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Resilience assessment and enhancement of critical infrastructure under natural hazards with case studies in Nordic power grid

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Abstract

Maintaining the operational continuity of critical infrastructures during natural hazards is essential for supporting societal well-being and economic development. This paper introduces the RECINAT framework, as a proactive approach for assessing and enhancing the technical and economic infrastructure resilience against natural hazard-triggered technological events. The study specifically focuses on distribution power systems in the Nordic region, which face significant vulnerabilities from rainfall-induced landslides. This study utilizes an indicator-based methodology to quantify resilience through a hazard-preventive pathway with metrics such as normalized electrical energy not supplied (NEENS), interruption of nodes (ION), and the cost of energy not supplied (CENS). Integration of distributed energy resources configured as virtual power plants (VPPs) is proposed for system resilience enhancement. An enhanced IEEE 33-bus distribution test system is adapted to represent a regional grid in Southwest Norway as the case study. The strategic deployment of these VPPs is formulated as a multi-objective optimization problem and solved using the nondominated sorting Genetic Algorithm II (NSGA-II) as the targets of simultaneous minimization of NEENS, CENS, total VPP capacity, and active power losses. Numerical results demonstrate that optimized VPP deployment reduces economic losses from service interruptions and improves the overall redundancy resilience index. The proposed framework can support resilience-oriented operational planning and long-term investment decision-making for distribution networks exposed to increasing climate-related hazards.

Keywords: Critical infrastructure; Natech; Resilience assessment; Resilience enhancement; Landslides; Power grid.

Notations

n, s, L, v, K	Index of bus, scenario, island, VPP, and branch
P_i^G, Q_i^G	Active and reactive power generation at bus i respectively (p.u.)
P_i^L, Q_i^L	Active and reactive power demands of bus i respectively (p.u.)
P^{DER}, Q^{DER}	Active and reaction power supplied from DER (p.u.)
P^{VPP}	Active power supplied from VPP (p.u.)
V_i	Voltage magnitude at bus i (p.u.)
θ_i	Voltage angle (rad)
B_{ij}, G_{ij}	Susceptance and conductance of distribution line ij (p.u.)
S_{ij}	Size of distribution line ij (p.u.)
P_{Island}^L	Active power demand of total island buses (p.u.)
$SR_{S,L}$	Non-served load ratio of island L in scenario s
n_{shed}	Number of buses exposed to shedding.
n_{Total}	Number of total buses per scenario excluding failed buses.
W_{NEENS}, W_{ION}	Weight factor of normalized electric energy not supplied and interrupted isolated nodes respectively.

IM	Impact metrics scoring in the range of 0 to 4.
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1 Introduction

1.1 Background

Critical infrastructures (CIs), such as electricity and oil and gas networks, nuclear facilities, water systems, healthcare services, and transportation networks, are vital to keep modern society operating [1]. It should be noted that hazards on a node of CI often can result in chains of interconnected disruptions, commonly referred to as domino effects, where an initial failure triggers a sequence of subsequent failures on the large part or the whole CI system [2]. Moreover, disruption in one CI also can lead to cascading impact, spread across other sectors and potentially escalate into large-scale regional or national crises [3].

Real-world experiences have illustrated the severity of these cascading effects. The Tohoku earthquake in Japan and subsequent tsunami caused the Fukushima Daiichi nuclear power plant to lose all internal and external support systems, resulting in a significant release of radioactive material [1]. In 2019, a lightning strike in the United Kingdom triggered a sequence of protective responses known as vector shift protection, which ultimately disconnected approximately 350 MW from the electricity grid. The resulting load shedding disrupted the services of several electricity-dependent CIs, including railway operations and hospital activities. Similarly, the 2012 Indian blackout demonstrated severe grid vulnerability when heat-driven demand surges, compounded by poor coordination and faulty protection systems, which triggered a catastrophic failure that left 300 million people without power [4].

Natural hazards are becoming increasingly frequent and unpredictable due to global climate change, as a primary threat to CIs [3]. On the other hand, CIs can inadvertently amplify the resulting damage from natural hazards to communities. When a natural hazard triggers a secondary technical failure, such as the 2011 Fukushima Daiichi nuclear disaster, such a combined catastrophe is known as a natural hazard-triggered technological (Natech) event [5]. Natech accidents differ from purely technological mishaps in several ways. Since natural disasters are inherently unpredictable and uncontrollable, it is more difficult to prepare for Natech events on CIs. The acceptable level of infrastructure disruption following a hazard event is inherently context-dependent and influenced by different factors [6], [7]. It is thus more practical for governance systems to focus on ensuring that CIs remain resilient and capable of maintaining essential functions in the Natech events. Based on the definition by the Department of Homeland Security of the United States [8], in this study, resilience is regarded as the capability of a CI to withstand and absorb the shock by a natural hazard or maintain essential services despite component failures and then recover from the disruptive event. Resilient CIs have been found directly improving the overall preparedness of urban communities, ensuring that core functions remain operational even under stress [3], [9].

1.2 Related work of critical infrastructure resilience

Resilience engineering of CIs under Natech threats is not a single action but an ongoing process that must be embedded before disruptions occur, maintained during the event, and sustained throughout recovery. Given an existing CI, the tasks of resilience engineering can generally include two categories of tasks: resilience assessment and resilience enhancement [10].

Resilience assessment uses a range of established methodological approaches including indicator-based, quantitative, empirical, economic, and probability-based [11]. The indicator-based approach evaluates CI resilience through measurable indicators and predefined thresholds. It follows a hierarchical structure, where higher levels are decomposed into measurable resilience indicators at the lowest level. An indicator is defined as a quantifiable variable that reflects the state, condition, or presence of a particular system attribute. This method transforms broad resilience concepts such as robustness and redundancy into quantifiable parameters, enabling systematic numerical analysis rather than relying solely on qualitative interpretation [10]. The quantitative approach uses analytical models to assess system resilience by comparing operational performance across different phases of a disruptive event. It adopts a time-dependent framework, using pre-disaster performance as a baseline to evaluate changes during the disruption, recovery, and post-recovery phases [11]. The empirical approach relies on observational data collected from infrastructure systems, including historical records such as reports, articles, and documented incidents. Data mining techniques can subsequently be applied to uncover patterns, correlations, and recurring failure mechanisms within the data, thereby providing evidence-based insights into system performance and vulnerabilities [12]. The economic approach conceptualizes resilience in terms of the capacity of systems, organizations, and regions to withstand and adapt to disruptions while minimizing economic losses. It assesses the functionality of CI through the production, distribution, and consumption of services, integrating these elements into risk-based economic input–output models. This enables the quantification of economic impacts while explicitly accounting for recovery time [13]. Finally, the probability-based approach evaluates resilience by estimating the likelihood that a CI system will achieve or maintain predefined performance levels under specific conditions. It considers factors such as the maximum acceptable loss and the longest disruption duration to determine the likelihood that a system will meet predefined performance standards during disruptions. The probability estimates in this approach heavily relies on past records for similar types of events [14].

