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RESEARCH ARTICLE

Optimizing Network Expansion and Battery Storage to Mitigate Cascading Outages via Detailed System Failures Simulations

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ABSTRACT Power networks have traditionally been designed to withstand credible outages, such as N-1 or N-2, often overlooking the complex interdependencies that can lead to cascading outages in modern systems. To address these evolving risks, planning models must adapt to better anticipate and mitigate cascading outages, while also guiding network expansion and the integration of advanced technologies. This paper presents a methodological framework for optimizing network expansion and battery storage investments to mitigate cascading outages. The framework uses an Optimization via Simulation (OvS) approach that incorporates detailed system failure simulations to assess the effectiveness of various network enhancements, including transmission lines, power transformers, reactive power compensation devices and battery storage units. In addition, a sampling process is used to select the number of trigger outage scenarios to be considered within the OvS approach. The effectiveness of the proposed framework is demonstrated on two test networks: a modified version of the IEEE 24-bus test network and the German transmission network. The main findings demonstrate: (a) that incorporating cascading outages into investment planning leads to different network enhancement decisions compared to conventional planning models (which exclude cascading outages), (b) that an optimal mix of network enhancements can significantly mitigate cascading outages, and (c) the computational scalability of the proposed framework.

INDEX TERMS Network expansion, battery storage, optimization via simulation, cascading outages, detailed failures simulations.

I. INTRODUCTION

A. MOTIVATION

The increasing complexity and interconnectivity of modern power systems have significantly increased their vulnerability to cascading failures, which can lead to large-scale blackouts with severe social and economic consequences [1]. Notable examples of these blackouts that occurred in the 21st century include the 2003 U.S.-Canada blackout, the 2012 Indian blackout, the 2016 South East Australian blackout, and the 2018 Brazilian blackout just to name a few [2], [3], [4], [5], [6], [7]. Despite the scale

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and impact of these outages, traditional network investment methodologies often fail to consider the cascading nature of such outages, focusing primarily on credible outages such as N-1 or N-2 contingencies.

Traditional network expansion planning is typically guided by reliability standards [8], i.e., the traditional N-1 criterion, which addresses credible failures. This approach tends to focus on network expansion and reinforcement measures, such as building new transmission lines, upgrading existing infrastructure, adding redundancy, and incorporating reactive power compensation devices to maintain voltage stability [9].

While these efforts can mitigate credible contingencies, they do not necessarily protect the system from the complex dynamics that can lead to cascading failures. In these situations, initial failures can propagate through interconnected systems, triggering widespread blackouts that are not adequately addressed by traditional planning models [10]. For example, key recommendations from major blackouts, such as those in India in 2012 and South Australia in 2016, highlight the need to improve system planning beyond the N-1 criterion [11]. There is also a need for enhancing network planning by building new lines, incorporating system protection schemes, and integrating advanced technologies. In particular, battery storage has emerged as a key technology due to its fast-response capabilities [3], [12], which allow better management of the variability of renewable energy and real-time balancing of the grid. This makes it a highly effective complement to traditional transmission infrastructure, reducing the need for costly expansions.

In this context, this paper presents a methodological framework for optimizing network expansion and battery storage investments in an integrated fashion, specifically aimed at mitigating cascading outages. The proposed framework uses an Optimization via Simulation (OvS) approach, which integrates detailed system failure simulations to evaluate the effectiveness of different network enhancements. The framework consists of three key modules: (1) the sampling module, which strategically selects the number of initial outage scenarios; (2) the optimization module, which identifies the most cost-effective network enhancements from a set of candidate options, including transmission lines, power transformers, reactive power compensation devices, and battery storage units; and (3) the simulation module, which evaluates the benefits of the selected investments by assessing their performance under the chosen outage scenarios. In addition, parallel computing can be used in the simulation module to evaluate multiple scenarios simultaneously, speeding up the process. This framework therefore enables the identification of cost-effective solutions by determining the optimal mix of network enhancements to mitigate cascading outages.

B. CONTRIBUTIONS

The main contributions of this paper are outlined as follows:

1) This work proposes a novel methodological framework for optimizing network expansion and battery storage investments using an OvS approach, which aims to effectively mitigate the risks posed by cascading outages in power systems.
2) The framework integrates a detailed system failure simulation model that captures dynamic phenomena, such as voltage and frequency protection mechanisms, and provides a comprehensive analysis of cascading outages and the effectiveness of network enhancements.
3) The framework strategically combines network expansion - including the addition of transmission assets - and the use of battery storage and reactive power compensation devices to identify the optimal mix of solutions to reduce the impact of cascading outages.

We evaluate the effectiveness of the proposed OvS framework by comparing its solutions with those obtained through various comparisons. Additionally, we demonstrate the importance of incorporating cascading outages into investment planning by contrasting our results with a conventional planning model that excludes cascading outages.

C. LIMITATIONS

While the proposed OvS framework provides a structured approach to mitigating cascading outages, it presents certain limitations. First, the sampling process assumes that trigger failures occur independently, which is a reasonable approximation for many practical purposes. However, we acknowledge that in some real-world scenarios, component failures may be correlated due to common external factors (e.g., extreme weather). Second, the accuracy of simulation results depends on the availability of detailed system data, including protection settings and control parameters, which may not always be accessible in practice. Third, the modeling of battery storage within this planning framework is simplified and does not explicitly capture aspects such as degradation or operational dynamics. These limitations define the current scope of the methodology and suggest directions for future improvements.

