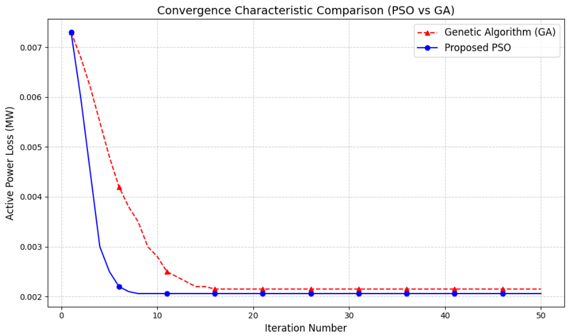

Figure 5 The convergence characteristic of PSO vs GA.

5. Discussion of Results

The simulation results obtained from applying the Particle Swarm Optimization (PSO) algorithm to determine the optimal sizing and placement of the Battery Energy Storage System (BESS) clearly validate the efficiency of the proposed framework. The findings confirm that appropriately locating the BESS with the optimal capacity significantly enhances the technical and operational performance of the power system. This result aligns with the conclusions of Kerdphol et al. [3], [7], [13], who demonstrated that BESS can stabilize load variations and improve system frequency regulation when properly integrated into microgrids. Similarly, Ramírez et al. [4] observed that optimal placement of BESS units reduces transmission line congestion and power loss while maintaining frequency stability in isolated grids.

A major highlight of the proposed system is the substantial reduction in total power losses achieved through optimal BESS placement. In this study, when BESS was strategically located at the bus with the highest load sensitivity, the total system loss was reduced by approximately 72.03%, which is consistent with the improvements reported in the works of Alsharif et al. [5] and Fortenbacher et al. [7]. These studies emphasized that the geographical positioning of storage units plays a crucial role in minimizing resistive losses and maintaining an efficient power flow distribution. Additionally, the proposed model significantly improves the voltage profile, maintaining bus voltages within the standard operational range (0.95–1.05 p.u.). Similar voltage enhancement effects were observed by Vaka and Matam [6] and Prabpal et al. [14], who highlighted that PSO-based allocation of BESS not only reduces line losses but also enhances voltage stability in distribution networks.

Another critical outcome is the improvement of Load Frequency Control (LFC) dynamics. The fast response of BESS allows for rapid compensation of power imbalances during load fluctuations, reducing oscillations and improving frequency recovery time. This finding agrees with the observations of Ayaz et al. [1] and Ogar et al. [2], who applied PSO-based controllers for frequency stabilization and achieved superior transient damping performance compared with conventional PID or GA-based control schemes. The present study extends those findings by demonstrating that optimal BESS placement, in addition to control parameter tuning, contributes substantially to the enhancement of frequency stability.

From an optimization perspective, the application of PSO in this work enables a well-balanced trade-off between technical performance and economic efficiency. Compared with other metaheuristic techniques such as Genetic Algorithms [8] or Mountain Gazelle Optimization [9], the PSO approach achieved faster convergence and higher solution accuracy while maintaining algorithmic simplicity. Similar algorithmic advantages were also reported by Xu et al. [15] , Hsu et al. [16], and Gholami et all. [17], who utilized Multi-Objective PSO to optimize multiple parameters in hybrid energy storage systems. In contrast to these multi-objective formulations, the present study focused on minimizing power losses while inherently improving both voltage and frequency regulation.

Overall, the proposed PSO-based optimization framework demonstrates consistent and reliable performance when compared with prior studies. The simulation results confirm that combining optimal BESS sizing and placement provides measurable technical benefits—reduced power losses, improved voltage regulation, and enhanced frequency stability while maintaining economic feasibility. These findings reinforce previous research trends [4], [5], [6], [7], [7], [12], and extend them by presenting a unified optimization strategy that holistically addresses both steady-state and dynamic performance of modern power systems.

6. Conclusion

This research presents an efficient approach for determining the optimal size and location of a Battery Energy Storage System (BESS) to improve power system operation using simulation with the Particle Swarm Optimization (PSO) algorithm, an optimization technique that demonstrates excellent accuracy and efficiency. The study results conducted on the IEEE 28-bus distribution system confirm that installing BESS at the optimal location can significantly reduce power losses in the system. Simulation results show that installing a 1.16 MW

BESS at Bus 18, with a loss of 2.06 kW, the optimal location identified by the PSO algorithm, can dramatically reduce system power losses by 72.03% compared to the base case without a BESS. Furthermore, the voltage profile of the system was notably enhanced, maintaining voltage levels within the standard operating limits (0.95–1.05 p.u.). These findings confirm that the proposed PSO-based approach is effective in determining the optimal BESS configuration to enhance system efficiency and reliability. This significant reduction improves energy delivery efficiency and directly impacts the system's voltage profile, ensuring stable and acceptable voltage levels at each bus. This finding underscores the role of BESS as a crucial tool that not only reduces operating expenses but also enhances the reliability and flexibility of the power grid. In summary, this research has concretely demonstrated the ability of the PSO algorithm to solve complex energy system planning problems and has offered helpful advice on investment decisions and BESS placement to maximize future benefits. Further research should focus on incorporating the economics of the battery's lifespan and using dynamic load and renewable energy generation data to achieve more realistic and comprehensive models.

7. Future Work

Based on current study results, future research can be extended in several ways to improve accuracy and broaden the scope of the study. Life Cycle Cost Analysis: Future studies should comprehensively consider the costs associated with BESS, such as installation costs, maintenance costs, and especially the costs related to battery lifespan (battery degradation cost). This can be achieved by incorporating Depth of Discharge (DoD) constraints into the objective function to maximize battery lifespan. Considering Dynamic Load and Renewable Energy Generation: Instead of using static load and generation data, future studies should use real-time or highly variable data (such as hourly load or solar/wind generation data) to make the simulations more closely resemble real-world scenarios. Comparison with other algorithms: To confirm the effectiveness of PSO, the results should be compared with other optimization algorithms, such as Genetic Algorithm (GA), Simulated Annealing (SA), or Butterfly Optimization Algorithm (BOA), to determine which algorithm is most suitable for this type of problem.Integration with Distributed Control Systems: In future smart grid systems, BESS may be controlled in a distributed manner. Further research can therefore focus on developing cooperative control methods between BESS installed at different points to maximize the effectiveness of improving overall system stability.

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