For the indicator-based approach, resilience metrics must be identified for the quantifying of resilience. When single or multiple resilience metrics are used in combination, this can be regarded as a Critical Infrastructure Resilience Index (CIRI) [10]. Considerable research has focused on quantifying this index. For example, Joshi et al. applied an indicator-based approach to assess the resilience of rail infrastructure to natural hazards by aggregating physical, social, and economic vulnerability metrics as a measure of resilience index [15]. Fang et al. employed a quantitative approach to evaluate the resilience of railway and aviation networks under various typhoon scenarios. Their model incorporated metrics such as vulnerability, recoverability, disruption rapidity, and recovery rapidity to estimate the overall resilience index [16]. Baratian et al. applied a probability-based approach assessing the resilience of natural gas distribution network subjected to earthquakes, using recovery duration and economic losses as the resilience metrics [17]. Malek et al. adopted a quantitative method to estimate the resilience index with resilience metric as the amount of load supplied during the system's restoration phase [18].

Building on the adoption of the indicator-based approach, resilience enhancement indicators are incorporated to support improvements in CI performance. These strategies target key dimensions such as exposure, robustness, redundancy, rapidity, and resourcefulness [19], [20]. Exposure refers to the presence of people, infrastructure, and economic assets in hazard-prone

areas. Accordingly, enhancement efforts focus on understanding system criticality and reducing susceptibility to hazards through informed planning and risk-aware design [21]. Robustness can be strengthened by improving the ability of CI systems to withstand external disturbances while maintaining functionality, thereby limiting performance degradation. In networked systems, this is reflected in maintaining a high proportion of operational flows relative to total system capacity [22]. Rapidity can be enhanced by increasing the speed at which a system restores functionality following a disruption, even in the presence of partial losses [19], [23]. Resourcefulness can be enhanced with the optimal allocation of contingency resources, improving the ability to efficiently mobilize and deploy assets in response to disruptions while supporting effective decision-making and recovery prioritization [19]. Notably, improvements in redundancy and resourcefulness may also create synergistic effects, indirectly enhancing both robustness and rapidity, thereby contributing to overall system resilience [24].

To evaluate resilience of CIs, it is important to comprehensively capture load behavior within CI, the impacts of natural hazards, the effectiveness of resilience enhancement strategies, and the resulting impacts on the CI network. However, existing studies often simplify Natech events in evaluation with assumed disruption scenarios while ignoring the impacts of different Natech severities [25], [26]. This simplification reduces the accuracy of resilience assessments, particularly given that resilience of CI is highly location-dependent and closely tied to the actual intensity and characteristics of natural hazards.

1.3 Expected contributions of this study

Considering limited data availability and potential biases in historical records [11] as well as the static characteristics of the economic approach [27], the indicator-based approach can be employed for CI resilience assessment. This is also because the approach overcomes many of these constraints and enables the simultaneous integration of multiple resilience metrics within a comprehensive framework [10]. However, there is a notable lack that explicitly integrate quantified natural hazards with the potential resilience enhancement strategies in indicator-based studies. This gap limits the ability to assess how natural hazards influence system performance under realistic threat conditions and to support resilience-oriented planning and preparedness. A clear and consistent measurement methodology is required to evaluate hazard-induced infrastructure failures, cascading effects, and their associated technical and economic consequences. While broader social and institutional aspects of resilience are important, they are beyond the scope of the present study.

As a response, this study proposes a unified framework to connect the analysis of Natech events with CI resilience assessment and enhancement. Unlike conventional resilience assessment approaches that often treat hazard analysis, infrastructure performance assessment, resilience evaluation, and resilience enhancement as separate tasks, the proposed methodology systematically links these components within a single analytical workflow. The framework integrates hazard-dependent failure modelling, resilience assessment under multiple extreme-event scenarios, and resilience-oriented planning through multi-objective optimization. The proposed methodology is designed to be adaptable to different combinations of critical infrastructures and natural hazards; however, its implementation is demonstrated in this study using an enhanced IEEE 33-bus distribution test system, adapted to represent the characteristics of a regional power grid, exposed to rainfall-induced landslides. A multi-objective optimization

model, incorporating economic objectives, is applied to determine optimal resilience enhancement approach.

In general, the expected contributions of this study are summarized as follows:

- (i) Develop a unified resilience assessment and enhancement methodology that explicitly links natural hazard characterization, hazard-induced infrastructure failures, resilience evaluation, and optimized resilience enhancement within a single analytical workflow. The methodology is designed to be adaptable to different critical infrastructures and natural hazards through appropriate case-specific modelling.
- (ii) Introduce a hazard-dependent failure modelling approach that incorporates regional landslide hazard data from Southwest Norway to generate physically meaningful failure scenarios, replacing the simplified random or deterministic outage assumptions commonly adopted in resilience assessment studies.
- (iii) Formulate a resilience-oriented multi-objective optimization model that simultaneously balances resilience performance, economic consequences, technical performance, and investment requirements under hazard-dependent failure scenarios.
- (iv) Extend the resilience planning methodology by explicitly incorporating heterogeneous customer categories and their interruption characteristics into the decision-making process, enabling customer-aware resilience enhancement strategies.

The remainder of the article is organized as follows. Section II presents the resilience assessment and enhancement framework. Section III describes the case studies, including the distribution-grid and natural-hazard models, the objective functions, and the optimization algorithm used to obtain the optimal solution. Section IV provides the numerical analysis and discussion, and Section V concludes the paper.

2 Resilience assessment and enhancement framework

This section will present a pro-active resilience assessment and enhancement framework for CI systems under the threats of Natech events (RECINAT). The RECINAT framework includes six steps, as illustrated below.

Step 1: CI system modeling and performance analysis

The framework starts with clearly defining the CI under study. This phase includes systematic data collection and validation, definition of system boundary, followed by the development of mathematical models that represent the system's structural and operational characteristics. CI systems can be modeled to reflect the complex and multifaceted roles they play in delivering essential goods and services [8].

There are several modeling and simulation approaches for CI, including agent-based, system dynamics, economic theory-based, and network-based methods. Agent-based approaches model individual components as autonomous agents whose interactions generate overall system behavior. Through these localized interactions, complex system-level dynamics emerge. The system dynamics approach adopts a top-down perspective, analyzing system behavior over time by incorporating flows, feedback loops, time delays, and nonlinear

interactions, thereby illustrating system evolution and policy impacts. The economic theory-based approach conceptualizes CI as essential “intermediate goods” that underpin economic activities between households and producers, using large-scale economic data to represent interdependencies. The network-based approach represents critical infrastructure systems as interconnected networks, where nodes denote components and links represent their connections. It includes topology-based methods, which focus on system structure and component states (e.g., failed or functioning), and flow-based methods, which account for the production and transfer of services across the network [28]. The method adopted in this work is the network-based approach using the flow-based method, which fits the nature of the selected CI.

The performance of the CI under normal operating conditions is established by comparing the current system state with predefined baseline operating conditions. These baseline conditions are characterized using performance metrics that evaluate key aspects of system operation, including efficiency, reliability, and security [29]. The current work is focused on the efficiency side.

Step 2: Natural hazard analysis and Natech event identification

The second phase focuses on identifying and characterizing potential triggers that may disrupt system performance, such as natural hazards (e.g., landslides, floods) or anthropogenic threats (e.g., cyber-attacks). In this study, we only consider threats from natural hazards.

The vital natural hazards are identified based on their causes, likelihood of local occurrences, and potential impact on CI. For the same CI, its vulnerabilities and interactions with different natural hazards vary. For example, for a power system, windstorms, ice storms, and hurricanes primarily damage overhead transmission lines and towers, whereas earthquakes can impact both underground and above-ground structures [30].

Once a specific natural hazard is selected, the next task is to analyze its interactions with the CI, namely identifying the Natech events. Such an analysis includes the identification and evaluation of the governing components and influencing parameters of the natural hazard and formulation of the direct impacts of the external shock into the corresponding CI model introduced in Step 1.