D. PAPER STRUCTURE

The remainder of the paper is organized as follows. Section II reviews the relevant literature. Section III presents the proposed methodological framework, detailing the OvS approach to identify the optimal portfolio of network enhancements. Sections IV presents the case studies, their results, and the discussions. Section V concludes.

II. LITERATURE REVIEW

The mitigation of cascading outages in power systems remains a significant challenge due to the large scale and increasing complexity of interconnected networks [13], [14], [15]. Numerous studies and models have been developed to analyze these outages, with comprehensive reviews provided in [16], [17], and [18]. These works emphasize the critical need to incorporate cascading failure risks into both operational and investment planning.

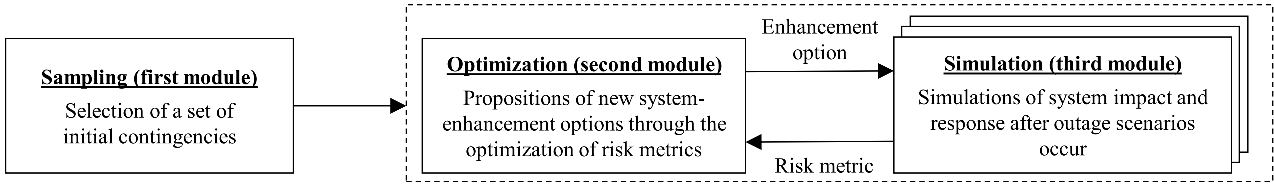

FIGURE 1. **The framework of the proposed OvS.**

Early network investment planning models predominantly used reliability standards, such as the N-1 criterion [8], [19], [20], [21]. With the development of computational capabilities, more sophisticated models have emerged that allow the simultaneous consideration of multiple failures (i.e., N-k contingencies) [22], [23], [24], [25]. While these approaches improve the understanding of blackout risks, they still fall short of addressing the cascading nature of failures.

Recent studies have made progress in addressing cascading outage risks in network investment planning [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40]. These works use various optimization models and simulation tools to provide insights into the mitigation of cascading outages. For example, probabilistic optimization models [31], [35], [37], [38], [39] evaluate investments by assessing the probability and impact of cascading failures in different system configurations. Risk-based optimization frameworks [26], [29], [36] focus on high-impact, low-probability events using metrics such as Conditional Value-at-Risk (CVaR). Multi-stage and adaptive optimization models [28], [32], [34] have been explored to sequentially optimize network investments while adapting to changing network conditions. These approaches add flexibility in responding to cascading outages as risks evolve. In addition, hybrid and heuristic optimization models [30] have been introduced to improve computational efficiency for large-scale systems. Simulation-based optimization models have been used to simulate cascading risks and guide network investment decisions [27], [33], [40], integrating cascading failure simulations directly into the optimization process.

In terms of strategies, several studies focus on the traditional expansion of the transmission network, advocating for the construction of new transmission lines, substations, and transformers to strengthen the resilience of the network and prevent cascading failures [26], [31], [32], [34], [37], [38], [40]. Others [27], [29], [33], [36] emphasize reinforcing existing infrastructure to better withstand specific risks, such as extreme weather or seismic events. Finally, advanced technologies are being integrated into network planning models to improve resilience. Studies such as [28], [30], [35] explore the integration of Energy Storage Systems (ESS), but assess their individual potential to provide greater operational flexibility and responsiveness to cascading risks.

While significant progress has been made in addressing cascading outages through various models and approaches, there remains a need for further integration of detailed failure simulations and advanced technologies, such as battery storage and reactive power compensation, into network investment models. Approaches that combine network expansion with these advanced solutions, while efficiently handling cascading risks and balancing investment strategies, remain underexplored in the current literature. Our work contributes to this gap by presenting a comprehensive framework that not only integrates network expansion and battery storage but also uses detailed system failure simulations to capture dynamic phenomena, such as voltage and frequency protection mechanisms. This provides a more realistic representation of cascading outages and complements previous research by exploring computational challenges through a scalable optimization methodology applicable to large-scale networks. This framework allows for the exploration of different combinations of enhancements, providing valuable insights into effective strategies for reducing the risk of cascading failures while managing investment trade-offs.

III. PROPOSED FRAMEWORK

This section presents a methodological framework designed to optimize investments in network expansion and battery storage to specifically mitigate cascading outages.

A. OVERVIEW

The proposed framework employs an OvS approach, that integrates detailed system failure simulations into the investment planning model. The framework operates through three interconnected modules (see Figure 1). First, the sampling module aims at the appropriate selection of a set of contingencies. These contingencies are then passed to the optimization module, which identifies the most cost-effective network enhancements from a set of candidate options, including transmission lines, power transformers, reactive power compensation devices, and battery storage units.

Since no analytical optimization function can fully capture the complexity of cascading outages, the optimization process relies on the simulation module to evaluate the performance of the selected network investments. The outputs from the simulation, which reflect how the network behaves under various failure conditions, are used as input to the optimization model. This ensures that investment decisions are based on representative system behavior in response to cascading outages, which cannot be easily modeled using conventional mathematical techniques.

Additionally, parallel computing can be used in the simulation module to evaluate multiple scenarios simultaneously, speeding up the process. By iterating through these modules, the framework determines the optimal portfolio of network investments, ensuring that the final solution is both cost-effective and capable of mitigating the risks associated with cascading outages.

