

Article

A Novel Musk Ox Optimizer-Based Non-Wire Alternative Framework for Optimal BESS Allocation in the EGAT Transmission Network Under N-1 Contingencies

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Abstract

Escalating energy demand and the evolving landscape of power transmission have intensified the operational pressures on electrical grids, specifically during N-1 contingency events. The unexpected loss of a single transmission circuit often precipitates critical system instabilities, including power flow congestion, voltage degradation, and heightened transmission losses. While conventional grid expansion remains the standard for maintaining reliability, its implementation is frequently hindered by lengthy permitting processes, significant capital investment, and regulatory complexities. This research offers an alternative by presenting a robust optimization-based framework for the strategic placement and sizing of a battery energy storage system (BESS) within the Electricity Generating Authority of Thailand (EGAT) transmission network. Focusing on the N-1 contingency resulting from the 115 kV Thatako Substation (TTKS)–Bueng Sam Phan Substation (BGSS) circuit outage during peak load hours, this study introduces the musk ox optimizer (MOO) to solve the complex, non-linear allocation problem. The objective function is formulated to minimize cumulative system costs while enforcing strict network operational envelopes. Simulation results indicate that the optimized BESS configuration achieves compliant grid performance, successfully restoring the post-fault bus voltage, enhancing voltage profile, reducing transmission losses, and mitigating peak line loading. These findings demonstrate that the proposed MOO-based strategy provides a physically compliant, flexible, and robust non-wire alternative for transmission constraint management, confirming its viability as a sustainable, low-environmental-impact framework for enhancing modern grid resilience and utility development.

Keywords: battery energy storage systems (BESSs); musk ox optimizer (MOO); non-wire alternatives (NWAs); N-1 contingency mitigation; optimal allocation; sustainable infrastructure; transmission network



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1. Introduction

Modern electrical grids face severe operational pressures due to escalating energy demands, shifting generation profiles, and aging infrastructure. These pressures are acutely magnified during contingency events such as the sudden, unexpected loss of a single

transmission asset (N-1 contingency). An unmitigated N-1 outage routinely precipitates severe network instabilities, including catastrophic transmission line overloads, widespread voltage degradation, and escalating active power losses [1,2]. Driven by robust economic growth and total electrification, such as the proliferation of electric vehicles (EVs) and industrial machinery, global power demand is projected to rise by an average of over 3.5% annually through the decade [3–5]. Such escalating load profiles mandate that modern infrastructures possess the resilience to uphold rigorous security and reliability standards [6–8]. Central to this operational philosophy is the N-1 security criterion, a fundamental benchmark dictating that a power system must maintain operational integrity and continuity of supply even upon the failure of any single critical component [9,10].

Historically, constructing new high-voltage overhead transmission corridors has been the primary strategy for alleviating capacity bottlenecks during N-1 contingency events [11–13]. Nevertheless, physical line expansion is increasingly obstructed by intensive capital costs, multi-year permitting cycles, and the difficulty of securing rights-of-way (ROWs) [14,15]. These projects frequently intersect with ecologically sensitive regions, causing habitat fragmentation and environmental degradation [16]. While alternative options such as pumped hydro energy storage (PHES) offer grid equilibrium, their implementation is marred by adverse geomorphological impacts, soil erosion, and localized deforestation [17,18]. In the absence of infrastructure expansion, traditional operational measures such as load shedding are often employed to stabilize voltage profiles, but these curtailment-based approaches inherently diminish service quality and impose substantial economic penalties due to supply interruptions [19,20]. Furthermore, while distributed generation (DG) and demand-side management provide modern pathways for grid efficiency, their efficacy remains contingent upon high-precision forecasting and sophisticated control architectures to avoid exacerbating system instability [21].

To circumvent these barriers, battery energy storage systems (BESSs) have emerged as a pivotal non-wire alternative capable of providing short-duration support, voltage regulation, transient stability, and capital deferral [22–24]. Innovative utility applications, such as virtual transmission lines and grid booster (GB) systems, have successfully demonstrated localized congestion relief, thermal overload mitigation, and post-contingency scheduling capabilities globally [25–28]. However, maximizing these multi-faceted benefits requires solving a complex engineering challenge: the simultaneous optimization of BESS placement and sizing. This is a factor that is crucial for justifying high capital investment, and it is often undervalued or overlooked in existing transmission frameworks [29].

Over the last decade, an increasing number of publications in the literature have explored metaheuristic techniques to determine BESS allocation for emergency management and frequency stabilization [30]. Various computational tools, including particle swarm optimization (PSO), genetic algorithms (GAs), and mixed-integer architectures, have been utilized to pinpoint optimal locations for congestion relief and oscillation damping [31–34]. Advanced methodologies, such as DC optimal power flow (DC-OPF), fitness-scaled chaotic artificial bee colony (FSCABC) algorithms, and probabilistic non-linear models, have further been implemented to manage storage portfolios and maximize energy arbitrage revenue [35–40]. Despite these significant advancements, two critical research gaps remain. First, while BESS allocation has been studied in various international contexts, the specific operational complexities and N-1 contingency requirements of the Thai transmission network remain largely unexplored. Second, the existing literature relies heavily on traditional metaheuristics, which often struggle with premature convergence or computational inefficiency when navigating the highly non-linear, multi-constrained search space of large-scale bulk transmission networks. There is a clear need for more robust, bio-inspired optimiza-

tion techniques that offer superior search capabilities and convergence stability for this specific challenge.

As the primary entity responsible for nationwide bulk power transmission in Thailand, the Electricity Generating Authority of Thailand (EGAT) prioritizes a robust infrastructure adhering strictly to the N-1 contingency criterion. However, this safety margin is increasingly compromised by an unprecedented rise in Thailand's peak electricity consumption [41]. A single circuit failure during peak hours carries a severe risk of overloading adjacent lines and inducing critical voltage drops, yet conventional line construction is heavily impeded by protracted land acquisition negotiations and geographical terrain complexities. Consequently, BESS units have emerged as a strategically viable alternative to mitigate these transmission bottlenecks without requiring extensive new ROWs. Nonetheless, the substantial capital expenditure required for utility-scale BESS deployment mandates a highly precise allocation strategy to ensure economic feasibility.

To address these gaps, this study introduces the musk ox optimizer (MOO), a recently developed, high-performance, bio-inspired algorithm originally proposed by Sadollah et al. [42] to determine the optimal placement and sizing of BESSs within the EGAT transmission network. The MOO mathematically replicates the defensive herd organization, foraging behaviors, and migratory patterns of Arctic musk oxen. Since its inception, the algorithm has been successfully applied to various complex, non-linear engineering optimization problems, including structural design optimization, mechanical component sizing, and constraint-handling benchmarks, where it has consistently demonstrated superior global exploration and local exploitation capabilities. This high efficiency is primarily driven by its structured herd organization and adaptive position-tracking controllers, which dynamically regulate search steps. This unique mathematical architecture makes the MOO exceptionally suited for navigating the highly rugged fitness landscapes inherent to bulk transmission system constraint management, where traditional metaheuristics frequently suffer from premature convergence or slow execution trajectories. By leveraging the unique search mechanisms of the MOO, this work provides a robust and efficient solution for mitigating N-1 contingency constraints. A mind map to present the framework structure of this article is shown in Figure 1.

