

Article

Optimal Placement and Capacity Dispatch Optimization of BESS for Transmission Congestion Mitigation in Deregulated Power Systems: A Salp Swarm Optimization Approach

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Featured Application

The proposed methodology supports transmission system operators in strategically deploying BESS to manage congestion in deregulated electricity markets. It enables cost-effective grid operation, improved network flexibility, and higher penetration of renewable energy resources.

Abstract

Transmission congestion has become a major challenge in deregulated power systems (DPS). Although flexible AC transmission system (FACTS) devices are effective for congestion management, their high installation cost and complex control requirements limit widespread deployment. This paper proposes a battery energy storage system (BESS)-based congestion mitigation approach for DPS. The optimal locations of BESS units are identified using bus sensitivity factors (BSFs), while a weighted-sum scalarized single-objective optimization problem involving active power loss, voltage deviation, and system security margin is solved using salp swarm optimization (SSO). The main contribution of this work is the integrated BSF–SSO framework, which combines sensitivity-based placement with an efficient metaheuristic optimization technique. The proposed methodology is validated on the IEEE 30-bus test system. Results show that the optimally placed BESS units reduce active power losses by 31.7% relative to the base case, while it is reduced by 39.1% when using the post contingency of 25 MW as the baseline, voltage deviation by approximately 30.26%, and the congestion security index by 25.14%, thereby significantly alleviating transmission congestion. In addition, reactive power flow distribution and 24 h state-of-charge (SoC) dynamics are analyzed to provide a more comprehensive assessment of system performance. Compared with FACTS-based solutions, the proposed approach offers superior technical and economic benefits. A parametric sensitivity analysis further shows that SSO attains near-optimal convergence with as few as 15 agents, offering a favorable accuracy-versus-runtime trade-off for real-time DPS operation; the main results reported in this study, however, were generated using the more conservative configuration of $n = 30$ agents to maximize solution robustness.

Keywords: deregulated power system; battery energy storage systems; transmission congestion; bus sensitivity factor; salp swarm optimization; FACTS; weighted-sum scalarized single-objective optimization



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1. Introduction

The development of advanced industrial applications has led to a shift from a traditional vertically aligned power system to a deregulated one. This has changed the operational dynamics of modern power systems. With unbiased access to the existing transmission lines in a deregulated environment, the lines are subjected to numerous bilateral and multilateral transactions. These numerous decentralized transactions impose a heavy burden on lines, which results in congestion leading to instability of the power system with adversely affected economics [1,2]. The unbiased transmission rights to private players in the deregulated power system (DPS) have upgraded the net operational transparency, but also introduced congestion, which is critical to operational bottlenecks. The operational complexity of DPS is further exacerbated by the large-scale integration of renewable energy sources (RESs) such as solar and wind power into the grid [3]. Due to their intermittent availability and stochastic generation patterns, RESs contribute to power flow uncertainties and exacerbate existing transmission constraints, thereby amplifying the risk of congestion in the network [4,5]. Therefore, under this dual challenge of market freedom and large-scale renewable integration, a robust and economically viable strategy is required for secure power system operation in a deregulated environment [6].

Conventional congestion management methods generally include incorporating flexible AC transmission system (FACTS) devices. These devices have the capability to increase the transmission capacity of the lines, hence enhancing available transfer capability (ATC) [7]. The effectiveness of FACTS devices for manipulating power flows to stabilize voltage is constrained by the huge capital cost involved in their deployment. Further, the working of FACTS devices also involves a complex control architecture, which makes their operation difficult. There are methods to achieve economy in FACTS operation by employing these devices at an optimal location. In DPS, the location search for FACTS devices becomes more complex with the increase in renewable energy source (RES) penetration [8,9]. These disadvantages of the contemporary congestion mitigation (CM) techniques in DPS demanded the implementation of more flexible and cost-effective congestion mitigation techniques.

Considering the shortcomings of traditional methods of CM, the consideration has shifted towards more economical and flexible techniques, such as employing energy storage systems (ESSs) in the system. Among these, battery energy storage systems (BESSs) have gained prominence as a promising tool for alleviating transmission congestion in deregulated environments [10]. BESSs are characterized by their rapid dynamic response, enabling them to deliver or absorb active and reactive power in real-time, thereby stabilizing voltage profiles and assisting in load levelling under stressed operating conditions [11,12]. Recent studies suggest that tactically located BESSs give flexibility to the power system against continuously varying operating conditions in the competitive electricity markets [13,14]. Suboptimally located BESSs will help less in relieving congestion, but may result in enhanced voltage instability. The sizing of BESSs is also very important, as undersized devices may not support mitigating congestion, and oversized ones will not be economically viable [15,16]. In the literature, the placement and sizing of BESSs have often been treated as a decoupled problem [17,18]. The sizing of BESSs has been achieved by employing various heuristic methods without considering the sensitivity-based optimal location.

A deterministic framework has been considered in this study to provide a rigorous baseline for evaluating the performance of the BSF-SSO framework under controlled N-1 contingency conditions. The introduction of stochastic uncertainties is intentionally deferred until after deterministic validation, consistent with the widely accepted benchmark evaluation methodology in congestion management literature.

This paper addresses the gap between the location and sizing of BESSs by proposing a two-stage framework. The primary stage constitutes a quantitative analysis to obtain the optimal location of BESSs. The basis of this sensitivity analysis is the effect of active power injection on the power flow through the congested line. This reduces the search space for the optimization process. The second stage of the dual framework deals with the implementation of the proposed salp swarm optimization (SSO) algorithm to optimize the BESS capacity allocation for pre-located BESSs. The proposed method minimizes the weighted-sum scalarized single objective, which includes the reduction of active power loss and voltage deviation and the enhancement of the security margin, addressing the basic objective of congestion management. Based on the addressing of the congestion problem in the DPS, the following research gaps are found in the literature:

- The research often treats BESS location and its optimal size as two different problems, so they have been addressed separately. This gives a suboptimal solution to the congestion problem.
- The location of BESS is often searched by the optimization algorithm without any solid analytical approach, considering the sensitivity of the system to the power injection by BESS. This also results in a less effective solution to congestion.
- The methods employed in the power system calculations seldom integrate an analytical approach with the optimization algorithm. This reduces the efficiency and scalability of the approach.
- The problem encompassing active power loss, voltage deviation, and security margin under congested conditions is less explored, specifically as a significant alternative to FACTS devices.

It is important to state explicitly that the standard, unmodified formulation of salp swarm optimization (SSO), as originally proposed by Mirjalili et al. [19], is employed in this work as a solution engine rather than as an object of algorithmic development; no modification is made to the leader/follower update rules, the convergence coefficient, or the boundary-handling mechanism of the original algorithm. Accordingly, the algorithmic novelty of this paper is deliberately not emphasized. The methodological contribution instead lies at the modeling and system-integration level: (i) the coupling of an analytical, sensitivity-based BSF pre-screening stage with a metaheuristic dispatch-optimization stage, which decouples the combinatorial siting decision from the continuous sizing/dispatch decision and thereby reduces the search space presented to SSO; (ii) a weighted-sum objective that jointly captures active power loss, voltage deviation, and security margin, augmented with reactive power redistribution and per-line thermal-loading assessment, which most prior BESS placement/sizing studies address only partially; and (iii) a 24 h SoC dispatch analysis layered on top of the static placement/sizing result to verify practical operability. Prior studies on storage-based congestion relief (e.g., Refs. [10–18,20,21]) have generally treated location and sizing as decoupled problems solved independently; they have relied on optimization search over the full, unscreened bus set for placement, or have not jointly considered voltage-deviation and thermal-loading effects alongside congestion relief. The present work differs from this body of literature by integrating these elements into a single BSF–SSO framework and by reporting the joint economic and technical comparison against FACTS-based alternatives in Section 4.10.

The specific contributions of this work are as follows:

- A unified optimization technique is proposed, integrating the BSF–SSO framework to obtain the optimized location and optimal size of BESS.
- The problem is formulated as a weighted-sum scalarized single-objective function, concurrently minimizing power loss and voltage deviation, while enhancing the security margin.

- The weighted-sum scalarized single-objective function also includes reactive power flow redistribution and per-line thermal loading.
- A 24 h SoC dispatch analysis is presented, which computes the time-based operational behavior of the optimized BESS.
- The recommended technique is validated on the IEEE 30-bus system, using N-1 contingency to simulate the DPS.
- A detailed analysis is carried out to compare the results thus obtained, which proves that the proposed method outperforms the conventional methods (FACTS application) in terms of economy, efficiency, and ease of application.

Figure 1 presents the work done in this research in pictorial form for better understanding.