The description of each module is detailed below.

B. SAMPLING MODULE

This module aims to generate potential trigger scenarios for cascading outages, with a specific focus on N-k outages. Since cascading outages often involve the simultaneous failure of k elements, analyzing all possible combinations in a large-scale network would be computationally prohibitive. To address this challenge, the sampling module employs a sampling-based strategy that selects a representative subset of N-k outages [41], prioritizing those with the highest probability of initiating cascading outages. This sampling approach ensures that the most critical scenarios are captured while avoiding the computational burden of analyzing a full set of N-k outages. These selected outage scenarios are then used in the OvS approach to identify necessary network enhancements.

C. OPTIMIZATION MODULE

This module identifies the most effective network enhancements to mitigate cascading outages. Given the complexity of cascading failures, which cannot be expressed by an analytical function, this module relies on outputs from detailed system failure simulations. As a result, the objective function has an unknown structure, and the goal is to minimize the expected risk across various outage scenarios, formulated as follows:

$$\min_{\mathbf{x}\in\Theta} \ \mu(\mathbf{x}) = \mathbb{E}[F(\mathbf{x}, \xi)] \tag{1}$$

where $F(\mathbf{x}, \xi)$ is the simulation output for a given enhancement configuration $\mathbf{x}$ and scenario ξ. The set of possible enhancement decisions is defined by $\mathbf{x} \in \Theta$, where Θ represents the feasible solution space. The expectation $\mathbb{E}[F(\mathbf{x}, \xi)]$ is estimated through simulation, as the cascading behavior of the system cannot be captured analytically.

In this module, network enhancements are selected based on their effectiveness in reducing the severity of cascading failures, as measured by the Expected Load Not Served (ELNS). Prioritization is subject to a budget constraint, favoring enhancements that deliver the highest risk reduction per unit cost. Battery storage and reactive compensation devices are prioritized when they improve system flexibility, particularly by mitigating voltage or frequency instability. In addition, enhancements are strategically placed in network locations where cascading failures are more likely to originate or propagate.

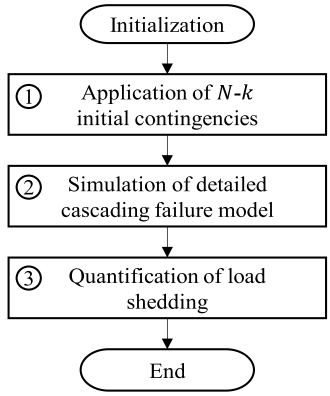

FIGURE 2. Flowchart of the simulation module.

The problem (1) is subject to a budget constraint, represented as:

$$\sum_{i\in Q} c_i \mathbf{x}_i \leq b, \tag{2}$$

where c_i represents the cost of each enhancement $\mathbf{x}_i$ and b is the total budget available. The optimization ensures that the allocated budget is directed toward the enhancements that most effectively minimize the risk of cascading outages.

The optimization procedure involves evaluating different portfolios of network enhancements through simulation experiments. The expected risk of each portfolio is estimated by averaging the results across the sampled outage scenarios, as follows:

$$\bar{F}(\mathbf{x}) = \frac{1}{\Omega}\sum_{j=1}^{\Omega} F(\mathbf{x}, \xi_j). \tag{3}$$

where Ω represents the number of simulation replications used to approximate the expected value of the objective function.

Since the problem (3) involves evaluating system performance through simulations, a genetic algorithm (GA) is used as part of the OvS approach. Genetic algorithms are well-suited to this type of optimization problem due to their ability to efficiently search large, complex solution spaces without requiring an explicit mathematical representation of the objective function [42]. This approach helps to identify (near) optimal solutions within reasonable computational times.

Due to the probabilistic nature of GA, the results may vary between runs. To ensure robustness, we use a two-step strategy to finally identify the best network enhancement solution [43]. First, a set of good candidate solutions is built by running the optimization process multiple times (e.g., 10 iterations). In the second step, a large number of evaluations/simulations are performed on each candidate solution to determine the best one.

D. SIMULATION MODULE

This module evaluates the impact of cascading outages by simulating the behavior of the power system under various