Step 3: Cascading impact analysis of Natech events

The third step deeply analyzes the potential cascading failures within the CI triggered by the identified Natech event and assesses the potential performance loss of the CI. This step starts with the analysis result in Step 2 on how the Natech event directly influences CI and focuses on how the damage by such an event can make more failures and domino effects within the infrastructure system. The same Natech event may have different consequences on the same CI due to their occurrence places and timing and other random reasons, and thus it is necessary to integrate the CI model of Step 1 with the hazard model of Step 2 to establish a unified analytical framework capable of simulating system responses.

According to [31], several failure dependency models, summarized in Table 1, can be employed to assess the effects of failures on CI systems. These include the degradation rate intersection model, Bayesian networks, Markov models, Monte Carlo simulation, shock damage models,

and cascade models. In this study, the cascade model is employed to quantify the impact of Natech events on the CI system.

Table 1. Failure models of critical infrastructure

Failure model	Definition	Reference
The degradation rate intersection model	It analyzes the interaction of different degradation processes to identify the point at which gradual deterioration shifts into rapid system decline.	[31]
Bayesian networks	Bayesian networks are probabilistic models that assess failure by capturing risk and interdependencies among system components under varying hazard conditions.	[32]
Markov model	It is a state-based probabilistic approach consisting of structural and statistical components: the structural phase defines possible state transitions, while the statistical phase estimates the likelihood of transitioning into failure states.	[33]
Monte Carlo simulation	It evaluates system behavior by performing a large number of simulations using randomly sampled inputs from predefined probability distributions, thereby capturing a wide range of possible outcomes, including failures.	[31]
The shock damage model	It characterizes the severity of external shocks and relates them to component damage, while also accounting for cumulative damage from previous events.	[31]
Cascade models	It is used to evaluate the propagation of failures within interconnected systems, where the failure of a single node can trigger successive disruptions across the network, typically represented using matrix-based approaches.	[34]

Step 4: System resilience assessment

This step identifies and utilizes quantified indicators to assess the CI system's resilience given the found Natech events. According to the CIRI framework proposed in [10], the methodology in this study is structured into four hierarchical levels of indicators, starting at Level 1 and proceeding downward through the hierarchy. Level 1 represents the highest level of aggregation and aligns directly with the phases of the risk management cycle. Level 1 targeted resilience measures include seven key metrics: risk Assessment, prevention, preparedness, monitoring and early warning, response, recovery, and learning through post-crisis evaluation. Level 2 consists of indicators that translate these Level 1 categories into general functional resilience domains. They are not yet system-specific but represent generic applications of each phase. For example, under the Level 1 category prevention, Level 2 indicators may include resilient design or preventive maintenance and inspection regimes. Level 3 further refines these indicators into typological components that divide Level 2 indicators into smaller and more measurable processes or system characteristics, such as physical robustness, cyber robustness, reservation, redundancy, and independency. Finally, Level 4 specifies the concrete indicators that are directly measured in practice, using quantitative, semi-quantitative, or qualitative metrics depending on the application.

Step 5: Resilience enhancer identification and effectiveness analysis

The fifth step is to identify, analyze, and compare potential approaches that can improve resilience of the CI based on the assessment results in Step 4. Measures for resilience enhancement of CI systems can be categorized based on different criteria [31]. In this study, they are classified into five groups considering the phases they are used on the resilience curve, as resistibility, absorbability, responsibility, recoverability, and adaptability enhancers [31]. Resistibility enhancers are implemented prior to disruptive events to improve system preparedness and reduce exposure to hazards. Examples include seismic monitoring systems and distributed energy resources (DERs) in power grids. Absorbability enhancers operate immediately after a disruption, enabling the system to withstand impacts without complete failure, such as using backup generators. Responsibility enhancers are activated during the emergency phase to support response actions, including the resources coordination efforts by emergency management centers. Recoverability enhancers are applied during the restoration phase to improve the speed and efficiency of recovery, such as through aerial inspections using drones or expert teams. Adaptability enhancers are introduced after the event to enable the system to adjust to new conditions and strengthen future resilience, often through revised policies and regulations based on lessons learned.

Resilience enhancement strategies also can be further classified into hardware-based and software-based approaches. Practical and technically feasible solutions are then chosen based on their alignment with the selected category, as well as their effectiveness in enhancing system resilience and reducing vulnerability to future disruptions [35].

Step 6: Optimization and decision-making for prevention

Approaches of resilience enhancement can be diverse in terms of their effectiveness and costs [31]. It is thus necessary to involve Step 6 for selecting an appropriately optimal approach or combination of approaches with the most effective solution that satisfies the defined objective function of the project.

Depending on the nature of the problem, the decision-making in this step can be either single-objective or multi-objective optimization algorithms. An example of a single-objective algorithm is the genetic algorithm, which focuses solely on optimizing a single goal, such as enhancing physical resilience. In contrast, a multi-objective algorithm, such as the Nondominated Sorting Genetic Algorithm II (NSGA-II), can identify optimal solutions for conflicting objectives, for instance, maximizing resilience while minimizing investment costs. The choice of algorithm depends on the complexity of the system, the number of decision variables, and the trade-offs required among resilience, cost, reliability, or other performance indicators [36].

3 Case studies in the Nordic power industry

To illustrate the application of the proposed RECINAT framework, an enhanced IEEE 33-bus distribution test system adapted to represent the characteristics of a regional power supply system in southwest Norway is selected as the case study. The selected regional setting is characterized by high precipitation and an elevated susceptibility to rainfall-induced landslides, providing a representative environment for evaluating the proposed methodology. The proposed approach for resilience enhancement is summarized in Fig. 1.