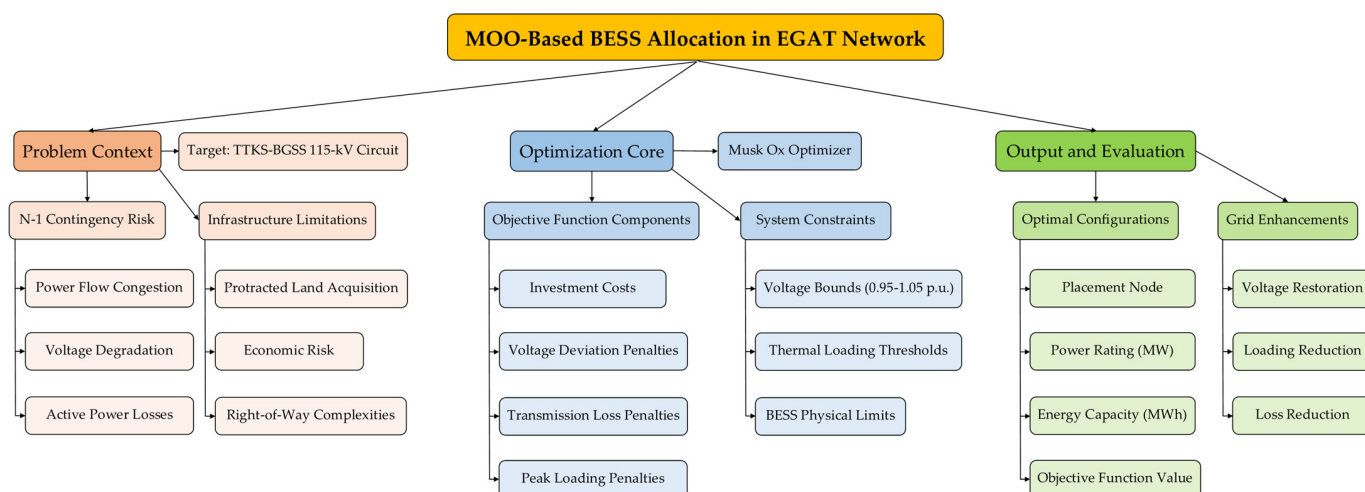


Figure 1. Mind map to present the framework structure of this work.

The primary contributions of this research are summarized as follows:

- (1) A robust allocation framework is proposed for the strategic placement and sizing of a BESS within the EGAT network to address N-1 contingency vulnerabilities on the 115 kV Thatako Substation (TTKS)–Bueng Sam Phan Substation (BGSS) transmission line in Thailand, addressing a unique network architecture that has not been investigated in prior storage literature.
- (2) The MOO is implemented for the first time to solve the high-dimensional, non-linear BESS allocation and capacity problem, demonstrating robust numerical convergence and stable tracking capabilities when navigating the complex constraints of a utility-scale transmission system.
- (3) The proposed methodology formulates a comprehensive objective function designed to minimize cumulative system expenditures, including the harmonization of BESS capital investment and operational costs with penalties for voltage deviations, transmission losses, and line congestion violations.
- (4) Through pre- and post-deployment grid analysis, this work demonstrates significant improvements in the technical performance of the EGAT network. Specifically, the MOO-based approach is shown to successfully mitigate line congestion, stabilize substation voltage profiles, and reduce total active power losses, thereby offering a technologically highly capable and viable alternative to conventional grid reinforcement.

The remainder of this paper is organized as follows: Section 2 establishes the mathematical modeling of the BESS, followed by the comprehensive problem formulation detailed in Section 3. The theoretical framework and operational principles of the MOO are introduced in Section 4. Section 5 delineates the system efficiency evaluation criteria and the procedural implementation of the proposed methodology. In Section 6, the simulation results are presented and discussed in detail to validate the approach. Finally, Section 7 summarizes the core findings and provides concluding remarks.

2. Mathematical Modeling of the Energy Storage System

In this research, lithium-ion technology is selected for the BESS owing to its superior power density and high round-trip efficiency (typically 85–97% [43]), which makes it the most effective candidate for mitigating transmission-level bottlenecks [44]. To ensure the longevity of the storage units and prevent accelerated degradation, operational state of charge (SOC) boundaries are strictly maintained between 0.2 and 1 [30].

Unlike static power models, the BESS in this study is characterized as a dynamic, time-varying power source. Given the cyclic nature of daily demand and storage dispatch, the energy profile, $E_B(t)$, is decomposed into a series of sinusoidal components using a Fourier expansion [45–47]:

$$E_B(t) = a_0 + \sum_{n=1}^m \left[a_n \cos\left(\frac{2\pi n t}{T}\right) + b_n \sin\left(\frac{2\pi n t}{T}\right) \right] \quad (1)$$

where m represents the number of harmonic coefficients (fixed at eight for this study [48]), a_n and b_n are Fourier series coefficients that serve as the main decision variables within the optimizer's solution space to compactly represent the daily periodic profile of the battery, and T is the 24 h time horizon divided into discrete intervals. The power injected or absorbed by the BESS, $P_B(t)$, is derived from the energy variation between consecutive steps, ΔE_B , accounting for charging (η_c) and discharging (η_d) efficiencies as follows:

$$P_B(t) = \begin{cases} \frac{\Delta E_B}{\Delta t \times \eta_c}, & \Delta E_B > 0 \\ \frac{\Delta E_B \times \eta_d}{\Delta t}, & \Delta E_B < 0 \end{cases} \quad (2)$$

where $\eta_c = \eta_d = 0.95$, η_{bat} .

The final BESS capacity is determined by the maximum excursion between the peak and minimum energy states relative to the permissible depth of discharge (DOD), which is 0.8 in this work. These parameters serve as the primary decision variables optimized by the optimizer to satisfy grid requirements during an N-1 event.

3. Problem Formulation and Objective Function

The main objective of this work is to determine the optimal siting and capacity of a BESS unit to ensure the EGAT network remains within operational limits following the outage of a 115 kV circuit. This is framed as an optimization problem aimed at minimizing the cumulative system cost.

3.1. Objective Function

This work aims to minimize the total system cost function (C_{system}), which serves as the fitness value for the optimizer and is synthesized from capital investments and technical performance penalties using the following equations [46]:

$$f(C_{Fi}) = \min(C_{system}) \quad (3)$$

$$C_{system} = C_{Investment} + C_{performance} \quad (4)$$

The investment cost ($C_{Investment}$) represents the total lifecycle cost, including power and energy ratings, installation fees, and long-term maintenance expenditures of the BESS.

$$C_{Investment} = P_B \times \gamma_P + E_B \times \gamma_E + E_B \times \gamma_{Install} + P_B \times \gamma_{O\&M} \quad (5)$$

where γ_P , γ_E , $\gamma_{Install}$, and $\gamma_{O\&M}$ are the rates of battery power (320 \$/kW), battery energy (360 \$/kWh), battery installation (15 \$/kWh), and operation and maintenance (5 \$/kWh-year) [47,49].