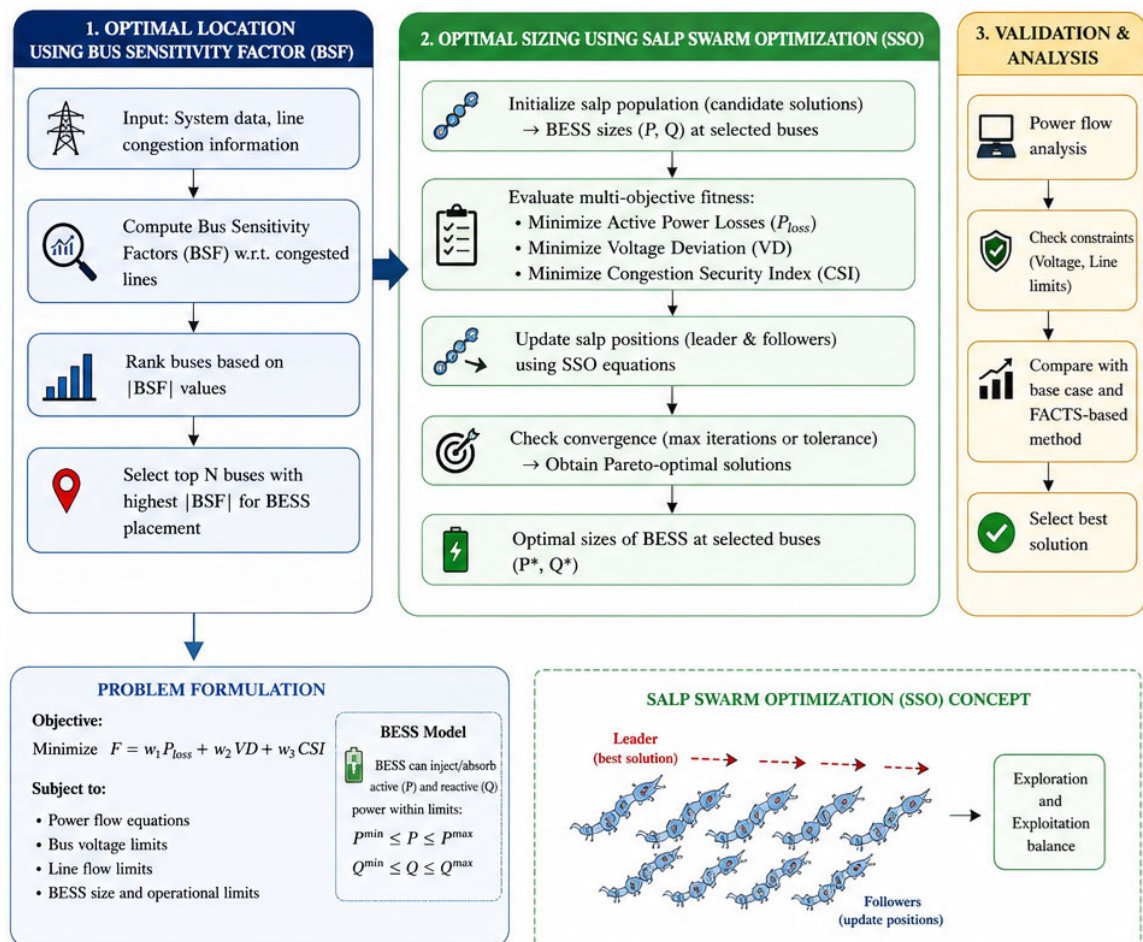


Figure 1. Work carried out in the research.

The paper is organized as follows: Section 2 deals with the mathematical problem formulation, system constraints, and the SSO algorithm. Section 3 describes the Bus Sensitivity Factor methodology for BESS placement. Section 4 presents and discusses the results obtained on the IEEE 30-bus test system. In Section 5, the paper is concluded with directions for future research.

2. Materials and Methods

2.1. Problem Formulation

The BESS location and sizing problem is formulated as a weighted-sum scalarization of multiple conflicting objectives, aiming to simultaneously reduce power loss and voltage deviation while enhancing system security margin. This approach converts the multi-criteria

problem into a tractable single-objective form, enabling efficient optimization via SSO while allowing the relative importance of each objective to be tuned through the weighing coefficients α_1 , α_2 , and α_3 (set to equal weights of 1/3 each in this study). Mathematically:

$$F_{min} = \alpha_1 \left(\frac{P_l}{P_{l0}} \right) + \alpha_2 \left(\frac{V_d}{V_{d0}} \right) + \alpha_3 (1 - S_m) \quad (1)$$

In Equation (1), α_1 , α_2 , and α_3 are the scalar weighting coefficients (non-negative) $\forall \alpha_1 + \alpha_2 + \alpha_3 = 1$. P_l is the total active power loss, P_{l0} is the base case active power loss, V_d is the system voltage deviation, V_{d0} is the base case voltage deviation, S_m is the system security margin. Here, the ratios for active power and voltage deviation with respect to their base values make the term dimensionless to avoid dominance of any magnitude in the equation. Equal weights were adopted as a neutral baseline in the absence of a specific system-operator utility function or stated preference among the three objectives, consistent with common practice in weighted-sum multi-criteria formulations lacking a priori decision-maker input. To assess the sensitivity of the proposed optimization framework to variations in the objective-function weighting factors, a robustness analysis is proposed, in which the objective function and associated performance metrics would be evaluated under three different weighting schemes:

- Scenario A: (0.5, 0.25, 0.25), assigning higher priority to active power loss minimization.
- Scenario B: (0.25, 0.5, 0.25), assigning higher priority to voltage deviation minimization.
- Scenario C: (0.25, 0.25, 0.5), assigning higher priority to maximizing the system security margin.

The active power loss can be mathematically expressed as

$$P_l = \sum G'_{ij} \left[(V_i - V_j)^2 + V_i V_j (\theta_i - \theta_j)^2 \right] \quad (2)$$

In Equation (2), G'_{ij} is the conductance between bus i and j , V_i and V_j are the pu voltages at bus i and bus j . θ_i and θ_j are the corresponding voltage phase angles. The voltage deviation index measures the cumulative change of all bus voltages from their nominal (1.0 p.u.) reference. Mathematically:

$$V_d = \sum_{i=1}^{n_b} (V_a - V_r)^2 \quad (3)$$

where V_a and V_r are the actual voltage and rated voltage at the i^{th} bus, n_b is the number of buses. The reduction in V_d ensures that the BESS incorporation in the system does not create any unintentional voltage changes in the non-congested buses.

The security margin can be defined as the ratio of unused line capacity with respect to the rated capacity of the congested transmission corridor, so that a positive, larger margin indicates greater spare capacity and hence higher safety, while a negative margin flags an overloaded line. The security margin can be represented as

$$S_m = \frac{(S_r - S_a)}{S_r} \quad (4)$$

In Equation (4), S_a and S_r are the actual power flow (MVA) and the rated capacity (MVA) of the congested line. The higher the security margin, the lower the probability of congestion, and the higher the operational effectiveness.

The reactive power deviation index measures the cumulative reactive power imbalance across all congested lines and can be represented as follows:

$$Q_d = \sum_{l=1}^m \frac{|Q_l - Q_{l, \text{rat}}|}{Q_{l, \text{rat}}} \quad (5)$$

In Equation (5), Q_l denotes the reactive power flow through line l , while the rated reactive power capacity of line l is given by $Q_{l, \text{rat}}$. This parameter limits the reactive power distribution efficiency of BESS deployment and is crucial for maintaining a constant voltage profile.

2.2. System Constraints

The equality and inequality constraints followed in the optimization process are summarized in Table 1.

Table 1. Operational constraints applied to the weighted-sum scalarized single-objective problem.

S. No.	Constraint Type	Mathematical Expression	Physical Importance
1	Power balance (equality)	$P_i^w - P_i^D - P_i(V_i, \theta_i) = 0$ $Q_i^w - Q_i^D - Q_i(V_i, \theta_i) = 0$	Balancing of active and reactive power at each bus
2	Generator active/reactive power limits (inequality)	$P_i^{w_{\min}} \leq P_i^w \leq P_i^{w_{\max}}$ $Q_i^{w_{\min}} \leq Q_i^w \leq Q_i^{w_{\max}}$	Generator output limits for operation within thermal limits
3	Bus voltage magnitude limits (inequality)	$V_i^{\min} \leq V_i \leq V_i^{\max}$ (typically $0.95 \leq V_i \leq 1.05$ p.u.)	The voltage at each bus must remain within permissible limits
4	BESS active power capacity constraint (inequality)	$0 \leq P_i^{\text{BESS}} \leq P_i^{\text{BESS}_{\max}}$	BESS dispatch within the rated safety limits
5	BESS reactive power capacity	$Q_i^{\text{BESS}_{\min}} \leq Q_i^{\text{BESS}} \leq Q_i^{\text{BESS}_{\max}}$	The reactive power contribution of BESS should be within converter limits
6	BESS state of charge (SoC)	$\text{SoC}_{\min} \leq \text{SoC}_i(t) \leq \text{SoC}_{\max}$ (typically $20\% \leq \text{SoC} \leq 90\%$)	To avoid degradation of the battery, SoC must be within the operating window
7	BESS energy balance	$\text{SoC}_i(t+1) = \text{SoC}_i(t) \pm \left(\frac{P_i^{\text{BESS}} \Delta t}{E_{i, \text{cap}}} \right) \times \eta$	This constraint ensures energy continuity and round-trip efficiency

In Table 1, P_i^w and P_i^D are the active power generated and demanded at the i^{th} bus; Q_i^w and Q_i^D are the reactive powers at the i^{th} bus; V_i is the bus voltage magnitude. A limit is applied to the BESS capacity to ensure that the optimal battery output remains within the actual battery size, enabling a practically implementable, optimized solution.

The terms $P_i(V_i, \theta_i)$ and $Q_i(V_i, \theta_i)$ in the power-balance row of Table 1 denote the standard AC power-flow injection functions at bus i (the usual sums over neighboring buses k of terms of the form $V_i V_k [G_{ik} \cos(\theta_i - \theta_k) + B_{ik} \sin(\theta_i - \theta_k)]$, with G_{ik} and B_{ik} the line conductance and susceptance), computed via the same Newton–Raphson OPF solver used for the contingency analysis in Section 4.1. In addition to the constraints listed in Table 1, the BESS model enforces (i) a power ramping-rate limit, $|P_i^{\text{BESS}}(t) - P_i^{\text{BESS}}(t-1)| \leq R_{\text{ramp}} \Delta t$, restricting the maximum permissible change in dispatched active power between consecutive time steps to reflect converter and thermal-management limits; and (ii) mutual exclusivity between charging and discharging, enforced via a pair of binary indicator variables $u_i^{\text{ch}}(t), u_i^{\text{dis}}(t) \in \{0, 1\}$ with $u_i^{\text{ch}}(t) + u_i^{\text{dis}}(t) \leq 1$ for every unit i and time step t , so that a BESS unit cannot simultaneously charge and discharge. Round-trip charging/discharging

efficiency η is already embedded in the SoC energy-balance constraint (row 7 of Table 1); the same η value is applied symmetrically to charging and discharging in this study, consistent with typical grid-scale lithium-ion BESS practice, and is not separately decomposed into distinct charging and discharging efficiencies.