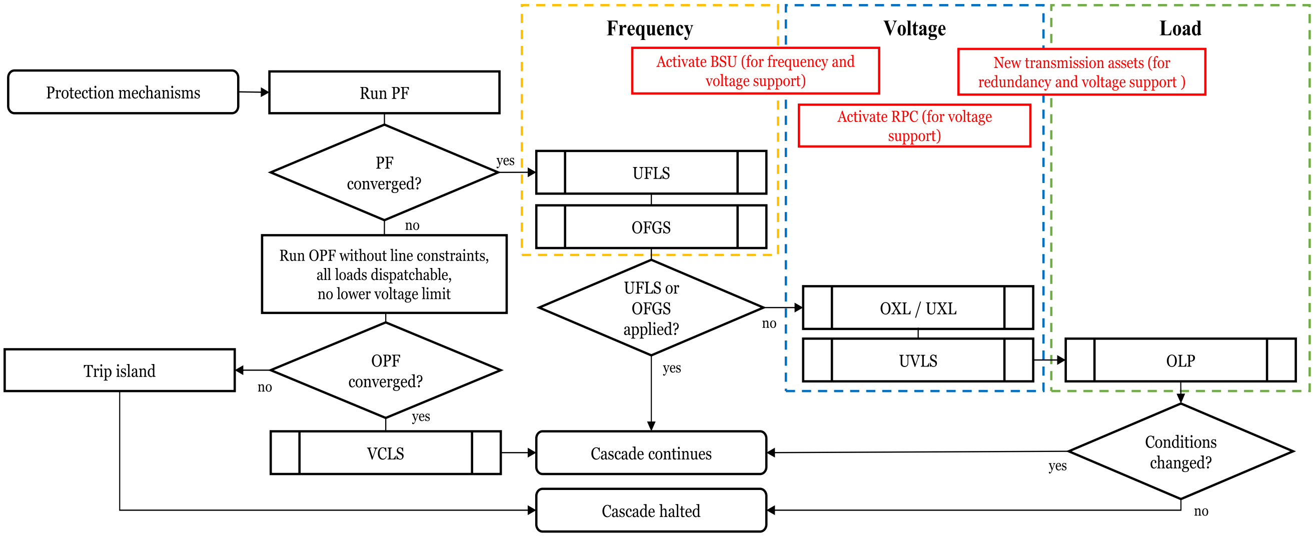

FIGURE 3. **Flowchart of detailed AC cascading failure simulation model with protection mechanisms and network enhancements highlighted in red. Adapted from [44].**

failure conditions. To do so, this module uses detailed system failure simulations to quantify load shedding and assess the effectiveness of the selected network enhancements.

Each simulation begins with a security-constrained AC optimal power flow (SC-ACOPF), which determines the initial operating conditions while ensuring N-1 security. This step takes into account the network configuration, the proposed enhancements, and all single outages. After this initialization, each triggering scenario is simulated in three sequential stages as shown in Figure 2.

1) APPLICATION OF N-K INITIAL CONTINGENCIES

Each of the N-k outages, from the previously defined set of scenarios, is applied to the test network with N components. k is the number of electrical components that fail. In this work, such contingency is particularly related to branch outages. However, generator outages can also be evaluated. These triggering outages serve as inputs for the subsequent analysis of cascade simulations.

2) SIMULATION OF DETAILED CASCADING FAILURE MODEL

Once the initial outages are applied, the cascading failure model simulates the sequence of dependent failures that follow. The model, based on a detailed AC power flow simulation [44], employs a recursive approach, analyzing cascading failures within each island individually. The simulation begins with an in-depth analysis of power flow in each island, applying protection mechanisms dynamically to prevent failures from escalating. These protection mechanisms include:

- *Under- and Overfrequency:* Protects the system from sudden imbalances between electrical and mechanical power, such as unintentional islanding. By employing Underfrequency Load Shedding (UFLS) or Overfrequency Generator Shedding (OFGS), the system restores the balance between mechanical and electrical power, ensuring frequency remains within acceptable limits.
- *Over- and Underexcitation:* Prevents damage to generators caused by fluctuations in reactive power demand. Using Overexcitation Limiters (OXL) and Underexcitation Limiters (UXL), the model constrains the generator's field current, adjusting terminal voltage.
- *Undervoltage:* Mitigates voltage drops caused by inadequate reactive power flow, preventing voltages from falling below safe limits. Undervoltage Load Shedding (UVLS) is applied to gradually reduce demand until voltage levels are restored to within acceptable limits.
- *Overload:* Ensures safe operation of transmission lines by tripping those that exceed their load rating. Overload Line Protection (OLP) is activated to prevent damage from overheating and stop the cascading failure from escalating.
- *Voltage Collapse Load Shedding (VCLS):* This mechanism is triggered when the AC power flow solver fails to converge, often due to voltage collapse. By converting all loads to dispatchable, the model uses an Optimal Power Flow (OPF) solver to identify the minimum amount of load shedding required to restore solvability and avoid voltage collapse.

When protection mechanisms are insufficient to stabilize the network, emergency protection measures are applied to prevent further destabilization of the grid:

- *Island Tripping (nOPF):* This is applied when the network reaches a point where it is beyond its physical capabilities. If non-convergence persists even after applying protection mechanisms like load shedding or

OPF, the entire island is disconnected to ensure the stability of the rest of the system. Island Tripping occurs when no feasible solution exists, even after reducing all loads to zero.

- *Tripped Load Shedding (TLS):* This occurs when buses or lines are disconnected due to other protections, such as OLP or generator tripping. It typically results from buses being part of an island with insufficient generation or from lines being tripped by overload protection, causing associated loads to be shed to maintain network balance.

Figure 3 illustrates the sequence of protection mechanisms in the detailed AC cascading failure simulation model with network enhancements highlighted in red. These enhancements include battery storage units (BSU), reactive power compensation (RPC) devices, new transmission lines, and power transformers, have been incorporated through extensions to the original model [44] and contribute to a more comprehensive analysis of cascading failures. BSU are modeled to inject or absorb active power and reactive power. These units are integrated into the cascading failure process by stabilizing frequency imbalances before load shedding or generator tripping occurs, supporting frequency-related protection mechanisms such as UFLS and OFGS. RPC devices are modeled to inject reactive power and are used to stabilize voltage levels during cascading failures, providing voltage support. These devices are incorporated into protection mechanisms to prevent undervoltage conditions. New transmission lines are modeled to redistribute power across the network, reducing stress on existing lines during cascading failures. These assets help prevent overloads and limit the cascading effect, supporting OLP by providing alternative routes for power flow. Power transformers are modeled with tap changers for voltage control and load balancing during cascading failures. Transformers can reduce the need for actions such as UVLS by maintaining system voltage and supporting power flows.