The performance cost ($C_{performance}$) penalizes deviations in bus voltages (C_{VD}), active power losses (C_{loss}), and overloading of the remaining transmission line (C_{peak}), and it can be determined as follows:

$$C_{performance} = C_{VD} + C_{loss} + C_{peak} \quad (6)$$

$$C_{VD} = \left(\sum_{t=1}^T \sum_{i=1}^{N_{bus}} |V_i(t) - V_{ref}| \right) \times \gamma_{VD} \quad (7)$$

$$C_{loss} = \left(\sum_{t=1}^T \sum_{i=1}^{N_{br}} |P_{L,i}(t)| \right) \times \gamma_{loss} \quad (8)$$

$$C_{peak} = P_{max} \times \Delta t \times \gamma_{peak} \quad (9)$$

where γ_{VD} , γ_{loss} , and γ_{peak} are the rates of voltage deviation (0.142 \$/p.u.), active power loss (0.284 \$/kWh), and peak of line loading (200 \$/kWh-year), respectively [47,49]. $V_i(t)$, V_{ref} , N_{bus} , $P_{L,i}(t)$, N_{br} , and P_{max} are the bus voltage of bus i at time t , reference voltage (1 p.u.), number of buses, active power loss of bus i at time t , number of branches, and maximum power demand, respectively.

3.2. Operational Constraints

The optimizer explores the search space while adhering to the following strict grid and storage constraints:

$$V_{min} \leq V_i(t) \leq V_{max} \quad (10)$$

$$P_{Bmin} \leq P_B(t) \leq P_{Bmax} \quad (11)$$

$$E_{Bmin} \leq E_B(t) \leq E_{Bmax} \quad (12)$$

where the bus voltages must be maintained between 0.95 p.u. (V_{min}) and 1.05 p.u. (V_{max}), and the BESS must operate within its physical minimum and maximum power outputs (P_{Bmin} and P_{Bmax}) and minimum and maximum energy capacity ratings (E_{Bmin} and E_{Bmax}) at all times.

4. Musk Ox Optimizer (MOO)

To solve the complex optimization problem in this work, MOO is adopted. The MOO is a newly proposed meta-heuristic algorithm based on the biological behavior of musk ox populations [42]. It comprises three activities, including migrating, foraging, and defending. Among the population of musk ox, 80% are adult males and females, while the remainder are immature. To mathematically model the MOO calculation step for the optimization problem, the formulations of the behaviors are described below.

4.1. Alert and Safety Signals

Musk oxen possess a high degree of sensitivity to environmental threats. When danger is detected, sentinels broadcast “alert signals” to prompt the herd to initiate defensive measures. Within the MOO, “alert signals” and “safety signals” are defined as follows:

$$Alert_signal = 2 \times \alpha_1 \times (1 - r_1) \quad (13)$$

$$\alpha_1 = 1 - t/T \quad (14)$$

$$Safety_signal = r_2 \quad (15)$$

where t and T are the current and maximum iteration number, respectively, and r ($r_1, r_2, r_3, r_4, r_5, r_6$) is a uniformly randomly generated number between 0 and 1.

4.2. Migration

For migration behavior, which is the exploration phase, musk ox populations relocate to secure environments when environmental threat levels exceed a critical threshold. The following equation presents a mathematical framework representing these migratory dynamics.

$$X^{t+1} = X^t + S \quad (16)$$

where X^{t+1} is the updated position, X^t is the current position of musk oxen, and S is the movement step length of the musk oxen calculated with the equation below:

$$S = \alpha_2^2 \times r_3^4 \times \pi(X_a^{-t} - X_b^{-t}) \quad (17)$$

$$\alpha_2 = 1 - \frac{1}{1 + \exp\left(\frac{(T/2) - t}{T} \times 10\right)} \quad (18)$$

where X_a^t and X_b^t are the positions of two guards that are randomly generated, and α_2 is the step influence factor.

4.3. Roosting Behavior

In the roosting phase, which is the exploitation phase, musk oxen initiate roosting when external risk factors are negligible. Depending on the current margin of safety, the population adopts one of two states: foraging or defense. Within this phase, all members of the group, including adult males, females, and juveniles, reorganize their locations and interact socially.

For foraging behavior, when the margin of safety exceeds a critical threshold, the population shifts to a foraging state to replenish energy reserves. During this phase, individuals coordinate their movement and feeding activities relative to the spatial distribution of the herd. This collective behavior enables the group to efficiently identify and occupy habitats that optimize its survival. In this situation, the musk ox position can be updated using the following equations:

$$X^{t+1} = X^t + \Delta x_1 \quad (19)$$

$$\Delta x_1 = rand \times (X_{best}^t - X^t) + r_4^3 \times W_i \times (X^t - X_{best}^t) \quad (20)$$

$$W_i = G_1 \times \frac{1}{\exp\left(\frac{\beta \times t}{T}\right)} \quad (21)$$

where X_{best}^t is the best musk ox position obtained so far, *rand* is the randomly generated number between 0 and 1, W_i is the step influence factor, and G_1 and B are constant numbers, which are 0.001 and 0.01, respectively.

For defensive behavior, musk oxen frequently inhabit ecosystems shared with apex predators such as polar bears and Arctic wolves. Upon the detection of a threat, the herd exhibits an innate defensive aggregation behavior. Coordinated by acoustic signaling, the group assumes a defensive circular formation, utilizing their cranial horns as the primary mechanism for repulsion. This structure is dynamic; if an individual is incapacitated during a predation event, the remaining herd members immediately reorganize to close the gap, thereby maintaining the integrity of the defensive perimeter. In this situation, the position of male musk oxen is updated as follows:

$$X^{t+1} = X^t + \Delta x_2 \quad (22)$$

$$\Delta x_2 = r_5^2 \times (X_{second}^t - X_{best}^t) + r_5 \times M_i \times (X_{best}^t - X_{worst}^t) \quad (23)$$

$$M_i = G_2 \times \frac{1}{\exp\left(\frac{\beta \times t}{T}\right)} \quad (24)$$

where X_{second}^t is the second-best position of the musk oxen obtained so far, X_{worst}^t is the worst position of the musk oxen obtained so far, M_i is the factor for controlling the step, and G_2 is a constant number which is equal to 100. For the female and juvenile musk oxen, the positions can be updated by the following equations:

$$X^{t+1} = r_6 \times (X_{best}^t - X^t) \times LF \quad (25)$$

where LF is the Levy flight function for a random walk, which is determined using the equation given below:

$$Levy(a) = 0.05 \times \frac{x}{|y|^{\frac{1}{a}}} \quad (26)$$

where $x \sim N(0, \sigma_x^2)$, $y \sim N(0, \sigma_y^2)$, a is a constant value which is equal to 1.5, and σ_x can be found by using the equation below:

$$\sigma_x = \left[\frac{\Gamma(1 + \alpha) \sin\left(\frac{\pi\alpha}{2}\right)}{\Gamma\left(\frac{1+\alpha}{2}\right) \alpha \times 2^{\frac{(\alpha-1)}{2}}}\right]^{\frac{1}{\alpha}}, \sigma_y = 1 \quad (27)$$

where σ_x^2 and σ_y^2 are the standard deviations, and $\Gamma(x) = (x + 1)!$.

5. System Efficiency Evaluation

To quantify the impact of BESS integration on the 115 kV Thai transmission network, a multi-dimensional evaluation framework is established. This section details the technical indices used to assess grid performance and the procedural workflow of the MOO in solving the allocation problem.