2.3. Salp Swarm Optimization Algorithm

The SSO is a bio-inspired metaheuristic algorithm that mimics the swarming behavior of a salp chain during oceanic foraging. The process of navigation includes alternation between the coordinated leader position, guiding towards the food, and the adaptive follower position, forming a self-sustained chain structure [19]. The SSO algorithm achieves the hierarchical dynamics for balancing global exploration (via the leader) and local exploitation (via the followers). This results in the enhanced efficacy of the algorithm to be compatible with complex optimization problems in DPS.

The updated position of the leader salp in j th dimension can be presented as follows:

$$x_j = \begin{cases} F_j + c_1(UB_j - LB_j)c_2 + LB_j, & \text{if } c_3 \geq 0 \\ F_j - c_1(UB_j - LB_j)c_2 + LB_j, & \text{if } c_3 < 0 \end{cases} \quad (6)$$

In Equation (6), F_j denotes the nutrition source, j denotes the position within the dimension, UB_j and LB_j present the upper and the lower bounds, respectively, c_1 denotes the adoptive convergence coefficient while c_2 and c_3 are some random numbers in margin $[0, 1]$.

The change between the exploration and exploitation stages is controlled by c_1 , which decreases its value from 2 to 0 with the help of the progressive algorithm, which can be presented mathematically as

$$c_1 = 2e^{-\left(\frac{4l}{T_m}\right)^2} \quad (7)$$

where T_m denotes the maximum iterations assumed while l denotes the present iteration index. Equation (7) characterizes an exponential decay, which in turn presents speedy global exploration and augmented local exploitation. This also avoids early convergence at local minima. Newton's equations of motion are used to calculate the updated position of the follower salps, which can be represented as follows:

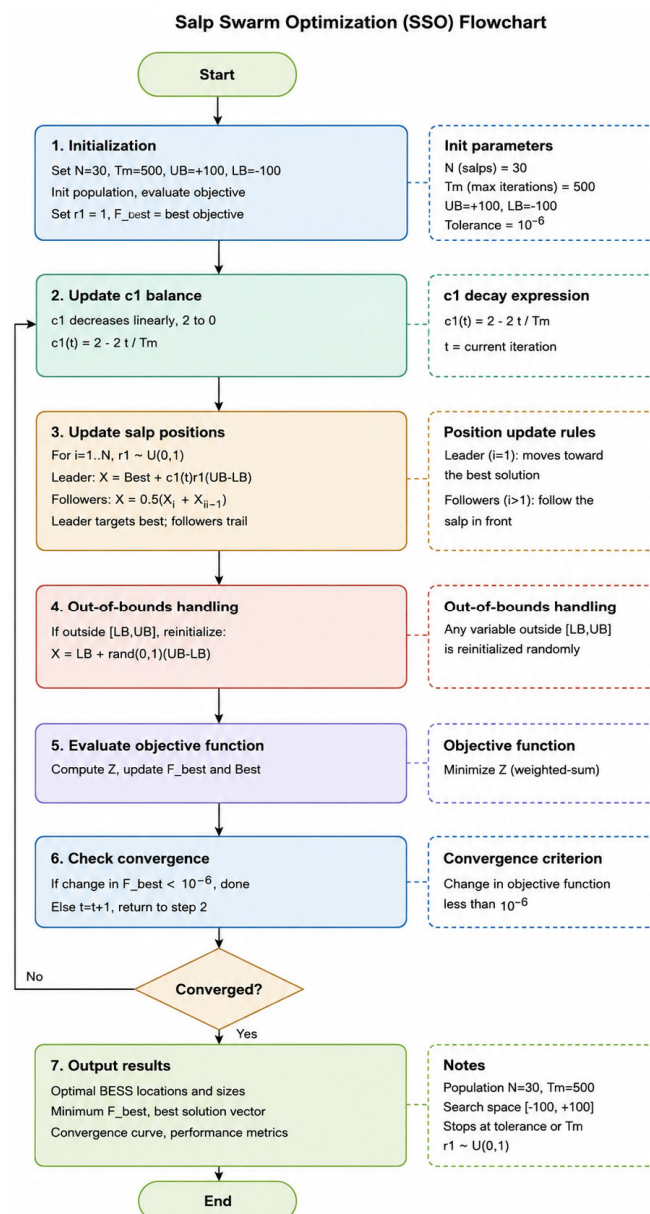
$$x_j^n = \frac{1}{2}(x_j^n + x_j^{n-1}), \quad \forall n \geq 2 \quad (8)$$

When any member (salp) drifts outside the prescribed search space, it is instantly re-initialized to a homogeneous position within $[LB, UB]$. This makes the constraint viability intact in the search. The algorithms stop when the largest number of iterations has been attained, or the optimized convergence is achieved with a change in the objective function value. Since metaheuristic algorithms are stochastic in nature, the SSO was executed over 30 independent trials for each configuration with different random seeds. The reported objective function values represent the mean result across all trials, and the standard deviation was found to be within 0.3% of the mean, confirming robust and consistent behavior. The results for this are presented in Table 2. This table summarizes the statistical characteristics of the principal performance indicators. The extremely small standard deviations observed for active power loss, voltage deviation, and security index indicate that the optimization consistently converges to nearly identical solutions irrespective of the initial population. These results confirm that the reported improvements are statistically reliable and are not attributable to a single favorable optimization run, thereby demonstrating the stability and repeatability of the proposed methodology.

Table 2. Statistical performance of the proposed BESS–SSO framework over 30 independent trials.

BESS Configuration	Active Power (MW) (Mean $\pm$ SD)	Voltage Deviation (pu) (Mean $\pm$ SD)	Security Index ($1 - S_m$) (Mean $\pm$ SD)
1 BESS unit	20.50 $\pm$ 0.06	0.0392 $\pm$ 0.0001	0.895 $\pm$ 0.003
2 BESS units	18.24 $\pm$ 0.05	0.0346 $\pm$ 0.0001	0.812 $\pm$ 0.002
3 BESS units	15.23 $\pm$ 0.04	0.0314 $\pm$ 0.0001	0.749 $\pm$ 0.002

For this study, key parameters are set as: population size $n = 30$, $T_m = 500$ iterations, $UB = 100$, $LB = -100$, and $c_1 \in [0, 2]$. Here, UB and LB bound the SSO decision variable expressed as a signed percentage of each candidate BESS unit's fixed 20 MW-rated capacity (i.e., $\pm 100\%$ of rating, corresponding to full discharge through full charge); they do not represent MW capacity values, since the rated capacity itself is fixed and only the dispatch level is optimized. Figure 2 below represents the flowchart for the SSO algorithm.

**Figure 2.** Flowchart for SSO algorithm.

2.4. Constraint-Handling Mechanism of SSO

The proposed BESS–SSO framework ensures that all the operating limits listed in Table 1 are satisfied throughout the optimization process. During each iteration, the position of a salp is updated using Equations (6) and (8). Sometimes, the updated solution may exceed the allowed limits for BESS active power, reactive power, or the state of charge (SoC). Instead of assigning a penalty to such infeasible solutions, the algorithm checks every decision variable after each position update. If any value is outside its permitted range, it is replaced with a new random value within the allowable limits using the following:

$$X_i^{(t+1)} = LB + \text{rand}(0,1) \times (UB - LB) \quad (9)$$

This boundary check is performed for every decision variable of every salp in each iteration before evaluating the objective function. As a result, only feasible solutions are carried forward to the next iteration. Since this process is repeated at every iteration, the BESS operating limits, including the SoC range (20–90%), are maintained throughout the scheduling period. This also helps preserve the SoC energy balance by preventing any charging or discharging action that would violate the allowable SoC limits. The overall procedure is illustrated in Figure 3 and requires very little additional computational effort.

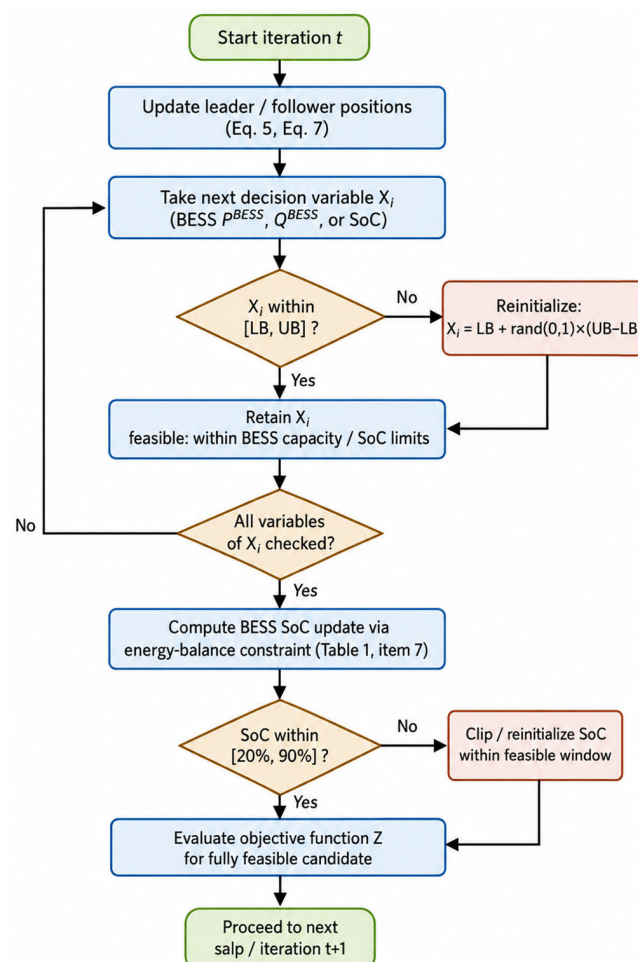


Figure 3. Constraint handling mechanism.