Furthermore, parallel computing can be used to accelerate the simulation by processing multiple scenarios simultaneously. This allows for a more efficient evaluation of the network response to cascading failures.

3) QUANTIFICATION OF LOAD SHEDDING

After the cascading failure simulation concludes, the total load shedding is quantified. The key metric used is the ELNS, which measures the average amount of energy not supplied due to cascading failures. This metric is derived from the probability-weighted average of load shedding across all contingencies, capturing both the likelihood and impact of each event. Additionally, the Conditional Value-at-Risk (CVaR) is computed to assess the expected impact of worst-case scenarios. These probabilistic metrics are critical for comparing the effectiveness of different network enhancements and identifying solutions that minimize the risk of severe outages [45].

IV. CASE STUDIES

The proposed framework is applied to two test networks: a modified version of the IEEE 24-bus test network and the German transmission network. These networks are used to validate and demonstrate the applicability of our framework to network investment planning problems considering cascading failures.

A. IEEE 24-BUS TEST NETWORK

We modified the IEEE 24-bus test network described in [3] by adding four additional lines connected in parallel to the original lines (6-10, 7-8, 14-16, and 15-24), totaling 42 existing branches. We also changed the installed generation capacity and peak demand conditions for each bus. Further details of these data can be found in [46]. For planning purposes, the following set of 15 candidate network enhancements are considered:

1) New transmission assets (line (L) and power transformer (T)): L12-23, L15-21, L3-9, L17-22, T10-12;
2) New battery storage units (B) in buses 1, 7, 13, 18, 21;
3) New reactive compensation devices (C) in buses 3, 5, 6, 10, 19.

Each battery storage unit has a capacity of 200 MW, and each reactive compensation device has a capacity of 200 MVAr. For illustrative purposes, we assume a uniform cost of 1 for each network enhancement ($a_k = 1$), simplifying the budget (b) to an integer representing the feasible simultaneous enhancements. This simplification aids in conceptual clarity and allows for a straightforward representation of the budget constraints in our analysis. In addition, all $N-2$ double line outages are considered to trigger cascading failures.

The settings used for the GA search (which have been enumerated through extensive simulations) are a population size of 200, with an 80% probability of crossover and reproduction.

The proposed framework is implemented in MATLAB on a laptop with an Intel Core (TM) i7 2.60 GHz CPU with four processors and 16 GB of memory.

1) VALIDATION OF THE PROPOSED OVS

We validate the proposed OvS approach by comparing its results with those from the Complete Enumeration (CE) method, which systematically evaluates every possible feasible solution (combination of candidates). Although the CE method guarantees comprehensive coverage, it is highly computationally expensive, especially as the size of the budget increases. Furthermore, CE is not scalable and thus it can only be applied in small-scale problems. The aim of this analysis is to demonstrate that the OvS approach provides a more efficient alternative. It avoids the need for exhaustive testing, yet still delivers consistent and robust outcomes comparable to the CE method.

Table 1 compares the portfolio solutions obtained between the CE method and the proposed OvS approach for different budget sizes (ranging from 1 to 5). For each budget, the table

TABLE 1. CE vs. OvS portfolios.

Budget	Solution	ELNS (MW)	CVaR (MW)	No. of feasible solutions	CE		Proposed OvS		
					No. of evaluations	Comp. time (sec)	No. of evaluations	Comp. time (sec)	Robustness
1	B1	96.3	781.4	16	13,776	128	110,000	811	1
2	T10-12, L12-23	36.7	441.1	121	104,181	763	130,000	2,378	1
3	T10-12, L12-23, L15-21	23.9	296.9	576	495,936	3,292	150,000	4,927	0.7
4	T10-12, L12-23, L15-21, B1	19.2	234.2	1,941	1,671,201	10,782	180,000	6,281	0.6
5	T10-12, L12-23, L15-21, L3-9, B1	16.2	212.3	4,944	4,256,784	27,709	200,000	7,910	0.6

details the ELNS and CVaR metrics, the number of feasible solutions, the number of evaluations, and the corresponding computation times for both methods. It also includes a measure of robustness for the OvS approach [43], which evaluates the number of times that an OvS solution hits the optimal value (or is, at most, 10% different from it). As mentioned above, the OvS model is run 10 times and the best solution is finally selected.

As the budget increases, both approaches show improvements in ELNS and CVaR. For example, ELNS reduces from 96.3 MW at a budget of 1 to 16.2 MW at the highest budget of 5, while CVaR decreases from 781.4 MW to 212.3 MW. This demonstrates that a set of enhancement options (portfolio) provides a better hedge against cascading failures. However, even for this small-scale problem, the computational effort required by the CE method increases significantly with the budget. For a budget of 5, CE performs 4,256,784 evaluations, taking more than 27,000 seconds (around 7.7 hours). In contrast, the OvS approach requires only 200,000 evaluations and completes in approximately 7,910 seconds (around 2.2 hours) at the same budget level. This highlights the efficiency of OvS, which significantly reduces computational requirements while delivering similar results. Figure 4 further illustrates this comparison, showing the sharp rise in computation time for the CE method as the budget increases, while the OvS approach maintains a more moderate and stable growth.