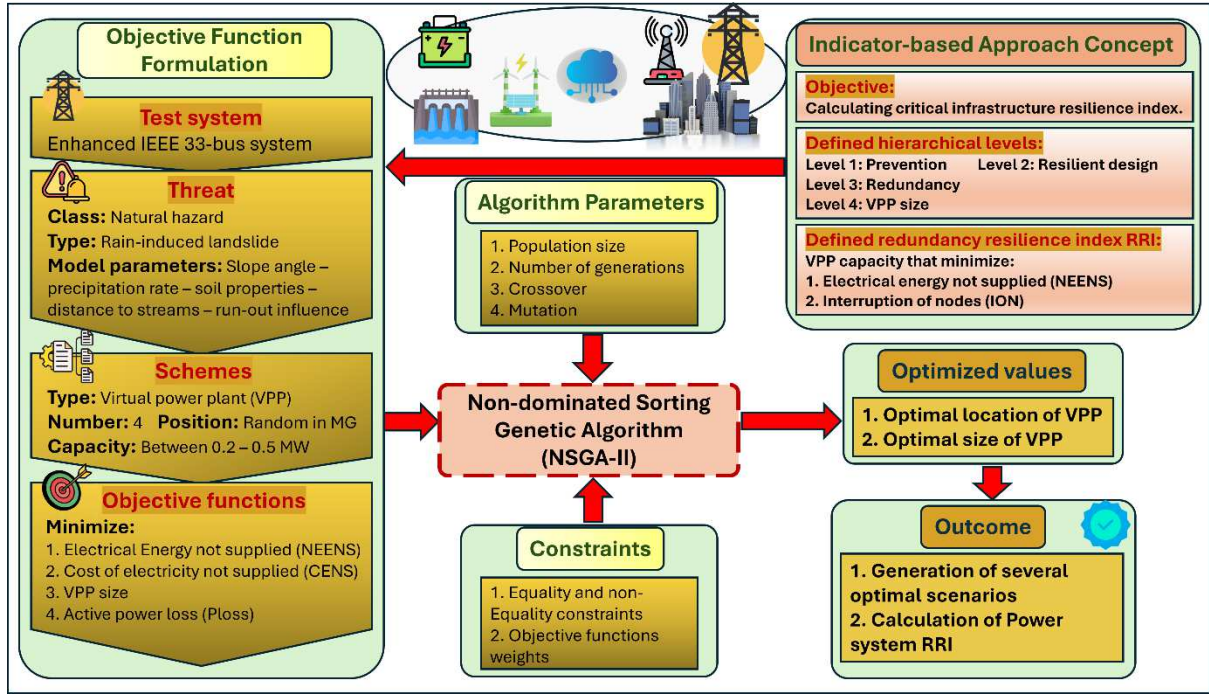


Fig. 1. Proposed approach to enhance power system resilience

3.1 Power grid system modeling and performance analysis

Firstly, we need to define the system boundary and model the power supply system. Enhanced IEEE-33 bus system, which is close to the installed power grid system in the specified location, is used to model the distribution power grid as presented in [37]. The network configuration is illustrated in Fig. 2, where the 33 nodes represent the system buses, the solid lines denote the distribution branches connecting these buses, and three dashed lines indicate the additional tie-lines introduced to enhance the conventional IEEE-33 bus structure. The distribution system has a radial configuration, where electrical power flows from a single slack bus located at Node 1 to all other nodes in the network. The power grid supplies electricity to various categories of customers, including agricultural, residential, commercial, and industrial sectors. Each customer category exhibits distinct load characteristics and sensitivity to service interruptions, which are considered in the resilience and economic assessment of the system.

It should be noted that the electrical network considered in this study is not an actual utility feeder. Instead, the standard IEEE 33-bus benchmark is employed as a representative distribution network and combined with regional landslide hazard data and customer-specific characteristics to demonstrate the applicability of the proposed resilience assessment and enhancement methodology. First, the system is modelled under normal conditions.

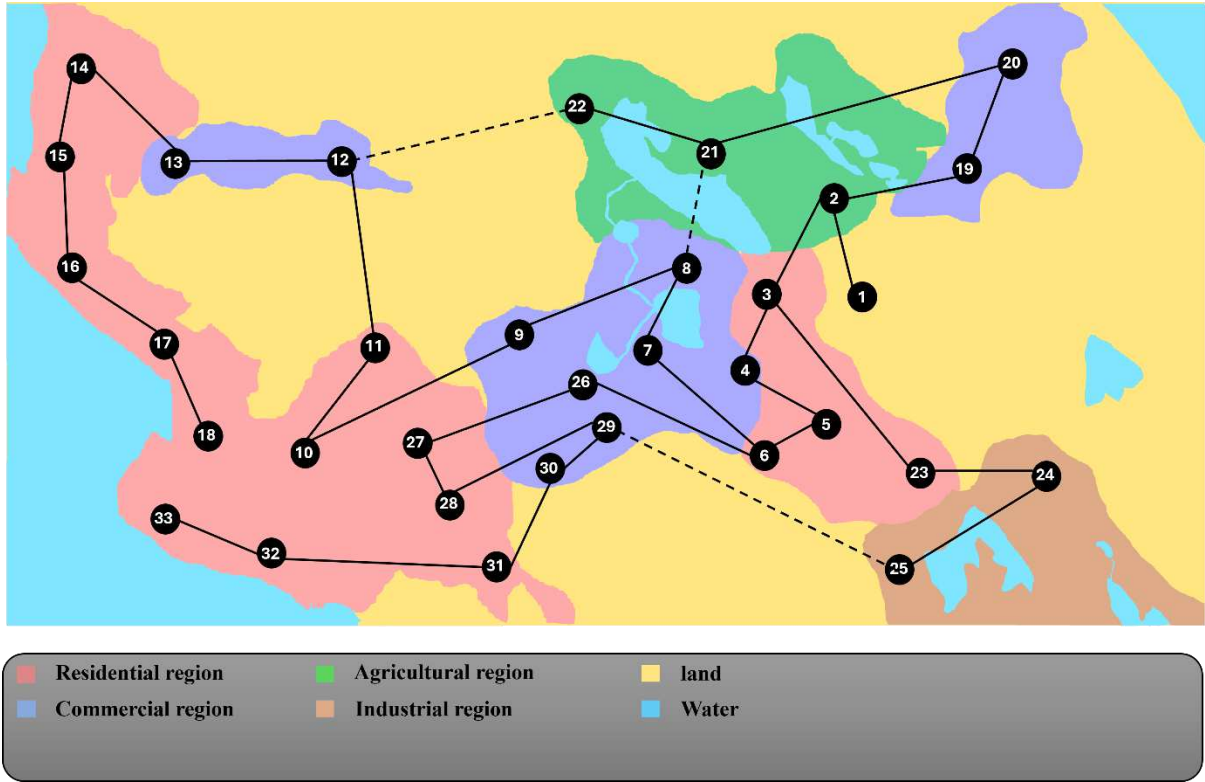


Fig. 2. Distribution power grid at southwest of Norway

The Newton–Raphson algorithm is employed to perform power flow calculations for the IEEE 33-bus distribution power grid. This iterative method linearizes the system of nonlinear equations governing power flow analysis [38]. For islanded microgrids, the power flow equality constraints are formulated using the nonlinear AC power flow equations that describe the active and reactive power balances at each bus i , as expressed in Eqs. (1)-(2). Additionally, Eqs. (3)-(5) incorporate the nodal voltage magnitude limits, the allowable power output range of each DER, and the thermal capacity constraints of the distribution lines. Reactive power balances are inherently satisfied through the AC power flow formulation; however, detailed reactive power capability limits and voltage-control strategies of the DERs are not explicitly modelled.

$$(P_i^{DER} + P_i^G) - P_i^L = \sum_{j=1}^N V_i V_j (G_{ij} \cos(\theta_i - \theta_j) + B_{ij} \sin(\theta_i - \theta_j)) \quad (1)$$

$$(Q_i^{DER} + Q_i^G) - Q_i^L = \sum_{j=1}^N V_i V_j (G_{ij} \sin(\theta_i - \theta_j) - B_{ij} \cos(\theta_i - \theta_j)) \quad (2)$$

$$V_i^{min} \leq V_i \leq V_i^{max} \quad (3)$$

$$P_{min}^{DER} \leq P_i^{DER} \leq P_{max}^{DER} \quad (4)$$

$$|S_{ij}| \leq S_{ij}^{max} \quad (5)$$

3.2 Landslide as the critical hazard and Natech event analysis

Natural hazards in this region cause infrastructure damage primarily due to storms, followed by floods and landslides, while earthquakes and volcanic eruptions have historically resulted in negligible damage according to insurance compensation claim records [39]. Resilience of distribution power systems under natural hazards such as storms and floods has been widely investigated in previous studies [40], [41]. However, although landslides are less frequently

addressed, they represent a significant hazard in Norway due to the strong influence of meteorological conditions.