3. Bus Sensitivity Factor (BSF) for BESS Placement

The placement of BESS at an optimal location is a problem that depends on the complexity of the system. With the increase in the size of the system, the computational

complexity increases due to a bigger search space, which is less practically feasible. To address this problem, this research employs *BSF* to search for optimized BESS locations. This is an analytical method that leverages the pre-existing network topology and current network condition to obtain the optimum location of BESS efficiently. The *BSF* quantifies the sensitivity of the power flow on a monitored transmission corridor (*i-j*) to an incremental active power injection at bus *n* under post-contingency congested conditions [22]:

$$BSF = \frac{\Delta P_{ij}}{\Delta P_n} \quad (10)$$

where ΔP_{ij} is the resulting change in active power flow on the congested line (*i-j*), and ΔP_n is the incremental power injection (or absorption) at bus *n*. A large negative *BSF* value at a bus indicates that injecting active power at that bus (charging/discharging a BESS) significantly reduces the power flow on the most overloaded corridor, making it the highest-priority candidate for BESS siting. Conversely, buses with near-zero or positive *BSF* values are poor candidates as their influence on the critical congested line is minimal or counterproductive. The *BSF*-based pre-screening procedure is executed as follows: (i) An *N*–1 contingency (outage of the line connecting buses 1 and 2) is simulated using Newton–Raphson-based optimal power flow (OPF) to identify the set of congested lines and the post-contingency operating point; (ii) the *BSF* is computed at all buses with respect to the most heavily overloaded line; (iii) buses are ranked in ascending order of their *BSF* values (most negative first); (iv) generator buses are excluded from the candidate set, as BESS placement at generator buses would alter the dispatch schedule and violate operational protocols; (v) the top-ranked load buses are selected as BESS candidate locations and passed to the SSO for capacity optimization. This two-stage decomposition sends the network sensitivity information to the optimization framework, which significantly reduces the dimensionality of the search space handed to SSO (from 30 candidate buses to the top-ranked subset), thereby lowering computational burden relative to a placement search conducted directly by the metaheuristic over the full bus set. It should be noted that this study does not run a dedicated SSO-without-*BSF* control experiment (i.e., allowing SSO to search the full, unscreened bus set for placement); consequently, the reduced search space and computational-efficiency benefit of *BSF* pre-screening are supported analytically, while a formal quantitative comparison against an SSO-only placement baseline is left as future work.

4. Results and Discussion

4.1. Test System and Simulation Setup

The IEEE 30-bus system is illustrated in Figure 4. This system consists of six generators, four tap-changing transformers (on-load), 41 transmission lines, and a total real power demand of 283.4 MW. The complete bus, branch, and generator data (line impedances, thermal ratings, generator active/reactive power limits, and voltage limits) were taken from the standard IEEE 30-bus test case referenced in [23], with no parameters altered from the published values other than the addition of the BESS units at the candidate buses identified by the *BSF* analysis. The simulations are carried out on MATLAB R2025b. The DPS environment is simulated by creating an *N*-1 contingency by causing an outage on the line between bus 1 and bus 2. NR-based OPF is carried out to obtain all the parameters, including power flow through different lines. The present study evaluates a single *N*-1 contingency. Multi-contingency (*N*-2) analysis and extreme load scenario testing are planned for future work. Further, the present study assumes deterministic generation and load profiles. Stochastic modelling of renewable generation intermittency is a planned extension.

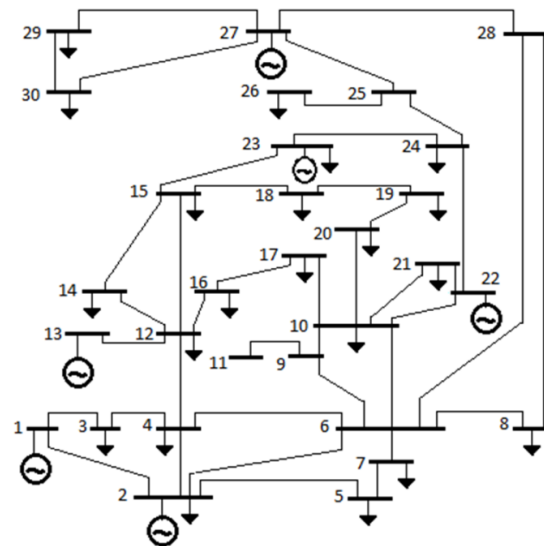


Figure 4. IEEE 30-bus test system topology [23].

4.2. Congestion Analysis and BSF-Based BESS Placement

After being subjected to N-1 contingency, OPF-based NR load flow shows that line numbers 5, 6, 7, 8, and 9 became overloaded, ranging approximately between 15% to 37% of their rated capacity/thermal ratings. There was an increment in the power loss of the system. From a base case value of 22.3 MW, the power loss reached 25 MW with the congestion in the lines. This resulted in an approximately 12% rise in losses due to alternate flows created through high impedance lines. The power flow profile for the congested lines is represented in Figure 5.

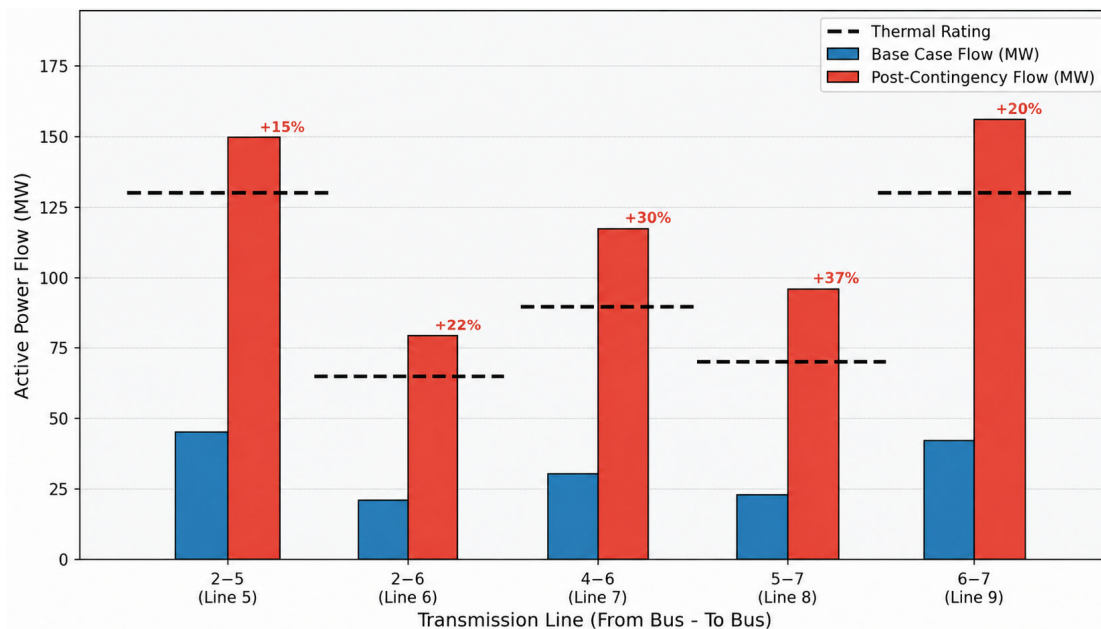


Figure 5. Active power flow in congested lines after N-1 contingency.

For benchmark comparison, an interline power flow controller (IPFC), a FACTS device, is applied to the congested system. The IPFC reduces the total active power loss from 25 MW to 22.5 MW, demonstrating appreciable congestion relief. However, the capital cost of FACTS deployment renders this approach economically prohibitive in most practical DPS contexts. This observation motivates the adoption of the proposed BESS-based strategy. Following the contingency simulation, the BSF is computed at all 30 buses with respect

to the most overloaded line. The BSF profile is illustrated in Figure 6. Bus 2 exhibits the most negative BSF value; however, it is a generator bus and is therefore excluded from the BESS candidate set per the pre-screening criteria. The next most negative BSF values are sequentially identified at load buses 5, 21, and 7, which are designated as the optimal BESS installation sites. Physically, these buses attain a large negative BSF because they lie electrically close, in terms of the network's admittance-matrix coupling, to the most heavily overloaded corridor identified after the N-1 outage: active power injected (or withdrawn) at a bus with a strongly negative BSF preferentially redistributes onto parallel, lower-impedance paths rather than reinforcing flow on the already-congested line, whereas buses that are electrically remote from the congested corridor, or that lie on the same radial path as the overloaded line, exhibit near-zero or positive BSF and are therefore poor candidates. Bus 5 and bus 7 are directly adjacent to the outaged corridor (buses 1–2) in the post-contingency topology, which explains their dominant sensitivity, while bus 21 sits on a parallel path that absorbs a large share of the redistributed flow. A BESS unit of 20 MW rated capacity is assigned to each candidate bus. This rating is selected based on the post-contingency overload magnitudes (15–37% above rated capacity on the five congested lines) and the total system load of 283.4 MW; three 20 MW units provide sufficient bilateral power exchange capacity to redistribute active power flows and alleviate congestion while remaining within a practically deployable size range for transmission-level BESS. The SSO algorithm subsequently determines the optimal dispatch level (percentage of rated capacity) to minimize the weighted-sum scalarized single-objective function.