5.1. Performance Evaluation Indices

The efficiency of the optimized BESS configuration is evaluated using three primary technical metrics:

5.1.1. Voltage Deviation Index (VDI)

The voltage deviation index (VDI) measures the cumulative deviation of bus voltages from the nominal value (1.0 p.u.) across all buses in the system. A lower VDI indicates superior voltage stability and power quality. It is calculated as follows:

$$\%VDI_i = \sum_{i=1}^{N_{bus}} \frac{|V_{ref} - V_i|}{V_{ref}} \times 100 \quad (28)$$

5.1.2. Total Transmission Loss Reduction

This index quantifies the effectiveness of BESSs in minimizing active power dissipation within the 115 kV lines. By strategically injecting power during the TTKS–BGSS outage, the BESS rebalances line flows to reduce total I^2R losses.

5.1.3. Maximum Line Power Flow (Congestion Management)

This metric tracks the peak loading on the remaining transmission circuits during the N-1 contingency. The goal is to ensure that no single circuit exceeds its thermal rating, thereby avoiding cascading failures.

5.2. Implementation

The execution of this study centers on the strategic allocation and capacity optimization of the BESS within the EGAT transmission infrastructure, leveraged by the computational capabilities of the MOO. To assess the efficacy of the proposed solution, a comparative analysis is performed across two operational frameworks, including a baseline scenario representing the grid under N-1 contingency without storage intervention, and an optimized configuration featuring BESS integration. The systematic workflow and decision-making logic of this MOO-based approach are illustrated in the procedural flowchart depicted in Figure 2.

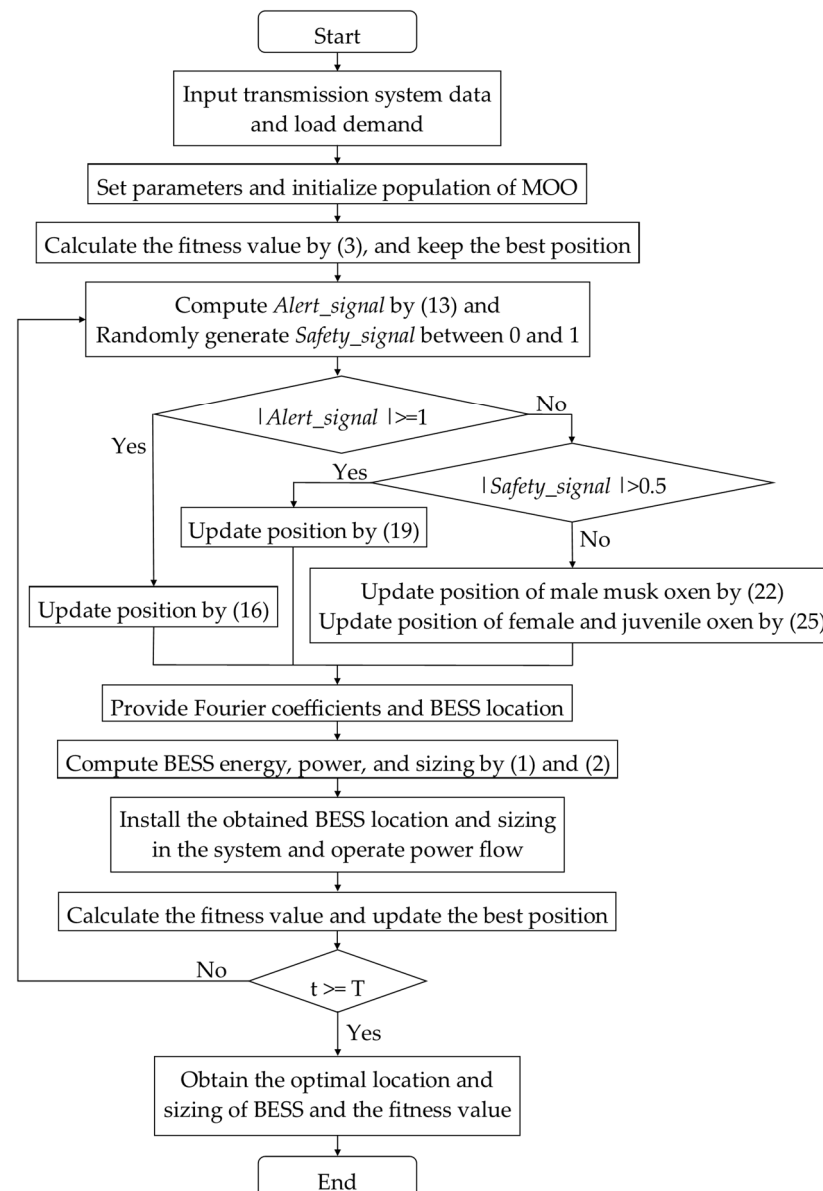


Figure 2. Implementation of the proposed musk ox optimizer (MOO)–battery energy storage system (BESS) framework.

6. Simulation Results and Discussions

This section evaluates the proposed framework across two subsections. It first establishes the baseline environment, outlining the network architecture and grid behavior under normal and uncompensated N-1 contingency conditions. Subsequently, it details the optimal BESS allocation achieved via the MOO and provides a critical analysis of the resulting system performance enhancements.

6.1. System Description and Baseline Operational Characteristics

Within the EGAT transmission framework, the BGSS is situated in Phetchabun Province within Thailand’s northern territory, whereas the TTKS is found in the central province of Nakhon Sawan. These two substations are interconnected via a double-circuit 115 kV tie-line, designated as TTKS–BGSS #1 and #2. Spanning a physical length of 66.68 km, these circuits utilize 477 thousand circular mils (MCM) aluminum conductor steel-reinforced (ACSR) conductors to transfer bulk power from the TTKS to BGSS. The BGSS is an end substation operating at two voltage levels, 22 kV and 115 kV, interconnected

with the Provincial Electricity Authority (PEA) system to supply electricity to end users. The substation is linked to the PEA network via three feeders consisting of two 22 kV circuits and one 115 kV circuit. The structural topology of this network under unperturbed, normal operating states is illustrated by the single-line diagram in Figure 3.