In addition, the OvS approach shows the robustness for each budget. While robustness is initially high (1.0) for lower budgets (1 and 2), it slightly decreases as the budget increases, reaching 0.6 for a budget of 5. Despite this slight decrease in robustness, the computational savings and reduced risk levels make the OvS approach a promising option as the budget grows larger.

The results highlight the trade-offs between the exhaustive CE method and the more computationally efficient OvS approach. While the CE method provides comprehensive solutions, its high computational cost makes it increasingly impractical for larger budgets. In contrast, the OvS approach provides a balance between efficiency and performance, delivering robust solutions within reasonable computational times. This makes it a promising alternative for network investment planning, especially as budget size increases.

It is worth noting that, to the best of our knowledge, no existing framework directly compares network expansion and battery storage optimization using detailed AC cascading failure simulations. As a result, direct comparisons with alternative methodologies are limited. Instead, we validate our approach by comparing it to a complete enumeration method, which provides an exhaustive solution benchmark. Our OvS method achieves nearly identical solutions while significantly reducing computational effort, thereby supporting the robustness and practicality of the proposed framework.

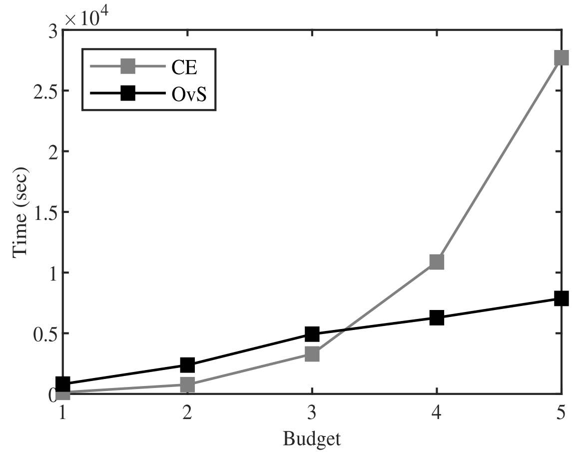

FIGURE 4. Computation time comparison between CE and OvS for different budget sizes.

2) OVS RESULTS AND ANALYSIS FOR DIFFERENT BUDGETS

Table 2 presents a comparison of the investment portfolios identified by the proposed OvS approach, plus the base case with no enhancement, for both the investment planning model with cascading failures and the model without cascading failures, across different budget sizes. For each budget size, the table shows the solution, the ELNS, and CVaR (which represents the average unsupplied demand across the 5% worst cases).

As the budget increases, the portfolio solutions incorporate different combinations of network enhancements. These combinations differ between the model that includes cascading failures and the model that does not, reflecting the distinct decisions required to address the respective risks. For example, the solution for cascading failures with a budget of 7 includes three transmission lines (L12-23,

TABLE 2. Comparison of budget solutions from proposed OvS: Portfolios with and without cascading failures.

Budget	With cascading failures			Without cascading failures		
	Solution	ELNS (MW)	CVaR (MW)	Solution	ELNS (MW)	CVaR (MW)
0	Base case	113.9	1,382.5	Base case	17.9	148.3
1	B1	96.3	781.4	B1	7.7	62.9
2	T10-12, L12-23	36.7	441.1	B1, C6	5.4	56.6
3	T10-12, L12-23, L15-21	23.9	296.9	L3-9, B1, B7, C6	3.4	47.0
4	T10-12, L12-23, L15-21, B1	19.2	234.2	L3-9, B1, B7, C6	1.9	46.0
5	T10-12, L12-23, L15-21, L3-9, B1	16.2	212.3	L3-9, B1, B7, C3, C6	1.7	46.0
6	T10-12, L12-23, L15-21, L3-9, B1, B7	12.4	190.6	L3-9, B1, B7, C3, C6, C19	1.6	75.3
7	T10-12, L12-23, L15-21, L3-9, B1, B7, C6	10.2	151.8	T10-12, L3-9, B1, B7, C3, C6, C19	1.5	75.3

L15-21, and L3-9), one power transformer (T10-12), and two battery storage units (B1 and B7), and one reactive power compensation devices (C3, C6, and C19). On the other hand, the solution without cascading failures includes a combination of one transmission line (L3-9), one power transformer (T10-12), two battery storage units (B1 and B7), and three reactive power compensation device (C6).

When cascading failures are considered, both ELNS and CVaR are significantly higher. For instance, in the base case, the ELNS is 113.9 MW with cascading failures, compared to 17.9 MW without cascading failures. As the budget increases, the ELNS and CVaR decrease consistently in both models, reflecting the effectiveness of the network enhancements. For a budget of 7, ELNS drops to 10.2 MW with cascading failures compared to 1.5 MW without cascading failures.

Hence, the portfolio solutions for network enhancements differ depending on whether cascading failures are taken into account. This difference highlights the importance of considering cascading failures in network investment planning.

Furthermore, Figure 5 illustrates the load shedding associated with different protection and post-fault mechanisms (UFLS, UVLS, VCLS, nOPF, and TLS) triggered by cascading failures. For a budget of 1, the inclusion of battery storage unit B1 significantly reduces the load shedding associated with frequency instability. As the budget increases to 2, investments in power transformer T10-12 and transmission line L12-23 effectively mitigate voltage related load shedding (UVLS and VCLS). At a higher budget level of 7, the portfolio consists of a combination of transmission assets, battery storage units, and reactive power compensation devices, effectively addressing load shedding across all post-fault mechanisms. These results highlight how an optimal mix of network enhancements can significantly reduce the impact of cascading failures.