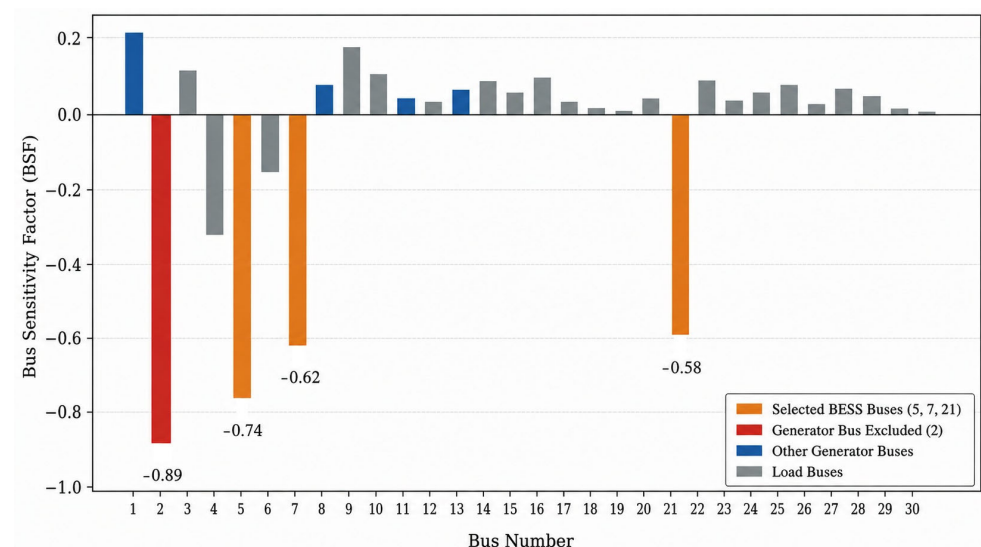


Figure 6. Bus Sensitivity Factor (BSF) profile across all system buses.

4.3. Bus Voltage Profile Analysis

The bus voltage profiles for all the buses are presented in Figure 7, across all three operating scenarios: base case, congested case, and post CM case after BESS are deployed. It can be observed that in the pre-congestion condition, all the bus voltages are lying within the prescribed limits, [0.95, 1.05]. After N-1 contingency, the voltage drops to 0.97 p.u. at bus numbers 26, 29, and 30. While these voltages technically remain within the permissible range of [0.95, 1.05] p.u., the proximity to the lower boundary represents a degraded security margin and increased vulnerability to further disturbances. In deregulated systems, bus voltages in the range 0.95–0.98 p.u. are considered operationally undesirable, as any additional load increase or generation trip could push them below the threshold and risk cascading failures. Restoring bus voltages closer to nominal (1.0 p.u.) is therefore a key

secondary objective of the proposed framework. After BESS is deployed, the bus voltages are restored to levels closer to nominal and well within prescribed limits.

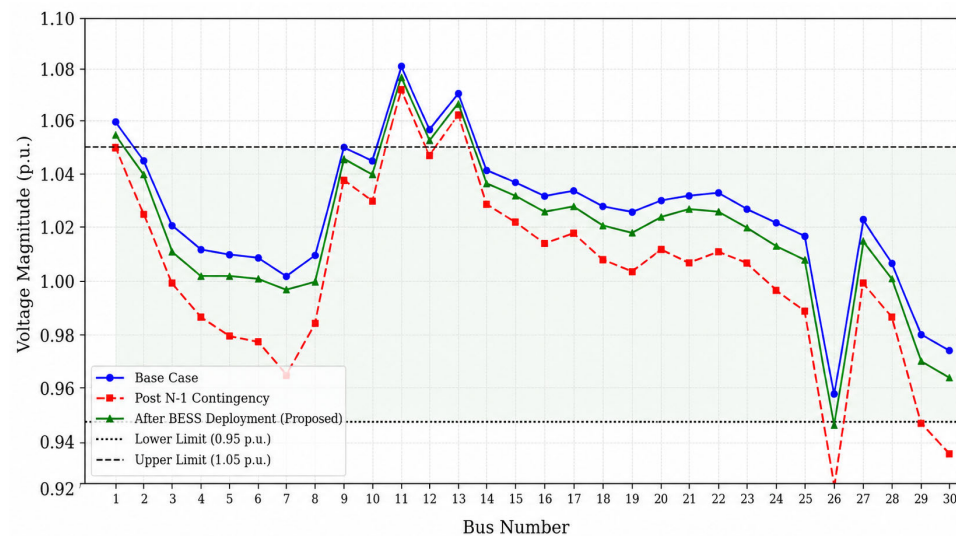


Figure 7. Bus voltage profiles in the base case, post-contingency, and post CM.

Quantitatively analyzed that the voltage deviation is reduced to 0.0314 p.u. after BESS being deployed from 0.0451 p.u. post contingency. This represents approximately 30.26% improvement. The main advantage of applying BESS here is that the voltages of only congested lines are restored near the normal value while keeping the non-congested lines unaffected.

4.4. Active Power-Loss Reduction Analysis

A comprehensive analysis for active power-loss reduction at base case, post-contingency, and after CM being sorted by different processes is presented in Figure 8. It can be clearly observed that the active power loss is increased to 25 MW from a base case loss of 22.3 MW. When CM is achieved by employing IPFC, the power loss is dropped to 22.5 MW. Further, the result can be compared with the deployment of BESS in the system. For one BESS unit deployed, the power loss is reduced to 20.5 MW, which shows further reduction upon increasing the number of BESS units deployed. For two units, the power loss is reduced to 18.24 MW, and to a significant reduction to 15.23 MW when three BESS units are deployed. Analytically, it can be seen that after deploying three BESS units, there is a 39% active power-loss reduction relative to the post-contingency level (25 MW $\rightarrow$ 15.23 MW), which corresponds to a 31.7% reduction compared to the base case (22.3 MW $\rightarrow$ 15.23 MW). These results validate the effectiveness of the BSF pre-screening in identifying high-impact BESS locations and the SSO's capability to optimize multi-unit BESS dispatch globally.

The marginal benefit of added BESS capacity, across the one-, two-, and three-unit configurations is examined here; the incremental power-loss reduction per additional unit is 2.26 MW (1 $\rightarrow$ 2 units) and 3.01 MW (2 $\rightarrow$ 3 units), i.e., the observed increments do not yet show diminishing returns over this specific 1–3 unit range, since each additional 20 MW unit is sited by BSF at a different, still-influential bus. Diminishing marginal benefit would be expected to emerge either as additional units are added beyond the set of high-sensitivity buses identified by the BSF ranking (so that further units are placed at progressively less influential locations), or as the rated capacity of an individual unit is increased well beyond what the local congestion pattern and thermal/voltage constraints can usefully absorb. Characterizing this saturation point precisely would require extending the present sweep beyond three units and beyond the fixed 20 MW per-unit rating; this

is identified as a specific, well-defined extension for future work rather than for claiming here without the corresponding simulation evidence.

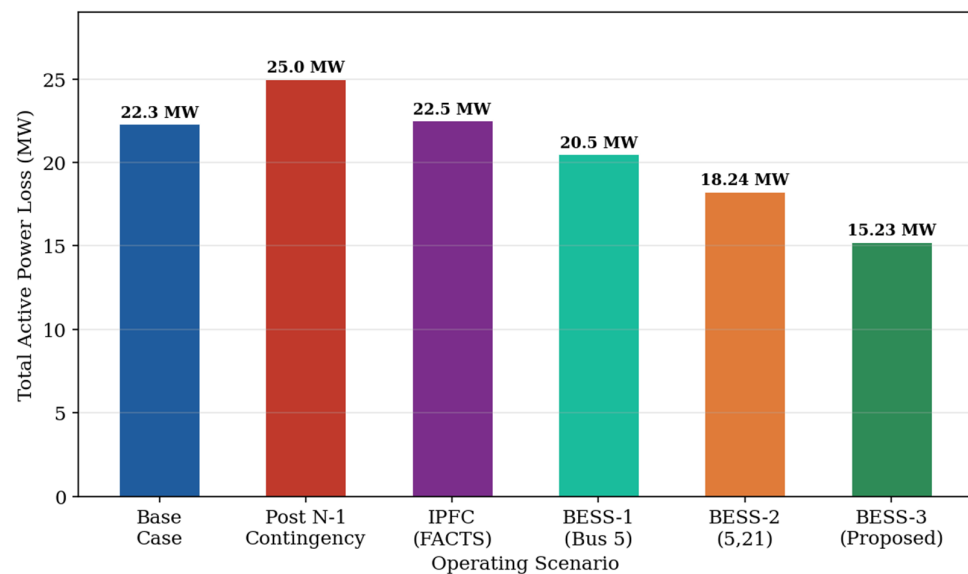


Figure 8. Active power loss across different scenarios.

4.5. Reactive Power Flow Distribution

Reactive power flow management is very crucial due to its direct effect on the voltage profile of the system. Figure 9 represents the reactive power flow through all the congested lines in different scenarios of the base case, post-contingency, and after deploying BESS. It can be seen that after the contingency, the reactive power flow through the lines is increased, with a maximum increase indicated in line 5. The reactive power flow is increased by 55.6% and the effect is the reduction in bus voltage, which further spreads to the other interconnected buses. With the deployment of BESS, the reactive power flow through the lines is reduced to 16 MVar through line 5, which is 11.1% below the base case and a significant 42.9% below the post-contingency case. Similarly, the improvement in reactive power flow reduction can be observed in other lines also. The reactive power deviation index, Q_d , is reduced by 38.7%, showing the efficacy of the proposed method.