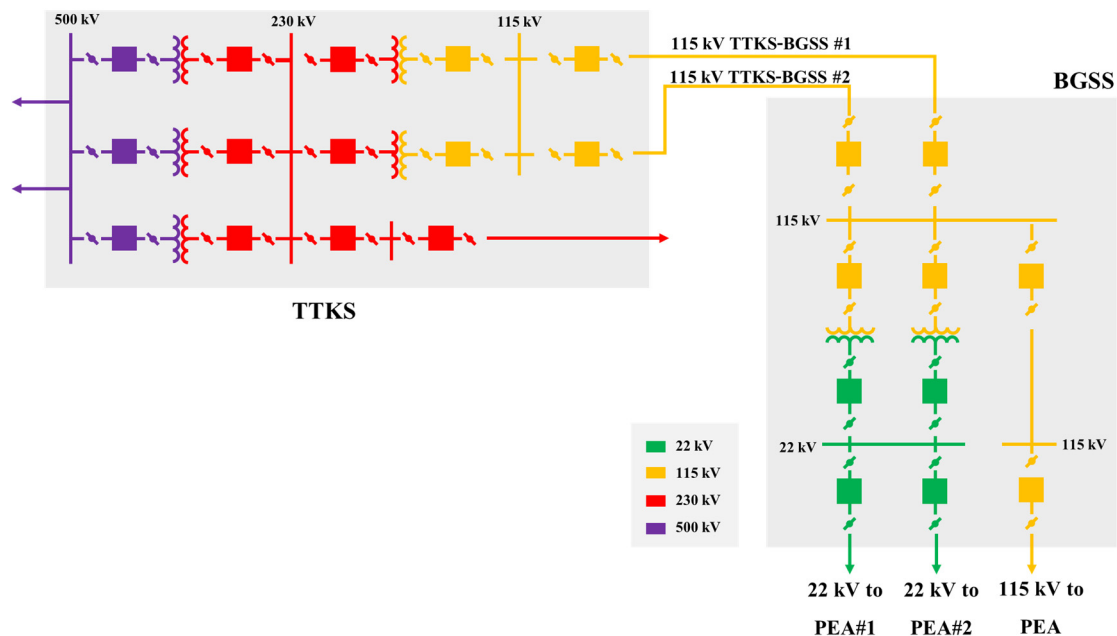


Figure 3. Single-line diagram between Thatako Substation (TTKS) and Bueng Sam Phan Substation (BGSS).

To evaluate system performance under critical loading, the load profiles are modeled based on historical data from April 2025, which was a peak summer period characterized by maximum seasonal electricity consumption. As detailed in Table 1, the daily demand profile at the BGSS is decomposed into three distinct components, including load drawn through the dual 22 kV feeders, demand from the 115 kV feeder, and the cumulative system demand. The network experiences its peak total demand of 102.3 MW during the 22nd hour (corresponding to 9:00 p.m.).

To evaluate the grid's vulnerability, a comparative analysis between standard steady-state operation and an uncompensated N-1 contingency event is performed. Figure 4 depicts the 24 h voltage profile at the BGSS 115 kV bus, Figure 5 illustrates the transmission line loading (which naturally mirrors the daily load cycle), and the allocation of active power losses between the parallel circuits is presented in Figure 6. As shown in these figures, under unperturbed operating states, the bus voltage remains stable, comfortably within the standard bounds, the transmission line loading hovers safely below 43% when both circuits share the network demand, and the total peak loss of 3.01 MW at hour 22 is shared between the two lines, with Line 1 and Line 2 dissipating 1.78 MW and 1.23 MW, respectively. However, when an N-1 outage strikes the BGSS–TTKS circuit at hour 22, the voltage experiences a severe drop, plunging down to 0.87 p.u. as expressed in Figure 4. This drop violates the permissible operational lower limit of 0.95 p.u., underscoring an acute localized voltage instability and directly correlating with circuit thermal limitations. Moreover, the forced outage of one circuit forces the entire bulk power flow onto the sole remaining 115 kV line; consequently, the line loading experiences a sharp surge, peaking exactly at 100.44% of its rated thermal capacity as shown in Figure 5. This severe bottleneck creates localized congestion that threatens grid security and significantly impacts the active power dissipation across the network. In addition, the power dissipation of the outage

line (Line 2) drops to zero, forcing the other line (Line 1) to carry the entire network load. Due to the non-linear relationship between current and power loss (I^2R), the active loss on Line 1 spikes violently to 9.74 MW as presented in Figure 6, exposing the remaining circuit to severe thermal stress.

These uncompensated baseline results highlight the urgent need for strategic energy storage placement to mitigate contingencies and restore system security parameters.

Table 1. Daily load profile at BGSS on a peak day in April 2025 (hours 1–24 represent hour-ending intervals).

Time (h)	Load Demand (MW)			
	22 kV Line 1	22 kV Line 2	115 kV	Total
1	18.5	12.3	52.9	83.7
2	17.2	11.5	49.1	77.8
3	15.6	10.8	45.4	71.8
4	15.9	10.1	41.5	67.5
5	15.8	9.8	39.0	64.6
6	15.6	10.2	41.4	67.2
7	15.9	11.2	44.0	71.1
8	13.7	9.7	36.0	59.4
9	10.4	8.6	33.0	52.0
10	8.7	8.5	30.7	47.9
11	7.5	8.1	31.7	47.3
12	8.2	8.7	28.0	44.9
13	8.0	8.6	29.0	45.6
14	9.0	9.0	34.2	52.2
15	10.3	9.7	46.2	66.2
16	12.3	10.1	41.4	63.8
17	13.9	10.0	44.7	68.6
18	13.3	9.6	46.0	68.9
19	14.9	10.1	47.3	72.3
20	18.2	12.8	59.2	90.2
21	20.5	14.1	66.6	101.2
22	20.8	14.2	67.3	102.3
23	20.0	13.7	64.2	97.9
24	19.2	13.9	62.5	95.6

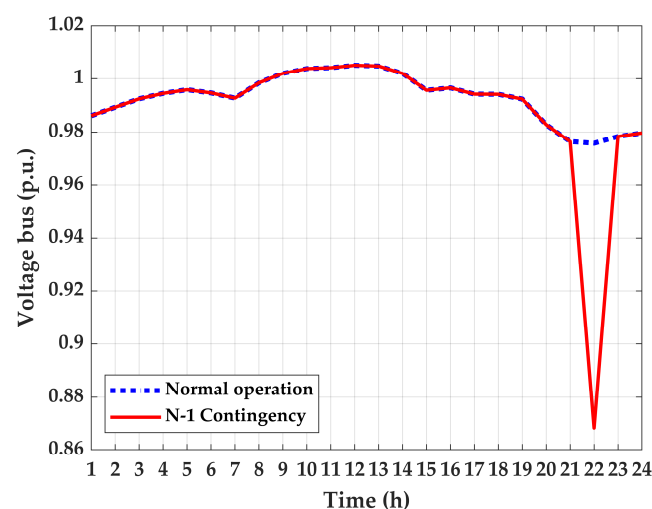


Figure 4. Voltage profile at the BGSS 115 kV bus under normal and N-1 contingency states.

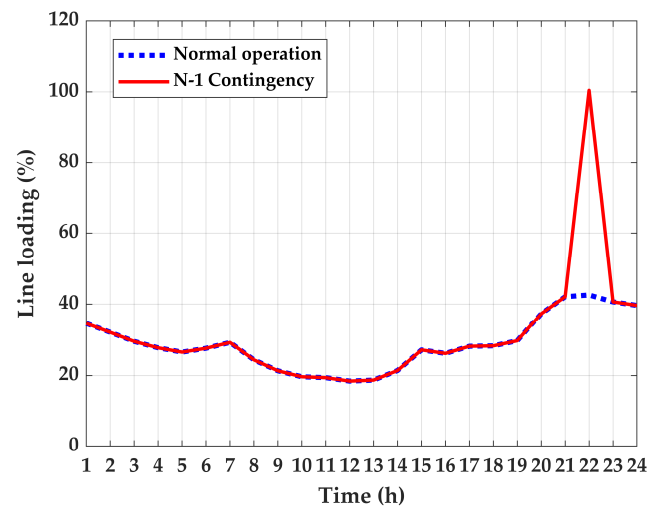


Figure 5. Transmission line loading percentage during peak and off-peak intervals under normal and N-1 contingency states.