In order to prove the importance of incorporating cascading outages in network investment planning, Table 3 compares the selected investment portfolios for budget 7 from Table 2, alongside the base case with no enhancements. These portfolios and the base case are evaluated using the detailed cascading failure simulator to measure their effectiveness in mitigating cascading outages. The assessment is based on

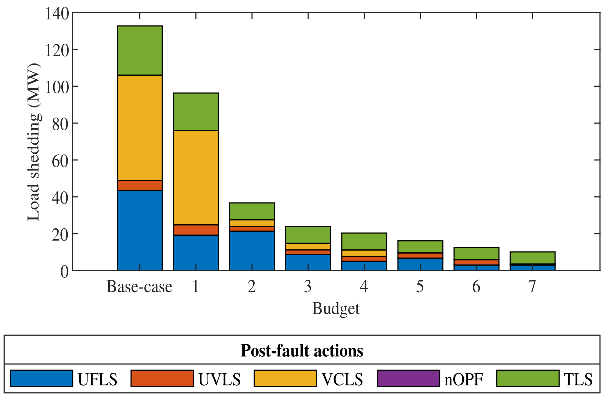

FIGURE 5. Load shedding by protection mechanism across various budget sizes in the IEEE 24-bus system.

TABLE 3. Comparison of investment portfolios in the IEEE 24-Bus system under cascading failures.

Solution	ELNS (MW)	CVaR (MW)	Reduction	
			ELNS (%)	CVaR (%)
Base case	113.9	1,382.5	-	-
T10-12, L12-23, L15-21, L3-9, B1, B7, C6	10.2	151.8	91.0	89.0
T10-12, L3-9, B1, B7, C3, C6, C19	46.6	556.2	59.1	59.8

ELNS, CVaR, and the percentage reduction in both metrics compared to the base case.

To better illustrate the advantages of the proposed framework over conventional planning approach, Table 3 provides a quantitative comparison of the resulting investment portfolios under cascading outage scenarios. The analysis considers two key reliability metrics: ELNS and CVaR, which capture both average and extreme system impacts. The results indicate that the portfolio derived from the proposed framework achieves significant reductions in ELNS and CVaR, by 91.0% and 89.0%, respectively, compared to the base case. In contrast, the portfolio obtained using the conventional model, which does not account for cascading failures, results in smaller reductions of 59.1% and 59.8%. These findings highlight the added value of explicitly

TABLE 4. Budget-specific solutions considering cascading failures in the German network for various sizes (Confidence intervals are negligible, thus omitted).

Budget (M$)	Solution	IC (M$)	ELNS (MW)	CVaR (MW)
100	B150, B226, C207	83	13,127.9	75,982.5
300	L594, B150, B226, C207	256	10,574.9	69,158.1
500	L594, L484, B150, B226, C207	485	8,462.3	55,429.0
700	L74, B150, B226, C207	681	6,848.0	42,755.9
900	L74, L484, B150, B226, C207	855	6,786.5	39,850.0

TABLE 5. Budget-specific solutions without considering cascading failures in the German network for various sizes (Confidence intervals are negligible, thus omitted).

Budget (M$)	Solution	IC (M$)	ELNS (MW)	CVaR (MW)
100	B150, B226, C38, C207	95	4,275.4	28,627.2
300	L484	299	3,854.2	24,112.8
500	L484, L376, C38, C207	498	2,758.6	22,985.7
700	L74, B150, C38, C207	659	2,565.3	22,671.2
900	L74, L376	898	2,368.9	22,505.1

modeling cascading outages in the planning process, as doing so leads not only to distinct investment decisions but also to demonstrably better outcomes in terms of risk mitigation and system reliability.

B. GERMAN TRANSMISSION NETWORK

We test the proposed framework on the German transmission network to demonstrate its scalability. The network, reduced to high and extra-high voltage levels as defined by the SciGRID project [47], consists of 489 buses, 441 generators, and 852 lines. From the PyPSA toolbox [48], both loads and generators are incorporated, with loads scaled proportionally to reach a peak load of 80 GW. Additionally, 21 candidate enhancements are considered for investment planning, including 7 new transmission lines, 7 battery storage units, and 7 reactive power compensation devices. Each enhancement option is assigned a different cost, with investment constrained by budget limitations. The capacities and investment costs associated with the various enhancement options considered in this study can be found in [46].

Similar to the previous test network, $N-2$ line outages serves as the triggering events for simulating cascading failures. However, the considerable size of this network, with 852 lines, makes it computationally infeasible to perform an exhaustive $N-2$ contingency analysis. Specifically, performing such an analysis for a network of this size would require over $3{,}393 \cdot 10^5$ rounds of simulation, a computational challenge that may even be considered impractical. To address this, we use an appropriate selection of a set of 1,000 contingencies as a reasonable and computationally feasible sample size for this network. Increasing the sample size to 2,000 raised the estimated risk by only 0.8%, but doubled the simulation time, highlighting that 1,000 contingencies offer an effective balance between accuracy and efficiency.

The settings used for the GA search (which have been enumerated through extensive simulations) are a population size of 300, with an 80% probability of crossover and reproduction.