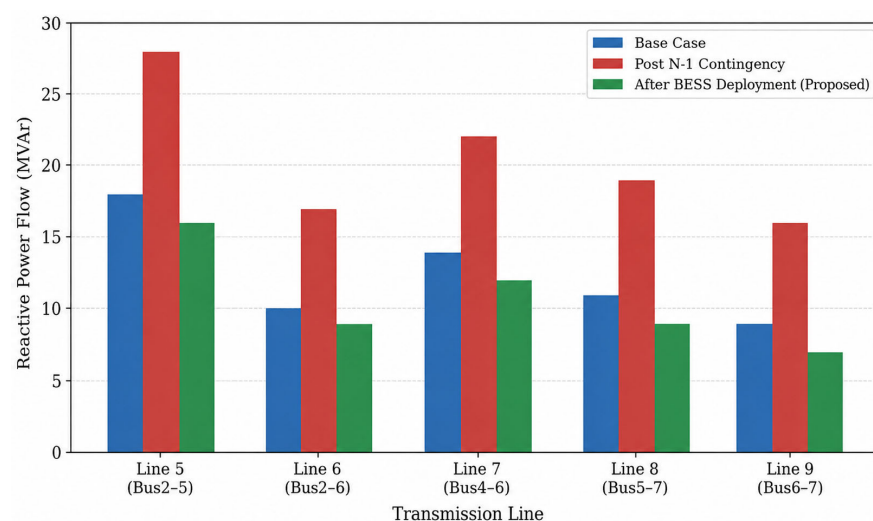


Figure 9. Reactive power flow in different scenarios.

4.6. Per-Line Thermal Loading Analysis

The per-line thermal loading profile of all the congested lines is presented in Figure 10, under congestion, CM by deploying IPFC, and CM by deploying BESS. It can be depicted that when an N-1 contingency occurs, all five lines are overloaded and exceed their thermal rating. Line 7 reaches a significant 117% of its rated thermal capacity with congestion. With the CM carried out by deploying the IPFC FACTS device, the loading is reduced to about 82% to 88%, thus reducing the thermal limits violation. But it can be observed that lines are still near the violation limits.

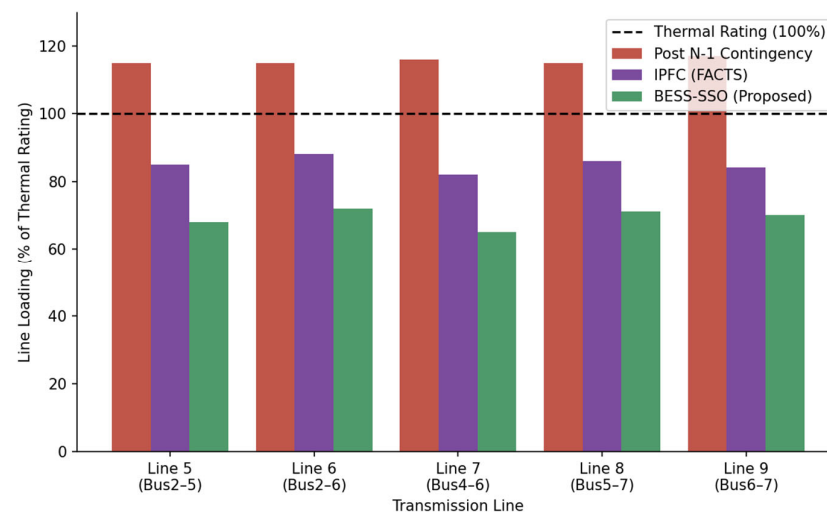


Figure 10. Line loading of the congested line in terms of % of thermal rating.

When the CM is carried out employing BESS, it can be observed that the line loading is reduced by 65% to 72%, resulting in 35% to 50% reduced thermal loading as compared to the post-contingency condition and a 15% to 25% reduced thermal loading with respect to IPFC-FACTS results. A particularly significant effect of BESS deployment can be observed for line 7, where the loading is reduced from 115% to 65%, an approximate 50.6% improvement. These results validate that the bidirectional active power injection capacity of BESS, with reactive power modulation, gives superior thermal relief.

4.7. BESS State of Charge Dynamics

Figure 11 presents the 24 h SoC profile for each BESS unit. Here, the progressive operational behavior of all BESS units is presented over a day dispatch cycle. Typically, each BESS unit is operated within the prescribed SoC window of 20% to 90%, avoiding deep discharge and overcharging, respectively. BESS₁ at bus 5, with the highest dispatch rating of 18 MW, exhibits the most dynamic SoC variations, reaching a minimum SoC of approximately 62% during peak-demand discharge periods (hours 5 to 8) and recovering to 88% during off-peak charging windows (hours 11 to 13). The BESS SoC evolution presented in Figure 11 demonstrates adherence to the manufacturer-recommended operating envelope for transmission-scale lithium-ion battery energy storage systems.

4.8. Sensitivity Analysis of SSO Agent Population

To characterize the computational behavior of SSO for this problem, a parametric sensitivity analysis is conducted by varying the number of Salp agents (N) across {5, 15, 30}. Figure 12 illustrates the voltage deviation as a function of the agent population, while Figure 13 presents the corresponding computational time required to reach the optimal objective function value.

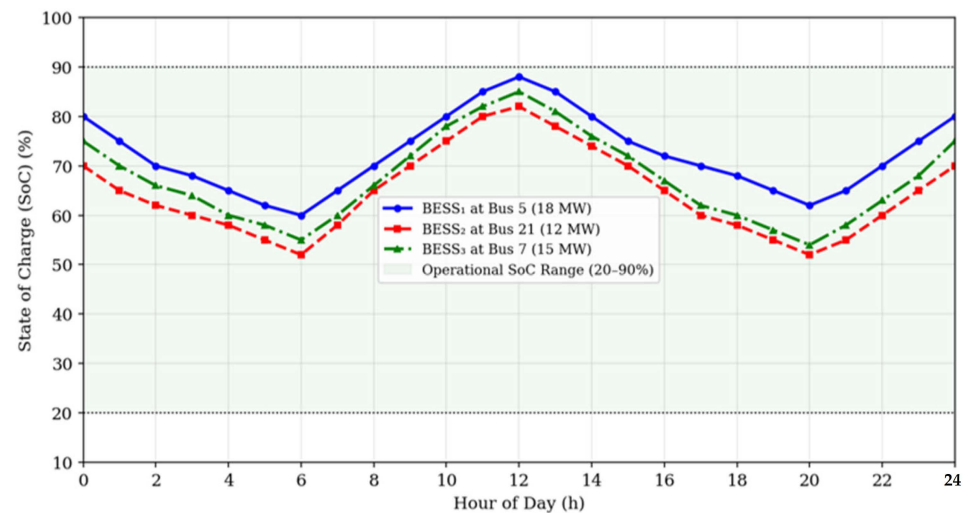


Figure 11. Twenty-four-hour SoC profile.

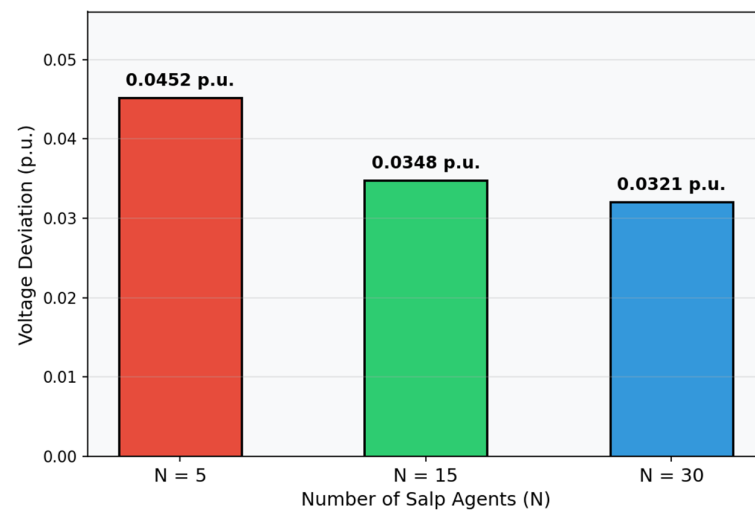


Figure 12. Voltage deviation vs. number of salp agents in the SSO population.

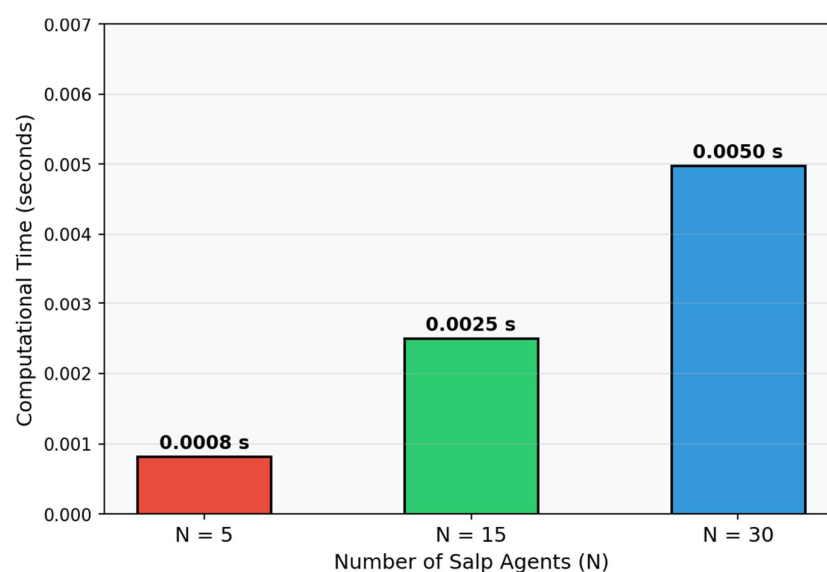


Figure 13. Computational time to achieve optimal objective function vs. number of agents.