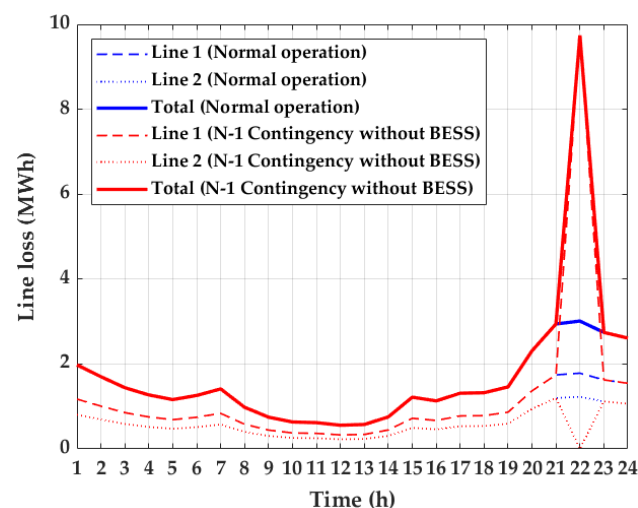


Figure 6. Individual and total active power loss breakdown for the 115 kV transmission lines under normal and N-1 contingency states.

6.2. Optimal BESS Allocation and Post-Contingency Grid Performance Analysis

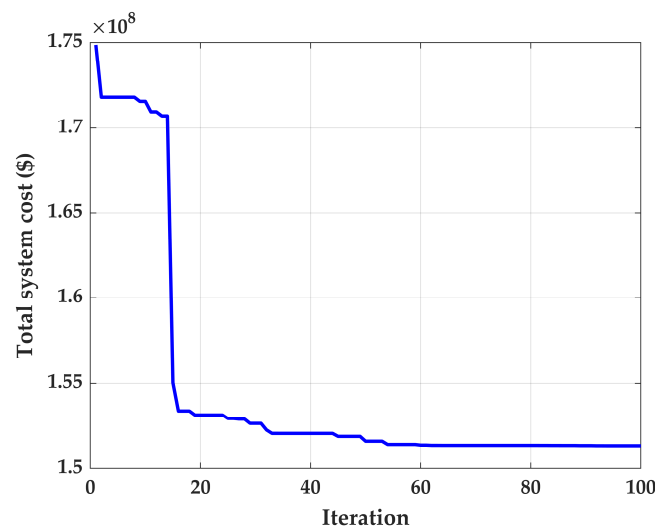
This subsection details the best feasible sizing and placement parameters for the BESS deployment within the EGAT grid, resolved via the MOO under the critical hour-22 peak N-1 contingency of the TTKS–BGSS circuit. The optimization model concurrently targets the minimization of cumulative capital and operational expenditures while enforcing strict grid compliance envelopes. Specifically, the framework restricts the post-fault BGSS bus voltage tightly within the standard 0.95–1.05 p.u. boundary and limits the emergency thermal loading of the remaining transmission line to a maximum threshold of 120% of its nominal capacity. To execute this computational framework, the core meta-heuristic logic of the MOO is scripted within the MATLAB 2024a, which dynamically interfaces with DIgSILENT PowerFactory to perform automated power flow simulations of the EGAT infrastructure.

The quantitative impact of the storage deployment is summarized in Table 2, contrasting the uncompensated network with the optimized MOO-BESS framework. Due to its radial topological position as the terminal substation, the BGSS is consistently selected as the mathematically best feasible installation site.

Table 2. Comparison results under the N-1 contingency condition before and after BESS installation.

Evaluated Parameter (Units)	Baseline Framework (N-1 Contingency Only)	Optimized Framework (With MOO-BESS Deployment)
Energy allocation (MWh)	-	312.16
Power capacity (MW)	-	47.96
Total system cost (million USD)	-	151.31
Minimum voltage bus (p.u.)	0.87	0.95
Voltage deviation index (%VDI)	13.17	5.00
Line loading at peak hour (%)	100.44	49.69
Line loading at peak hour (MW)	102.34	54.35
Total daily line loss (MWh)	41.90	36.32

It can be observed from Table 2 that the optimizer allocates a BESS capacity of 312.16 MWh with a power rating of 47.96 MW, demanding a capital expenditure of 151.31 million USD. This strategic injection successfully remediates the critical under-voltage condition, raising the minimum bus voltage from an unacceptable 0.87 p.u. to a compliant 0.95 p.u. while simultaneously compressing the overall voltage deviation index (%VDI) from 13.17% down to 5.00%. Furthermore, circuit loading at the peak hour is effectively halved, dropping from a thermal overload of 100.44% (102.34 MW) to a highly secure 49.69% (54.35 MW). This relief of line congestion yields a concurrent reduction in daily active energy dissipation, lowering total network losses from 41.90 MWh to 36.32 MWh. The numerical trajectory demonstrating the minimization of these expenditures is illustrated by the MOO convergence characteristics in Figure 7, while the corresponding daily state of energy (SOE) dynamics of the storage unit are detailed in Figure 8.

**Figure 7.** Convergence curve of the MOO.

It is seen from Figure 7 that the MOO displays a brief exploration before exhibiting a sharp, steep decline in total system cost between iterations 14 and 16. This rapid reduction demonstrates the algorithm's strong exploitation capability in concentrating the search around optimal parameters. The curve stabilizes into a completely flat trajectory by iteration 60, successfully converging at the mathematically optimal configuration relative to the defined objective function system cost of 151.31 million USD without getting trapped in local optima.

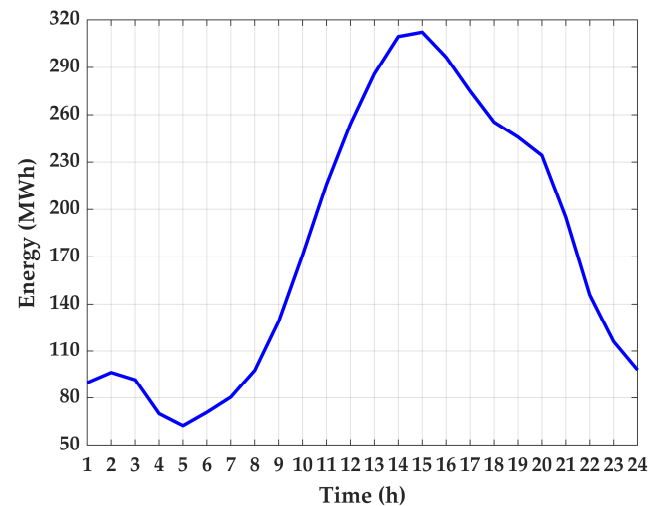


Figure 8. State of energy (SOE) of the optimized BESS.

From Figure 8, the BESS undergoes a minor early-morning discharge to a minimum of 62.4 MWh at hour 5, followed by a sustained charging phase during off-peak daytime hours to reach its peak capacity of 312.16 MWh at hour 15. Afterward, the system executes a controlled, strategic discharge ramp to inject power into the EGAT network during the high-demand evening window. By hour 22, the BESS has dynamically adjusted its output to safely mitigate the N-1 contingency, restricting the parallel line loading to 49.69% and restoring the bus voltage to a compliant 0.95 p.u. The dynamic validation of the proposed optimization framework on the BGSS 115 kV bus voltage is illustrated in Figure 9.