The framework is implemented on a computer with Intel(R) Xeon(R) CPU E5-2620 with 2.4 GHz and 32 GB of RAM. For the German transmission network, the optimization process required between 2 to 8 hours, depending on the budget constraint and the number of scenarios evaluated. Each AC cascading failure simulation took approximately 1-3 minutes per scenario, depending on the number of protection mechanisms triggered. Parallel computing is used to improve computational efficiency, reducing computation times by up to 60% compared to sequential execution. For even larger networks, implementing the framework on high performance computing clusters or dedicated servers with increased parallel processing capabilities would further improve scalability.

1) OVS RESULTS AND DISCUSSION

Table 4 presents the investment portfolios for the German network, considering cascading failures at different budget levels, while Table 5 shows the results without accounting for cascading failures at the same budget levels. Both tables show details of the budget, portfolio solution, investment cost (IC), ELNS, and CVaR (which represents the average unsupplied demand across the 5% worst cases).

In both tables, as the investment budget increases from 100 M$ (million) to 900 M$ (million), different portfolios emerge with corresponding improvements in ELNS and CVaR. For example, in the 900 M$ case, the portfolio with cascading failures includes a mix of transmission lines (L74, L484), battery storage units (B150, B226), and reactive power compensation device (C207). In contrast, without cascading failures, the focus is mainly on transmission lines (L74, L376). In terms of ELNS, the portfolio considering cascading failures achieves a significant reduction from 13,127.9 MW (corresponding to 100 M$) to 6,786.5 MW. Without cascading failures, the ELNS decreases from 4,275.4 MW to 2,368.9 MW (corresponding to 100 M$) to 2,368.9 MW, but this overlooks the potential risks of cascading failures.

The CVaR values further emphasize the difference between the two approaches. When cascading failures are considered, the CVaR ranges from 75,982.5 MW to 39,850.0 MW, significantly higher than the range of 28,627.2 MW to 22,505.1 MW range when cascading failures are ignored. This demonstrates the increased risk exposure when cascading events are considered and highlights the limitations of conventional planning models.

Additionally, Table 6 presents a comparison of the selected investment portfolios from Table 4 and Table 5, alongside

TABLE 6. Comparison of investment portfolios in the german network under cascading failures.

Solution	ELNS (MW)	CVaR (MW)	Reduction ELNS (%)	Reduction CVaR (%)
Base case	13,630.6	76,019.3	-	-
L74, L484, B150, B226, C207	6,786.5	39,850.0	50.2	47.6
L74, L376	9,573.1	57,682.0	29.8	24.1

the base case with no enhancements. These portfolios and the base case are evaluated using the detailed cascading failure simulator to measure their effectiveness in mitigating cascading outages. The assessment is based on ELNS, CVaR, and the percentage reduction in both metrics compared to the base case.

The first portfolio, comprising L74, L484, B150, B226, and C207, achieves notable reductions of 50.2% in ELNS and 47.6% in CVaR. Conversely, the second portfolio, consisting of two transmission lines, L74 and L376, yields smaller improvements of 29.8% in ELNS and 24.1% in CVaR. These results clearly demonstrate that the portfolio obtained through the proposed framework leads to more substantial improvements in risk mitigation and system reliability when compared to the conventional approach.

This analysis highlights the superior performance of the first portfolio, which effectively addresses cascading failures by incorporating a mix of enhancement options (network expansion and batteries). Moreover, the first portfolio addressing cascading risks is more cost-effective, delivering greater reductions in ELNS at a lower investment cost (see Table 4).

These findings underscore the benefits of explicitly considering cascading outages in network planning, as the second portfolio, obtained without accounting for cascading effects, results in less robust decisions and smaller improvements in system reliability. The comparison not only demonstrates the importance of incorporating cascading failure modeling into investment planning models, but also validates the scalability and practicality of the proposed framework when applied to a large-scale power system such as the German transmission network.

V. CONCLUSION

This paper presents a methodological framework for optimizing network expansion and battery storage in an integrated fashion to mitigate the risks associated with cascading outages through detailed system failure simulations. Using an OvS approach, the framework efficiently identifies optimal portfolios of network enhancements, including transmission lines, battery storage, and reactive compensation devices, designed to reduce cascading outages.

The proposed framework integrates three key modules: the sampling module, which strategically selects the number of initial outage scenarios; the optimization module, which identifies the most cost-effective network enhancements from a set of candidate options, including transmission lines, power transformers, reactive power compensation devices, and battery storage units; and the simulation module, which evaluates the benefits of the selected investments by assessing their performance under the selected outage scenarios. The case studies on both the IEEE 24-bus and the German transmission networks demonstrate the effectiveness and scalability of the proposed framework.

These results highlight three key insights for network planners. First, they highlight the critical importance of incorporating cascading outages into investment planning, as this approach leads to significantly different network enhancement decisions than conventional planning models that omit such considerations. Second, planning that neglects cascading outages compromises system reliability by underestimating risks and misrepresenting the value of network investments. Finally, the results demonstrate that it is possible to develop an integrated, optimized portfolio of network technologies specifically designed to effectively mitigate cascading outages.

Future work by the authors will focus on evaluating the practicality and improving the effectiveness of the framework by addressing multiple and simultaneous outages caused by high-impact low-probability (HILP) events, such as extreme weather or natural hazards. The integration of resilience metrics is expected to significantly improve the overall resilience of power systems. Additionally, the exploration of emerging technologies for network investments will further strengthen the mitigation of cascading outage, particularly in renewable-rich networks.

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