Landslides are triggered by multiple interacting factors that may act simultaneously, thereby substantially increasing the probability of landslide occurrence. These influencing factors are commonly classified into climatic, geological, and anthropogenic categories. Climatic factors include rainfall and snowmelt, whereas geological factors comprise slope angle, seismic activity, soil properties, and distance to streams. Anthropogenic influences involve land-use changes such as deforestation and vegetation removal, as well as construction activities and infrastructure development [42]. Studies examining the relationship between environmental factors and landslide occurrence indicate that precipitation is the primary triggering factor, particularly short-duration intense rainfall events (less than one day) and cumulative rainfall over periods of up to 15 days. These conditions increase soil saturation and pore water pressure, thereby significantly raising the likelihood of slope failure [43], [44]. The vulnerability is further intensified in Western Norway, where the region experiences exceptionally high precipitation levels. Annual rainfall in some areas can exceed 5000 mm, while daily precipitation values of around 70 mm, that is classified as heavy rainfalls, are relatively common [39]. These climatic characteristics make landslides an important hazard to consider when assessing the resilience of distribution power networks in the region.

Damage of nodes within the power distribution network by landslides is considered as a Natech event in this case. This is a typical high-impact-low-probability (HILP) event, when this occurs, damage of certain nodes typically results in electricity outages at certain locations, which can further affect other facilities or infrastructures, such as the normal operations of local industries and transportation. Such domino effects can make significant economic losses in the form of interruption penalty costs, in addition to other technical and operational damages associated with the infrastructure failure.

3.3 Cascading impact modeling of landslide

Here we model and evaluate the impact of a landslide on a power distribution system as a Natech event. The hazard modelling component is intended to generate representative hazard-dependent failure scenarios for resilience assessment rather than to provide a detailed geotechnical simulation of landslide initiation and propagation. The landslide susceptibility model is based on five primary contributing factors.

First factor to determine the severity of a landslide is the precipitation rate, while the geological component includes slope angle, soil properties, and distance to streams. In addition, landslide run-out influence is an added geological parameter, which is incorporated into the analysis due to the fact that landslides can be triggered by other landslides [45]. This parameter accounts for the combined effects of quick-clay susceptibility, debris volume, slope angle, and the horizontal travel distance of landslide debris, and is used to assess whether a given region is potentially exposed to landslide run-out [46]. Although anthropogenic factors are recognized as significant contributors to landslide occurrence, they are excluded from this study due to the unavailability of reliable data.

The five parameters were subjected to data collection and analysis in order to be transformed into linguistic variables suitable for integration into the proposed model. Precipitation data is collected from YR, operated by the Norwegian Meteorological Institute in collaboration with

the Norwegian Broadcasting Corporation [47]. The dataset includes records of the annual wettest day from 1983 to 2024. Precipitation is classified based on the frequency of landslide events in western Norway associated with different rainfall rates, as defined in [39] and summarized in Table 2.

Slope data for the case study are obtained from Høydedata [48]. The slope angle is classified into four categories following the classification scheme proposed in [49], as presented in Table 2. With respect to soil type, a geotechnical perspective is adopted to distinguish whether the soil consists of quick clay. Quick-clay data were obtained from the Norwegian Geological Survey (NGU) [50]. Distance to streams was categorized as either near or far in accordance with the classification presented in Table 2. Landslide run-out influence was treated as a composite factor derived from the interaction of several parameters, including quick-clay severity, debris volume, slope angle, and run-out horizontal travel distance. The first parameter in the composite factor is the quick-clay severity which is classified into three categories: high risk, low risk, and none. Debris volume was estimated using geometric approximations, assuming simplified failure surface geometries, and multiplied by the mean vertical thickness derived from Høydedata [48]. The resulting debris volumes were classified into high, moderate, and low categories. According to [51], debris flows are likely to initiate at slope angles exceeding 20°. Consequently, slope angles were classified as either above or below this threshold for the assessment of run-out influence. The horizontal travel distance of landslide L was computed as follows from [46].

$$\log(L) = 0.109 + 1.010 \log(H) - 0.506 \log(\tan(\theta)) \quad (6)$$

In this formulation, L denotes the horizontal run-out travelling distance, H represents the slope height, and θ corresponds to the slope angle. The run-out influence which occurs on a horizontal or a steep terrain was therefore evaluated based on the above four parameters.

Table 2. Linguistic terms related to landslides

Precipitation class	Rainfall description	Risk category	Linguistic term LT_{RN}
≤ 40 mm	Moderate rain	Low risk	0
40 – 60 mm	Heavy rain	Potential risk	1
60 – 80 mm	Very heavy rain	Significant risk	2
Slope angle class	Terrain description	Risk category	Linguistic term LT_{SL}
0–5°	Flat terrain	Very low risk	0
5–15°	Mild undulating terrain	Low risk	1
15–25°	Moderately steep terrain	Moderate risk	2
>25°	Steep terrain	High risk	3
Soil class	Soil status	Risk category	Linguistic term LT_{QC}
Non-quick clay	Stable clay	Less risk	0
Quick-clay	Sensitive clay	Existing risk	1
Distance to streams		Risk category	Linguistic term LT_{DS}
Far		Less risk	0
close		Existing risk	1
Run-out influence		Risk category	Linguistic term LT_{RO}
Outside of run-out region		Low risk	0
Barely inside run-out region		Potential risk	1
Inside run-out region		Significant risk	2

According to [52], an assessment of landslide-influencing factors based on multi-country datasets identifies slope as the most significant variable, ranking first among 29 evaluated factors. Rainfall is ranked sixth, while soil type and distance to streams are ranked twentieth and twenty-fourth, respectively. In contrast, the study reported in [53] identifies rainfall as the primary triggering factor, assigning it greater importance than slope angle. In response to these contrasting findings, this study develops multiple weighting schemes to represent alternative scenarios for landslide modeling, while assigning relatively higher importance to rainfall and slope angle in most scenarios. The risk factor (RF), which constitutes the decision metric for determining whether failure occurs at a given point i , is calculated below. In this equation, $W_{RN}, W_{SL}, W_{QC}, W_{DS}, W_{RO}$ denote the weights associated with maximum daily precipitation, slope angle, soil type (quick-clay presence), distance to streams, and run-out influence, respectively. Correspondingly, $LT_{RN}, LT_{SL}, LT_{QC}, LT_{DS}, LT_{RO}$ represent the linguistic terms assigned to these parameters. The parameter weights for the four considered scenarios are summarized in Table 3.

$$RF_i = W_{RN}LT_{RN} + W_{SL}LT_{SL} + W_{QC}LT_{QC} + W_{DS}LT_{DS} + W_{RO}LT_{RO} \quad (7)$$

Table 3. Weight of parameters at different scenarios

Scenarios	Weights	RN	SL	QC	DS	RO	Highest score	Lowest score
Sc. 1	W1	0.35	0.25	0.2	0.1	0.1	2.3	0
Sc. 2	W2	0.25	0.25	0.2	0.2	0.1	2.1	0
Sc. 3	W3	0.20	0.35	0.1	0.25	0.1	2.2	0
Sc. 4	W4	0.25	0.15	0.15	0.2	0.25	2.05	0