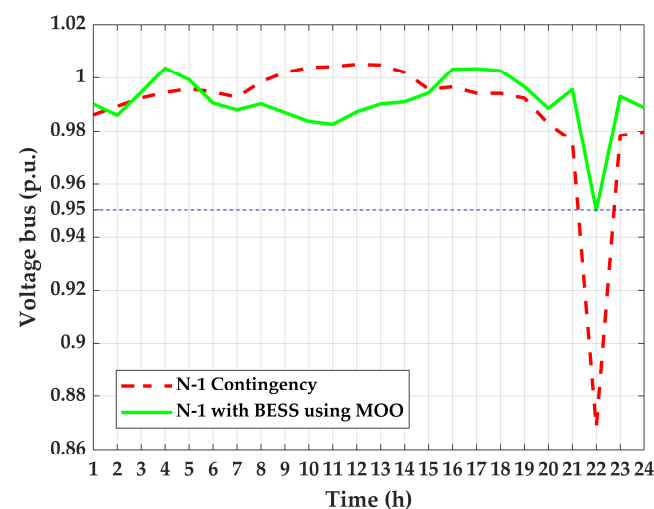


Figure 9. Daily voltage profile at the BGSS 115 kV bus under uncompensated and MOO-BESS optimized contingency states.

It is seen from Figure 9 that by integrating the BESS configuration derived by the MOO, the localized voltage profile is dramatically improved. During off-peak and peak intervals alike, the voltage trajectory is maintained comfortably above the lower operating limit. Most notably, at the exact moment of the hour-22 contingency, the targeted active power injection from the storage unit successfully clamps the voltage drop precisely at the 0.95 p.u. limit. This validation demonstrates that the MOO successfully minimizes battery capacity investments while guaranteeing strict adherence to grid voltage code requirements. The optimization framework's impact on thermal congestion management is illustrated in Figure 10.

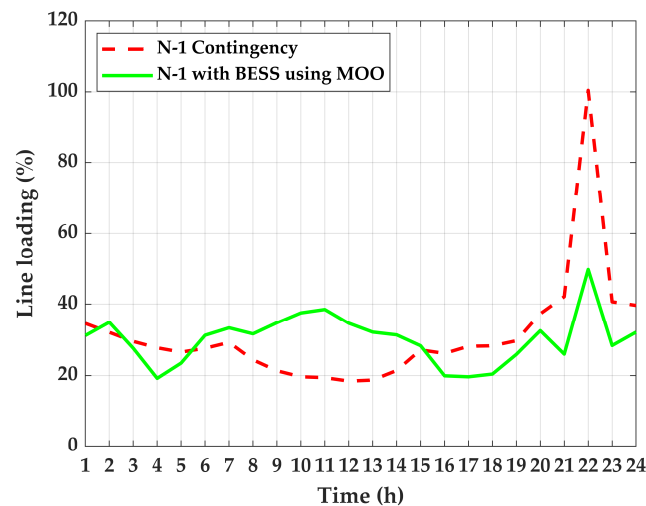


Figure 10. The percentage of line loading of the remaining line with respect to its rated capacity under uncompensated and MOO-BESS-optimized contingency states.

From Figure 10, in the unmitigated baseline scenario, the single-circuit contingency at the hour-22 peak forces the entire grid demand onto the sole remaining transmission line, driving its loading to a critical peak of 100.44%. This severe thermal stress presents an immediate bottleneck risk to grid operational safety. Integrating the BESS configuration optimized by the MOO successfully eliminates this transmission bottleneck. By strategically absorbing power during off-peak intervals and performing localized active power injection at hour 22, the storage system dramatically flattens the corridor's congestion profile. At the moment of the asset outage, the peak line loading is safely restricted to just 49.69%. This massive thermal margin expansion validates the algorithm's capability to preserve system reliability and prevent emergency overloads under severe N-1 operational stress. Following this, the mitigation of transmission network active power losses achieved via the optimized energy storage framework is illustrated in Figure 11.

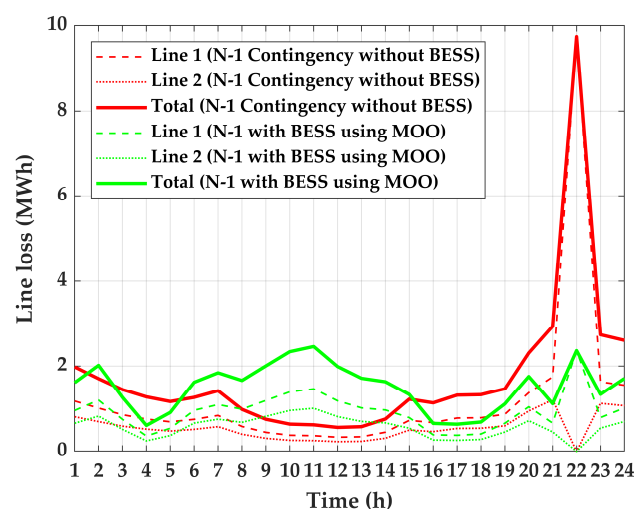


Figure 11. Comparative daily active power loss profiles per circuit under uncompensated and optimized contingency states.

It is noticeable from Figure 11 that by incorporating the BESS parameters resolved by the MOO, the severe localized thermal stress observed during the N-1 contingency is successfully neutralized. At the 22nd hour, the proactive power injection from the terminal BESS unit drastically reduces the net power flow demanded across the corridor, successfully compressing the peak active losses on Line 1 from 9.74 MW down to just

2.37 MW. Conversely, during the off-peak afternoon interval (hours 9–14), the integration of the BESS introduces a minor, symmetric increase in active losses across both operating circuits. This behavior reflects that the algorithm intentionally utilizes available off-peak circuit capacity to charge the storage unit. This slight operational loss trade-off during the day is heavily offset by the substantial peak-hour loss reduction, demonstrating how the proposed framework systematically coordinates global system efficiency under the defined objective criteria while shielding the remaining circuit from catastrophic thermal degradation. The total active power transmission trajectory through the combined circuits is monitored in Figure 12 to evaluate how the MOO-BESS configuration alters bulk power flow dynamics.

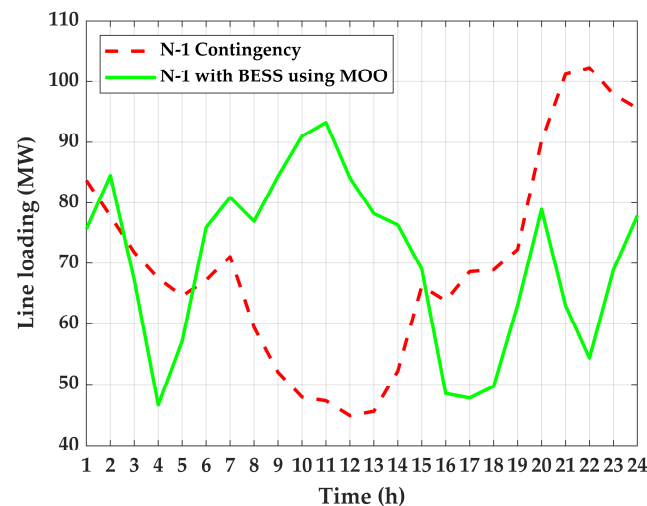


Figure 12. Daily total active power transmission profile across the monitored corridor under uncompensated and optimized contingency states.