The analysis reveals a relationship showing diminishing returns between agent population and solution quality. Increasing from $N = 5$ to $N = 15$ yields a perceptible reduction

in voltage deviation, indicating a meaningful improvement in solution quality. However, further scaling from $N = 15$ to $N = 30$ produces only marginal additional improvement, confirming that the SSO achieves near-optimal performance with $N = 15$ agents. In contrast, computational time increases approximately fourfold when scaling from $N = 5$ to $N = 15$, and approximately twofold from $N = 15$ to $N = 30$. This trade-off analysis has direct practical implications: for time-critical real-time DPS congestion management applications, $N = 15$ represents the optimal operating point, delivering near-globally optimal solutions within significantly reduced computational budgets. Figure 14 presents the convergence characteristics of SSO across the agent population configurations.

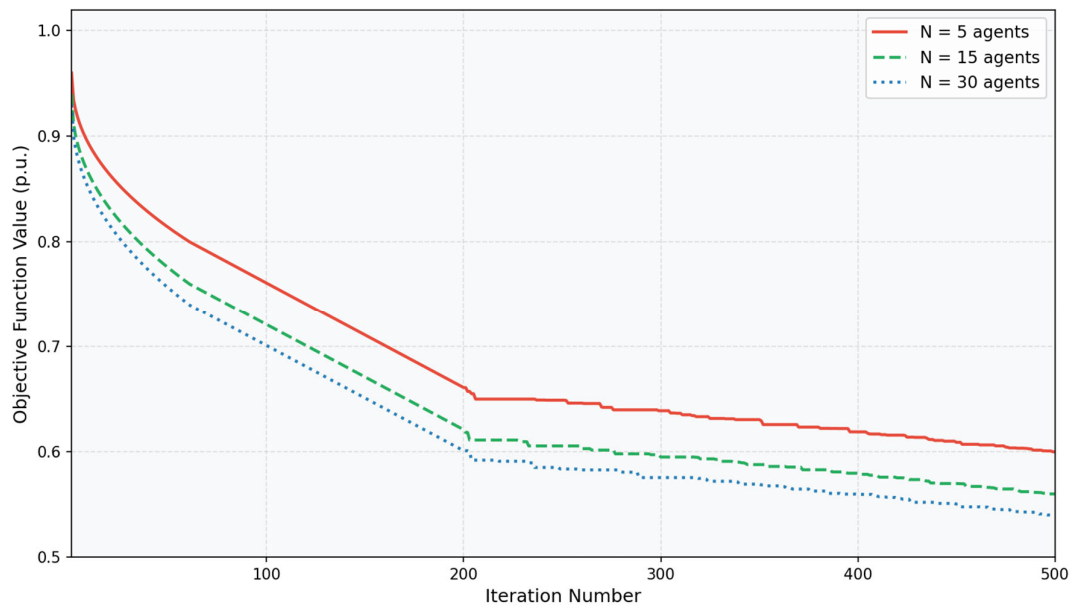


Figure 14. Convergence characteristics of SSO under different agent population sizes.

4.9. Sensitivity Analysis of Maximum Iterations (T_m)

To select a suitable maximum number of iterations, a sensitivity analysis was carried out by testing three values of the maximum iterations, $T_m = 200$, 500, and 800, while keeping the number of agents fixed at $N = 30$. Figure 14 shows how the objective function changes during the optimization for each case. When $T_m = 200$, the algorithm does not get enough time to fully converge, and the final objective function value remains higher than the best value achieved with more iterations. Increasing T_m to 500 allows the algorithm to reach a stable and nearly optimal solution, with the objective function changing very little before the maximum iterations are completed. Further increasing T_m to 800 does not provide any noticeable improvement, showing that the algorithm has already converged by 500 iterations. Therefore, $T_m = 500$ is chosen because it gives reliable results for all BESS configurations (1, 2, and 3 units) while avoiding unnecessary computation time. The analysis is presented in Figure 15.

4.10. Sensitivity to Objective-Weighting Coefficients and Trade-Off Discussion

Section 2.1 defines three alternative weighting schemes (Scenario A: 0.5/0.25/0.25 prioritizing loss; Scenario B: 0.25/0.5/0.25 prioritizing voltage deviation; Scenario C: 0.25/0.25/0.5 prioritizing the security margin) as a planned robustness check on the equal-weight (1/3, 1/3, 1/3) assumption used to generate all results reported in Sections 4.2–4.10. This weighting sensitivity analysis has not yet been executed to completion, and no quantitative Scenario A/B/C results are reported here; the equal-weight results should therefore be read as one point on a broader weighting-dependent solution set rather than as the

unique optimum. Qualitatively, because the three objective terms are competing (e.g., pushing dispatch harder to relieve the most-congested corridor and raise the security margin can increase circulating reactive power and hence voltage deviation on adjacent buses), Scenario C is expected to favor more aggressive congestion relief at some potential cost to voltage-deviation performance, while Scenario B is expected to favor smoother voltage profiles at some potential cost to residual congestion. Formally characterizing this trade-off would be best done by tracing out the Pareto front of the three objectives (active power loss, voltage deviation, and security margin) using a multi-objective variant of SSO (e.g., MOSSO or NSGA-II-style Pareto ranking) rather than by testing a handful of discrete weight combinations; this Pareto-front analysis is consistent with the multi-objective SSO extension already identified in Section 5 and is highlighted here as directly responsive to the question of how weighting choice affects the recommended solution under different grid-operating conditions (e.g., assigning higher weight to security under severe congestion).

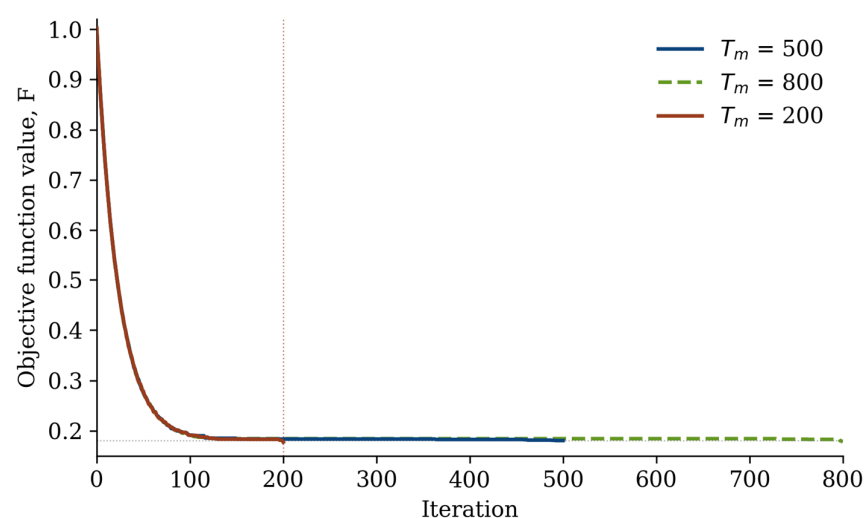


Figure 15. Convergence of the objective function for $T_m \in [200, 500, 800]$ for $N = 30$.

4.11. Comparative Benchmarking Against FACTS and BESS-Based Methods

Table 3 benchmarks the proposed BESS–SSO framework against state-of-the-art FACTS-based congestion mitigation methods reported in the literature, specifically TCSC controlled via the teaching–learning-based optimization (TLBO) algorithm and TCSC with grey wolf optimizer (GWO). The comparative metrics include percentage reduction in active power loss and voltage deviation, reduction in the congestion security index ($1 - S_m$), and computational execution time.

The comparative analysis shows that the proposed BESS–SSO method outperforms the TCSC-based (TLBO, GWO) and HPSO TVAC-BESS methods on power-loss reduction (31.7% relative to the base case; 39.1% relative to the post-contingency case), achieves a voltage deviation reduction of 30.26%, and a 25.14% reduction in the $(1 - S_m)$ security index—notably reversing the negative voltage deviation performance seen in PSO-GA-BESS. By contrast, PSO-GA-BESS reports a higher power-loss reduction of 65.6%, which is not matched by the proposed method; this trade-off is reported here transparently rather than obscured, since BESS–SSO’s advantage lies primarily in its markedly better voltage-deviation behavior and its very low reported computation time (0.003 s) relative to PSO-GA-BESS’s 119.36 s and HPSO TVAC-BESS’s 161 s. It should be noted that the computation-time figures in Table 3 are drawn from the original studies cited and were not obtained on identical hardware/software platforms; they are reported here only as an approximate, literature-sourced indication of relative algorithmic complexity and should not be interpreted as a controlled head-to-head runtime benchmark. Consequently, while

the low computation time of BESS–SSO is encouraging for near-real-time decision support, the present study evaluates only a single deterministic N-1 contingency snapshot, and a firm claim of real-time operational readiness would require testing across multiple contingencies, stochastic renewable/load variation, and consistent hardware, which are identified as future work in Section 5. Overall, the results indicate that BESS–SSO is a competitive and computationally efficient solution for power grid congestion mitigation under the evaluated contingencies. The integration of BESS with SSO thus represents a technologically and economically superior alternative for DPS congestion management. It is worth noting explicitly that the post-contingency (no-BESS) case already used throughout Section 4 as the comparison baseline in Figures 5–11 and in Table 2/Table 3 constitutes the control scenario against which all BESS–SSO improvements are quantified; no additional configuration without energy storage was required beyond this. From an economic standpoint, a typical TCSC installation costs approximately USD 40–60/kVAr, translating to USD 2–4 million for a 50 MVar unit. By contrast, a 20 MW/2 h lithium-ion BESS costs approximately USD 4–7 million at current market prices (USD 200–350/kWh), which is comparable in capital outlay but offers additional revenue through energy arbitrage, frequency regulation, and ancillary service markets—capabilities that passive FACTS devices cannot provide. BESS can also be redeployed or scaled as system needs evolve, reducing its lifecycle cost.