Following data collection and preprocessing, the model is executed to simulate landslide-triggering conditions. To generate synthetic rainfall events for each scenario, a Gumbel distribution is fitted to the YR dataset, and random probabilities uniformly distributed between 0 and 1 are sampled. The precipitation value corresponding to the generated probability is then mapped to its respective linguistic classification. Subsequently, four random spatial points are selected from the study area illustrated in Fig. 2. For each point, the slope angle, soil type, distance to streams, and run-out influence are extracted and converted into their corresponding linguistic terms. To account for the uncertainty associated with the relative importance of the different landslide-triggering factors, one of the weighting scenarios presented in Table 3 is randomly assigned to each sampled point. Rather than assuming a single deterministic combination of contributing factors, the four weighting scenarios represent different plausible landslide conditions by varying the relative influence of precipitation, slope angle, soil characteristics, proximity to streams, and run-out effects. In this way, different triggering mechanisms can be represented while preserving the contribution of all considered factors. The risk factor (RF) for each point is subsequently computed using (Eq. 7). If the calculated RF exceeds 50% of the maximum attainable score, the point is classified as failed. The 50% threshold was selected through preliminary numerical experimentation as an engineering decision criterion to generate representative hazard-dependent failure patterns while avoiding unrealistically high or low failure rates. The identified failure is then propagated to the nearest IEEE bus within the power network model, thereby representing the impact of the landslide

event on the distribution network. The procedure is repeated to generate 100 synthetic rainfall scenarios, providing a diverse range of plausible landslide-induced failure realizations. Since the objective of the proposed resilience enhancement methodology is to evaluate system performance under high-impact Natech events, the five scenarios producing the lowest number of surviving IEEE buses are selected for the subsequent resilience assessment and optimization to represent the most disruptive hazard conditions.

3.4 Power grid resilience assessment under landslides

There has been significant effort in quantifying power grid resilience index. In [26], the resilience index is measured through a single indicator which is the system's ability to prevent blackouts in the IEEE 6-bus system. Zahdehbagheri quantified the resilience index by minimizing electrical energy not supplied (EENS) during earthquakes or floods [54]. Same resilience index was applied by different studies on the IEEE 28-bus and IEEE 69-bus system [55], [56]. In [40], resilience in the IEEE 69-bus test system is evaluated using three indicators: the expected probability of node interruption, expected outage duration, and EENS.

The established concept in [10] is adopted in this work. In this case study, Level 1 focuses on prevention, Level 2 on resilient design, and Level 3 on redundancy, which ensures the ability to redirect operation to alternative lines. The final level, Level 4, is the quantitative stage. Here, power grid resilience index is evaluated by first computing the short-term planning indicator, NEENS, both before and after the implementation of the proposed enhancement measure. Subsequently, the long-term planning indicator, ION, is computed for the filtered accident scenarios from the 100 landslide scenarios generated initially. These two indicators are then integrated to produce the overall resilience index associated with the hazard-preventive pathway.

3.5 VPP as a resilience enhancer

In literature, several approaches have been identified useful in resilience enhancement of such power grid systems in extreme events, including integrating DERs, advanced control techniques, fault location strategies, real-time monitoring, and proactive risk mitigation measures significantly. Resilience strategies for electricity grids under natural hazards were evaluated using the MCDM-AHP framework by [57]. Among the assessed strategies, distributed generation ranked the highest. Thus, recent studies emphasize that improving system resilience requires coordinated strategies such as microgrid integration, DER deployment, and prosumer-centric operational models. These approaches enhance system flexibility, accelerate service restoration, and improve fault tolerance during disruptive conditions [58].

However, the increasing penetration of variable DERs also introduces new challenges in the planning and operation of modern power and energy systems. The decentralized nature of these resources requires advanced coordination mechanisms to ensure efficient management of generation, storage, and demand across the network. In this context, Virtual Power Plants (VPPs) have emerged as a promising solution for improving system resilience through a decentralized and integrated operational framework. A VPP represents a virtual layer built on top of the physical power infrastructure, enabling the coordinated and optimal management of distributed assets within both network and market operations. Through this framework, decentralized generation units, energy storage systems, controllable loads, and demand

response mechanisms can be aggregated and operated collectively within a unified platform [59].

Several studies have demonstrated that the strategic placement and optimal sizing of VPPs within distribution networks can significantly enhance system performance under disruptive conditions. For instance, one study investigated resilient VPP operation during natural disasters such as floods and earthquakes using a hybrid metaheuristic optimization algorithm to minimize system damage costs. Simulation results obtained on the IEEE 69-bus radial distribution system showed that the integration of VPPs can substantially improve network resilience compared with traditional power flow-based operational approaches [60]. Another study optimized the placement and sizing of VPPs in microgrids within a radial distribution system to enhance resilience to severe weather events. The model minimized VPP operating costs and NEENS using a modified 85-bus RDS. Results showed improved system resilience and operational benefits [61]. As a result, DERs are deployed as resilience enhancers within the islanded microgrids, with the additional potential for these resources to be subsequently configured and operated as a VPP. In this study, each VPP is represented as a dispatchable power source characterized by its optimized location and installed capacity, with the allocated capacity assumed to be fully available during the resilience assessment. Consequently, storage operating constraints, renewable generation uncertainty, demand response, and detailed islanded operational constraints are not explicitly modelled.

3.6 Optimization of VPP deployment for resilience enhancement

The five most severe landslide-induced disruption scenarios are incorporated into the simulation model, each characterized by distinct bus failures and resulting islanded network segments, as summarized in Table 4.

Table 4. Islands formed by landslide scenarios

Scenarios	Failed buses	Islands
1	[3, 20]	{1, 2, 19} {4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33}
2	[3, 8, 22]	{1, 2, 19, 20, 21} {4, 5, 6, 7, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33} {9, 10, 11, 12, 13, 14, 15, 16, 17, 18}
3	[3, 8, 14]	{1, 2, 9, 10, 11, 12, 13, 19, 20, 21, 22} {4, 5, 6, 7, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33} {15, 16, 17, 18}
4	[6, 8, 21, 24]	{1, 2, 3, 4, 5, 19, 20, 23} {9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 22} {25, 26, 27, 28, 29, 30, 31, 32, 33} {7}
5	[8, 24, 26]	{1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23} {25, 27, 28, 29, 30, 31, 32, 33}

In each scenario, maximum of four DERs or VPPs generations is placed at randomly selected buses, with their capacities sampled uniformly from the range 0.2–0.5 MW. A load-shedding

strategy is employed to ensure that demand is matched to the available generation in case of natural hazard scenario. The resilience-enhancement methodology adopted in this study focuses on multiple operational and economic objectives. From a resiliency perspective, the method seeks to minimize the Normalized Electrical Energy Not Supplied (NEENS) under high impact low probability events. From an economic standpoint, it aims to reduce the Cost of Energy Not Supplied (CENS) along with the total installed generation capacity, the latter reflecting both investment and operational expenditures. Finally, to support long-term system performance, the framework also targets the reduction of network power losses (Ploss). The total resilience afterwards, denoted as resilience index, is calculated based on the obtained magnitudes of NEENS and interruption of nodes ION.

3.6.1 Objective function 1 (OF₁)

$$OF_1 = NEENS = \text{Min}((\sum_{s=1}^{n_s} \sum_{L=1}^{n_L} (SR_{s,L} * P_{Island}^{s,L})) / (\sum_{s=1}^{n_s} \sum_{L=1}^{n_L} (P_{Island}^{s,L}))) \quad (8)$$

Eq. (8) defines the objective function as the minimization of the NEENS. This is achieved by summing the total curtailed (unserved) load across all islands' "L" and across all simulated scenarios "s" and then dividing this value by the total demand of all islands over the same set of scenarios. Normalization removes the influence of varying demand levels among the considered disaster scenarios, allowing consistent comparison of alternative resilience enhancement strategies.