Under the unmitigated baseline N-1 contingency, the active power routed through the corridor peaks at 102.34 MW during the 22nd hour. Because Line 2 is completely out of service at this specific moment, this total network load is entirely isolated onto the sole remaining transmission line (Line 1), creating a hazardous grid bottleneck. The application of the MOO-optimized storage system completely reshapes this transmission profile through strategic peak shaving and valley filling. During the off-peak afternoon period (hours 9–14), the total power transmitted through the corridor intentionally rises above the baseline to feed the storage charging cycle at the BGSS terminal node. Crucially, when the circuit outage strikes at hour 22, the local BESS shifts instantly into a major discharge phase, injecting localized power directly into the substation. This rapid generation injection unburdens the grid, dropping the total active power flow required from the incoming transmission branch from 102.34 MW down to a secure 54.35 MW. This drastic peak-flow reduction validates the algorithm’s capability to prevent line overload conditions by substituting centralized transmission delivery with localized bulk storage support.

In summary, the simulation outcomes validate the strategic deployment of a BESS as a structurally compliant and robust countermeasure against severe N-1 contingency events within the EGAT network. By optimizing the storage configuration, critical grid parameters, including bus voltage recovery, localized thermal bottlenecks, operational line losses, and global voltage deviation indices, are successfully maintained within secure operating limits during maximum load periods. Consequently, utility-scale storage presents a practical and viable engineering solution for grid reinforcement, particularly when ROW or environmental regulations restrict the construction of physical overhead lines. This

technical viability is further bolstered by the accelerating downward trend in battery capital costs.

Historically, expanding the physical transmission corridor has been the standard method to address localized N-1 vulnerabilities for EGAT. However, long-term infrastructure construction timelines expose the utility to immense financial risks and potential revenue deficits from unserved energy if a fault occurs before commissioning. Furthermore, severe unmitigated outages drastically degrade key performance metrics such as the System Average Interruption Frequency Index (SAIFI), the System Average Interruption Duration Index (SAIDI), and energy not supplied (ENS). Although the best feasible storage allocation profile resolved by the MOO algorithm requires a substantial capital layout of 151.31 million USD, this investment is strongly justified when evaluated through a grid-risk and asset-planning lens. Traditional transmission expansion projects in complex terrains frequently endure multi-year execution delays due to protracted ROW permitting and land acquisitions. The compounding financial liabilities associated with a catastrophic peak-load blackout during this interim, which are quantified via the exponential value of lost load (VOLL) across industrial sectors, frequently surpass the upfront cost of the storage system. Additionally, during non-contingency days, the asset actively recovers value through diurnal energy arbitrage and system frequency regulation. As a result, utility-scale BESS technology stands out as a rapidly deployable, flexible asset that effectively bridges infrastructure development gaps while elevating system-wide resilience and reliability.

6.3. Operational Scalability and Utility Implications

This study focuses its quantitative validation on the critical, peak-load N-1 outage of the 115 kV TTKS–BGSS circuit. However, the structural framework remains fully scalable to diverse operational topologies and multi-contingency events. The objective function resolves BESS capacity allocation through generalized boundary constraints, specifically targeting thermal limits, voltage thresholds, and active power losses. Consequently, utility operators can dynamically expand this model. To evaluate alternative network topologies or complex N-k contingency matrices, planning engineers only need to update the corresponding power flow admittance matrix (Y_{bus}) and load profile vectors within the objective fitness function. The underlying Fourier parameterization and optimization engine remain entirely unaltered.

7. Conclusions

This study has successfully developed and validated a robust, optimization-based non-wire alternative framework for the strategic placement and capacity sizing of a BESS to mitigate severe N-1 contingency vulnerabilities within the EGAT transmission network. The core novelty of this work lies in the successful utilization of a newly developed bio-inspired optimization mechanism (the MOO) with an authentic, high-voltage transmission model to solve this highly non-linear, multi-constrained allocation problem with severe post-contingency thermal and voltage bottlenecks. The framework bypassed traditional infrastructure expansion barriers such as multi-year project lifecycles, high capital outlays, and intensive ROW constraints. The methodology formulated a comprehensive cost function that harmonized storage investment expenses with grid performance penalty indices to guarantee system compliance under critical loading conditions. The application of the proposed framework to the 115 kV TTKS–BGSS circuit outage on a peak summer day yielded the following key technical insights and performance enhancements:

- (1) Optimal BESS allocation: The MOO algorithm converged stably to resolve the mathematically optimal BESS allocation profile of 312.16 MWh capacity and 47.96 MW power rating at the terminal BGSS node relative to the defined objective function.

This configuration requires a global system cost investment of 151.31 million USD, which is justified by the complete elimination of post-fault grid code violations and thermal overloads, offering a low-environmental-impact alternative to land-intensive transmission expansion.

- (2) Voltage profile correction: The optimized battery dispatch successfully neutralized the critical post-fault voltage collapse, raising the minimum bus voltage from a hazardous baseline of 0.87 p.u. back to a strictly compliant lower threshold of 0.95 p.u., while compressing the global VDI from 13.17% down to 5.00%.
- (3) Thermal bottleneck elimination: During the hour-22 maximum peak load interval, localized active power injection from the storage unit unburdened the corridor, dramatically reducing the maximum loading on the sole remaining circuit from an uncompensated 100.44% overload down to a secure operating margin of 49.69% (54.35 MW).
- (4) Network efficiency optimization: The framework achieved a global reduction in daily active power dissipation across the monitored transmission corridor, shrinking total daily transmission line energy losses by 13.32% (from 41.90 MWh down to 36.32 MWh).

Economic risk valuation: Ultimately, these findings verify that utility-scale BESS deployment represents a highly viable, flexible, and rapidly deployable alternative for transmission constraint management. By substituting long-term centralized infrastructure projects with localized bulk storage support, power utilities are demonstrated to hedge against immense financial risks and revenue deficits during construction delays. While the required capital layout is substantial, it functions effectively as an immediate grid insurance policy; the compounding financial liabilities associated with an unmitigated peak-load blackout during protracted ROW permitting are quantified via the exponential VOLL frequently surpassing the upfront cost of the storage system. This proactive deployment successfully prevents the deterioration of critical utility reliability metrics, including SAIFI, SAIDI, and ENS, while enabling active daily value recovery through diurnal energy arbitrage and system frequency regulation during non-contingency hours.

Methodological universality and future work: It is worth noting that the mathematical framework presented in this study possesses a high degree of universality and can be readily generalized to other power networks or contingency scenarios. Because the objective function maps generalized investment costs (CAPEX) directly against fundamental AC power flow penalty constraints (bus voltages, thermal limits, and active losses), the core formulation remains problem-agnostic. The compact Fourier-based storage parameterization can ingest any arbitrary 24 h diurnal utility load profile. Consequently, the entire optimization framework can be applied to different transmission or distribution networks by substituting the corresponding network data (the bus admittance matrix and loading curves) while leaving the optimization core completely intact. To further refine the operational boundaries and define the scope of this current work, future extensions of this research will evaluate the framework under diverse network topologies, varying load conditions, and multi-contingency planning scenarios. Additionally, these future efforts will focus on conducting comprehensive comparative benchmarking against other state-of-the-art optimization methods under this identical framework, as well as exploring the multi-node co-planning of hybrid storage configurations incorporating renewable energy integration.

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