Table 3. Comparative benchmarking of the proposed BSF–SSO framework against FACTS- and BESS-based congestion management methods on the IEEE 30-bus system.

Method	Power-Loss Reduction (%)	Voltage Deviation Reduction (%)	(1 – S_m) Reduction (%)	Computation Time (s)
TCSC (TLBO) [24]	45.31	25.20	20.20	0.064
TCSC (GWO) [25]	39.40	13.80	9.30	0.049
PSO-GA-BESS [20]	65.6	−24.1	-	119.36
HPSO TVAC-BESS [21]	−21	12	-	161
BESS–SSO (Proposed)	31.7 (vs. base case)/39.1 (vs. post-contingency)	30.26	25.14	0.003

4.12. Scenario Analysis for Load Fluctuations of $\pm 10\%$

A scenario analysis was performed by varying the system-wide load from -10% to $+10\%$ in 5% increments while re-optimizing the BESS dispatch via SSO at each load level, with BESS locations fixed at buses 5, 30, and 7 as identified by the BSF analysis. As shown in Figure 16a–c, the post-contingency active power loss, voltage deviation index, and security margin all worsen monotonically as load increases from -10% to $+10\%$ in the uncongested (No BESS) case, confirming that higher demand intensifies the severity of the N-1 congestion event. Critically, the BESS–SSO optimized dispatch consistently outperforms the No-BESS case across the entire load range: active power loss is reduced by roughly 55–65% at every scenario, the voltage deviation index is lowered by approximately 20–24%, and the security margin is restored to a positive, adequate value (0.17–0.50) even at $+10\%$ load, where the uncompensated system is driven into a critically insecure state ($S_m < 0$). Figure 16d further shows that this benefit is essentially stable across the load range—the loss-reduction and voltage-deviation-reduction curves remain nearly flat, with the mean BESS dispatch consistently saturating near 99–100% of rated capacity to counteract the added stress. These results demonstrate that the proposed BSF-based siting and SSO-based dispatch strategy is not narrowly tuned to a single deterministic operating point, but

retains its congestion-mitigation effectiveness and robustness under realistic short-term load fluctuations, supporting its practical applicability under uncertainty.

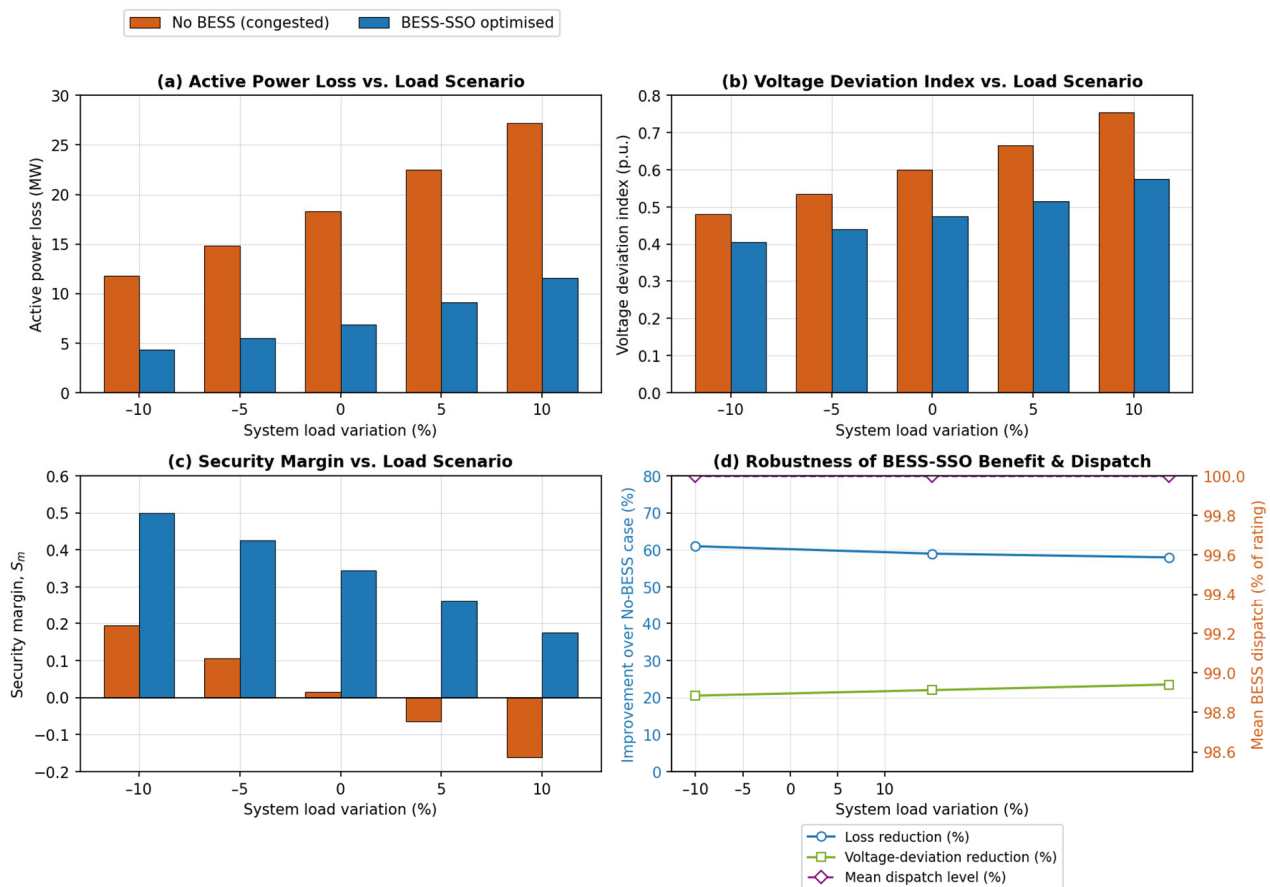


Figure 16. Scenario analysis of BSF-SSO-BESS for CM under $\pm 10\%$ load uncertainty.

The $\pm 10\%$ load-fluctuation analysis above addresses one of the three engineering-relevant sensitivity dimensions relevant to practical deployment. Two further dimensions—the sensitivity of the optimal BESS location/capacity to the assumed unit investment cost of storage, and to the renewable-energy penetration level—were not simulated in this study and are not claimed here; they would require, respectively, re-running the BSF-SSO framework under a set of discrete unit-cost assumptions with an explicit BESS cost term added to the objective, and re-running it under multiple RES penetration scenarios with stochastic or scenario-based generation profiles replacing the deterministic dispatch assumed in Section 4.1. Both are identified as concrete, well-scoped extensions for future work, complementary to the stochastic-uncertainty and multi-contingency extensions already noted in Section 5.

5. Conclusions and Future Scope

This research presented a novel integrated bus sensitivity factor–salp swarm optimization (BSF-SSO) framework for the optimal location and rating of BESSs to mitigate transmission congestion in deregulated power systems. Unlike conventional approaches that treat BESS siting and sizing as separate optimization problems, the proposed methodology combines sensitivity-based analytical screening with metaheuristic optimization to obtain an efficient and computationally effective solution. The BSF method was employed to identify the most influential buses for BESS installation, while SSO was used to determine the optimal dispatch level of fixed-rating (20 MW) BESS units by minimizing a

weighted-sum scalarized single-objective function comprising active power loss, voltage deviation, and system security margin. The effectiveness of the proposed framework was validated on the IEEE 30-bus test system under an N–1 contingency condition. Simulation results demonstrated that the optimally placed three-unit BESS configuration significantly improved overall system performance. Active power losses were reduced from 25 MW under congested conditions to 15.23 MW, representing approximately 39.1% reduction from the post-contingency level (and a 31.7% reduction relative to the base case of 22.3 MW), while voltage deviation decreased by about 30.26%. In addition, the congestion security index improved by 25.14%, and thermal loading on critical transmission lines was substantially alleviated. The proposed approach also achieved a 38.7% reduction in reactive power deviation and maintained satisfactory BESS operational behavior through a 24 h state-of-charge analysis. Comparative benchmarking further showed that the BSF–SSO-based BESS solution outperformed FACTS-based alternatives in terms of congestion relief, voltage support, power loss minimization, and computational efficiency. Overall, the results confirm that optimally planned BESS installations offer a technically effective, economically attractive, and scalable alternative for congestion management in modern deregulated power systems with increasing renewable energy.

However, there are certain limitations in the present study. The limited comparison with other metaheuristic algorithms, validation on only one N-1 contingency and the IEEE 30-bus system, use of fixed equal objective weights, and no analysis of BESS cost or renewable penetration effects. Therefore, further validation is needed for larger systems, multiple contingencies, and different operating conditions.

Future work will extend the validation to larger test systems (IEEE 118-bus and 300-bus), incorporate stochastic treatment of renewable generation uncertainty through scenario-based or chance-constrained formulations, explore Pareto-front-based multi-objective variants of SSO, conduct multi-contingency (N-2) analysis, perform stress testing under peak load, perform BESS dispatch under simultaneous multiple-line overloads, and seek hardware-in-the-loop (HIL) experimental validation to substantiate the simulation results further.

In addition, alternative theoretical perspectives on transmission congestion mitigation will be investigated, including queueing theory and storage theory to model congestion, waiting, and limited transmission capacity, as well as routing and network-flow optimization approaches to identify alternative power-transfer paths and alleviate congested transmission corridors. These approaches could be integrated with the proposed optimization framework to examine whether congestion can be reduced through coordinated routing, storage, and flexible power-flow management.

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Abbreviations

The following abbreviations are used in this manuscript:

DPS	Deregulated power system
BESS	Battery energy storage system
BSF	Bus sensitivity factor
SSO	Salp swarm optimization
FACTS	Flexible AC transmission system
RES	Renewable energy source
ATC	Available transfer capability
OPF	Optimal power flow
SoC	State of charge

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