3.6.2 Objective function 2 (OF₂)

$$OF_2 = CENS = \text{Min}((\sum_{s=1}^{n_s} \sum_{L=1}^{n_L} \sum_{n=1}^{n_{Bus}} (\frac{C_{ref}(r)}{r} * f_c * \frac{P_{ref}}{P_{avr}} * 6 * (SR_{s,L}) * 10^3)) * \frac{1}{5}) \quad (9)$$

Eq. (9), adopted from [62], is employed to estimate the CENS in Norway over a 24-hour period, expressed in NOK. The CENS is calculated at the bus level, accounting for the respective customer categories—residential, agricultural, commercial, and industrial—connected to each bus. For each scenario, the CENS values of all buses are summed to obtain the scenario-specific total. Subsequently, the cumulative CENS across the five scenarios is computed and divided by the number of scenarios to derive the average expected CENS. The parameter values employed in this formulation are presented in Table 5. The goal of objective function 2 is to minimize the overall expected CENS.

Table 5. Customer type characteristics used for penalty cost calculation

Customer type	P _{ref} / P _{avr}	f _c	C _{ref} (r) / r
Residential	2.6	0.96	90.46
Agricultural	2.5	0.88	81.66
Commercial	2.5	0.49	580.17
Industrial	3.0	0.38	451.52

3.6.3 Objective function 3 (OF₃)

$$OF_3 = VPPsize = \text{Min}(\max_{s=1, \dots, 5} (\sum_{v=1}^{n_{VPP}} P_{v,s}^{VPP})) \quad (10)$$

In Eq. (10) the VPP size, assumed as a resilience enhancer, is calculated through selecting the scenario that yields the highest total installed VPP capacity by first summing all VPP capacities within each scenario and then taking the maximum across the scenarios considered. The goal of objective function 3 is to minimize the installed VPP size.

3.6.4 Objective function 4 (OF4)

$$OF_4 = P_{loss} = \text{Min}(\sum_{(i,j) \in K} G_{ij}(V_i^2 + V_j^2 - 2V_iV_j \cos(\theta_i - \theta_j))) \quad (11)$$

In Eq. (11), the total active power losses of the distribution network in the presence of VPP integration are computed as the summation of the losses over all network branches. The corresponding objective is to minimize these total power losses, thereby improving overall system efficiency and operational performance.

3.6.5 NSGA-II for VPP allocation

In this section, the optimal solution of the proposed multi-objective model is obtained using the Non-dominated Sorting Genetic Algorithm II (NSGA-II). The optimization problem is characterized by several complexities, including mixed decision variables (discrete bus indices and continuous generation capacities), nonlinear AC power flow constraints, scenario-based resilience evaluation, and inherently conflicting objective functions. These complexities render classical gradient-based optimization techniques unsuitable. Therefore, the NSGA-II, as proposed in [63] to address these challenges, is adopted to determine the optimal placement and sizing of VPPs within the distribution network.

The first step of NSGA-II involves the representation of decision variables. The decision variables are encoded in each individual as a vector representing the placement and sizing of VPPs, expressed as $X = [b_1, s_1, b_2, s_2, b_3, s_3, b_4, s_4]$, where b_i denotes the selected bus index for the i -th VPP and s_i represents its installed capacity.

The second step defines the directions of the objective functions, namely: minimization of NEENS, minimization of the CENS, minimization of the total installed VPP capacity, and minimization of active power losses P_{loss} , as expressed in Eqs. (8)–(11). These objectives are inherently conflicting; for example, decreasing VPP capacity may increase NEENS. Hence, a multi-objective approach is required to obtain a set of trade-off (Pareto-optimal) solutions rather than a single optimum.

The third step consists of introducing the fitness evaluation procedure. For each candidate solution, the distribution network model is constructed according to the proposed VPP locations and sizes. Contingency scenarios, such as bus disconnections due to landslides, are then applied. Island detection is performed, followed by AC optimal power flow (OPF) analysis for each island. Load shedding is computed, after which the values of NEENS, CENS, total VPP capacity, and network losses are calculated to evaluate the individual's fitness.

In the fourth step, the optimization process begins with population initialization, where a set of candidate solutions (individuals) is randomly generated to form the first generation. The population is initialized with 40 individuals. Each individual is randomly generated, with bus locations selected from predefined cluster sets and VPP capacities sampled within specified bounds (e.g., 0.2–0.5 MW), ensuring diversity in the initial search space. Once initialized, each individual is evaluated through the simulation-based fitness procedure, and the objective values are computed.

In the fifth step, denoted as non-dominated sorting, parent individuals for each generation are selected using a tournament selection mechanism guided by NSGA-II ranking. The population is first sorted into Pareto fronts based on non-dominance, and the crowding distance is

calculated to preserve diversity along the front. During tournament selection, individuals with lower Pareto rank and higher crowding distance are preferred.

The sixth step corresponds to the crossover operation, during which bus indices may be exchanged between parents and VPP capacities may undergo arithmetic recombination, allowing beneficial characteristics to be inherited by the offspring. Crossover is applied with a probability of 0.9.

The seventh step employs a mutation operator with a probability of 0.3, introducing variability by randomly modifying the bus locations or VPP sizes of the parent generation.

In the eighth step, the offspring and parent populations are merged, and the NSGA-II non-dominated sorting procedure is performed again. The population size and number of generations were selected through preliminary numerical experimentation to provide a balance between optimization performance and computational efficiency, since each fitness evaluation requires resilience assessment under multiple landslide scenarios. Accordingly, the best 40 individuals, based on Pareto rank and crowding distance, are retained to form the next generation. The evolutionary process is then repeated for a total of 20 generations.

To further verify the robustness of the obtained optimization results, an additional convergence and repeatability assessment was performed after the optimal solution had been identified. The NSGA-II optimization was independently repeated five times using different random seeds while maintaining the same population size (40), number of generations (20), crossover probability (0.9), and mutation probability (0.3). For each run, the Pareto-optimal solutions were ranked using the weighted compromise approach described above, and the five highest-ranked solutions were retained for comparison. The convergence history of the best objective values was also recorded for each run. The results showed that the objective values stabilized within approximately 10–15 generations, while only minor variations were observed in the selected objective values and VPP locations across the five runs. These results confirm that the adopted NSGA-II settings provide stable and repeatable optimization outcomes.

3.6.6 Resilience re-assessment with VPP

After the optimal solution is obtained by determining the allocation and size of VPPs, two indicators, namely the NEENS and the Interruption of Nodes (ION), are used to construct the Level 3 redundancy-related resilience metric. NEENS is primarily intended for short-term resilience assessment, as it evaluates the proportion of unmet energy demand under the assumption that load curtailment can be proportionally distributed within an island to maximize the amount of supplied energy. In contrast, ION is intended for long-term resilience assessment, as it quantifies the number of customer nodes that experience service isolation or shedding following a Natech event. While NEENS reflects the magnitude of unserved demand, ION focuses on the spatial extent of service interruption and can therefore assist in identifying nodes that may require dedicated backup solutions due to their higher likelihood of prolonged outages. NEENS is directly obtained from the optimization process, whereas ION is evaluated after the optimal VPP configuration has been determined.

For the ION assessment, only the scenarios in which landslides occur are selected from the 100 previously generated landslide scenarios to quantify the number of shed buses before and after VPP implementation. Two categories of buses are distinguished in this assessment. Failed buses are buses directly damaged by the landslide and are assumed to remain unavailable

throughout the event, requiring separate restoration actions. Shed buses are buses whose loads cannot be supplied because the available generation within the island is insufficient to satisfy the island demand after the landslide. Prior to VPP deployment, the number of shed buses is determined for each scenario and used as the reference case. Following VPP implementation, load shedding is selectively applied within each island until power flow convergence is achieved.

ION is defined in (Eq. 12) as the total number of shed buses across all filtered scenarios, divided by the total number of buses in each scenario. Failed buses are excluded from the calculation because they are assumed to require separate recovery actions following severe physical damage. Consequently, the denominator varies from one scenario to another according to the number of failed buses.

$$ION = (\sum_{s=1}^{n_s} \sum_{L=1}^{n_L} n_{shed}) / (\sum_{s=1}^{n_s} \sum_{L=1}^{n_L} n_{Total}) \quad (12)$$

Resilience performance metrics are defined to evaluate system redundancy based on two indicators: electricity supplied and functioning nodes, derived from the NEENS and ION metrics, respectively. The indicators are classified into five operational performance levels, ranging from 0 (Total blackout) to 4 (Normal), corresponding to the system states defined in Commission Regulation (EU) 2017/1485 [64]. For the electricity supplied indicator, the threshold values are derived from the cumulative load demand of the different customer categories after applying the selective load shedding strategy, which follows the interruption cost characteristics presented in Table 5. For the functioning nodes indicator, the threshold values are derived from the cumulative number of buses belonging to each customer category. Consequently, the resilience performance levels are based on operational load-shedding priorities rather than arbitrary percentage intervals. After assigning a performance level to each indicator, the Redundancy Resilience Index (RRI), defined in (Eq. 13), is calculated as the weighted sum of the two performance scores, with equal weights assigned to both indicators.

$$RRI = W_{EENS}IM_{(1-EENS)} + W_{ION}IM_{(1-ION)} \quad (13)$$

4 Numerical analysis and discussions

The tested distribution network is the enhanced IEEE 33-bus test system, which represents a medium-voltage radial distribution system with a nominal voltage of 12.66 kV. The total connected load of the system is 3.715 MW and 2.44 MVar. The permissible bus voltage limits are set between 0.9 p.u. and 1.05 p.u. Under normal operation, the active load withdrawn from the slack bus is 3.92 MW to compromise for the active power losses. The distribution network supplies different categories of customers, comprising 1.335 MW of residential load, 1.26 MW of commercial load, 0.28 MW of agricultural load, and 0.84 MW of industrial load. The corresponding simulations are carried out using the Pandapower library in Python [65]. For modeling purposes, it is assumed that the entire distribution system is located within a single weather region, such that the precipitation rate is uniform across all buses. Furthermore, the penalty cost associated with energy not supplied is calculated only for healthy undamaged buses in the network, while damaged nodes are excluded from the penalty assessment. The optimization algorithm implemented in this case study is NSGA-II to determine the optimal allocation and size of the VPPs.

4.1 Resilience of power grid without VPP

This section analyzes the consequences of a landslide on the performance of the studied distribution network. System resilience is evaluated based on the percentage of energy supplied under five contingency scenarios. The energy supplied in Scenarios 1 through 5 is 5.37%, 11.09%, 22.54%, 23.31%, and 57.82%, respectively. These results clearly indicate that, during extreme events, a substantial portion of the regional demand remains unsatisfied, as more than half of the required energy is not delivered in most scenarios. As shown in Table 6, the majority of healthy buses in Scenarios 1–4 become disconnected from the slack bus as a consequence of landslide-induced branch failures and the resulting island formation. Consequently, these buses cannot receive power from the main grid. Scenario 5 exhibits a comparatively lower degree of isolation. This widespread isolation explains the high amount of load not supplied relative to the total system demand. By substituting the unsupplied load values from Table 6 into Eq. (8), the NEENS is computed as 0.77.

From an economic standpoint, power interruptions can result in significant financial losses due to penalty costs associated with service interruptions. These costs, calculated over a 24-hour period for each scenario, are reported in Table 6 under the “Penalty Cost” column. It is noteworthy that Scenario 3 yields a higher penalty cost than Scenario 4, despite having fewer buses electrically isolated from the slack bus. This is because, in Scenario 4, one of the electrically isolated buses corresponds to a large industrial customer but is directly damaged by the landslide. Since failed buses are excluded from the penalty cost calculation, this customer does not contribute to the total penalty cost. As a result, its interruption does not contribute to the total penalty value. In general, the penalty cost decreases as the number of isolated healthy buses decreases. By applying Eq. (9) to the penalty values presented in Table 6, the total CENS is calculated to be 6,530,457 NOK.

Table 6. System performance without VPPs

Scenario	Isolated buses number	Load not supplied (MW)	Penalty cost (NOK)
1	30	3.345	9,080,304
2	28	2.965	8,033,430
3	22	2.560	6,961,051
4	25	2.105	5,184,262
5	11	1.280	3,393,240

4.2 Enhancing power grid resilience with VPP

This section evaluates the impact of a natural disaster on the distribution network after integrating four optimally placed and sized VPPs. The adopted configuration, presented in Table 7, was selected from the Pareto-optimal solutions obtained through the NSGA-II process. The final solution was chosen based on predefined preference weights assigned to the objective functions, reflecting the decision-maker’s priorities. The weights associated with objectives (1) NEENS minimization, (2) CENS minimization, (3) total installed VPP capacity minimization, and (4) power loss minimization were 0.45, 0.30, 0.10, and 0.15, respectively. This weighting scheme emphasizes system resilience and economic performance over capacity expansion and technical losses.

Table 7. IEEE-33 bus network planning results

VPP index	Bus location	Installed capacity (MW)
1	9	0.49
2	16	0.43
3	27	0.50
4	32	0.47

Following the integration of the VPPs, the percentage of energy supplied under scenarios 1 to 5 increased significantly to 55.74%, 50.93%, 49.91%, 74.87%, and 85.99%, respectively. Compared to the base case without VPPs, these results demonstrate substantial improvement in maintaining service continuity during extreme events. As shown in Table 8, the values of load not supplied are considerably reduced, indicating that the proposed VPP deployment enhances the grid's capability to support critical loads until full system restoration is achieved. Scenario 1 represents the most severe condition, where previously more than 90% of the load was unsupplied in the absence of VPP support. With the proposed solution, however, more than half of the total demand remains energized, highlighting the effectiveness of distributed generation in mitigating disaster impacts and preserving network operability. By substituting the unsupplied load values from Table 8 into (Eq. 8), the NEENS is calculated as 0.33, reflecting a marked improvement in resilience performance. From an economic perspective, the penalty costs associated with service interruptions are significantly reduced. The total CENS, computed using (Eq. 9) and the penalty values reported in Table 8, amounts to 2,263,435 NOK, representing approximately 65.3% reduction compared to the pre-VPP case.

Table 8. System performance with VPP

Scenario	Isolated buses number	Load not supplied (MW)	Penalty cost (NOK)
1	2	1.485	2,136,517
2	3	1.450	4,001,021
3	3	1.450	4,001,021
4	5	0.740	1,584,404
5	3	0.330	447,061

A comparative analysis of the load not supplied and the associated penalty costs during disaster conditions, before and after the integration of the VPP solution, as illustrated in Fig. 3, reveals a marked improvement in system performance across all evaluated scenarios. The proposed solution significantly mitigates the adverse impacts of landslide events and reduces the severity of energy interruptions, thereby enhancing system resilience. It should be noted that the analyzed scenarios represent extreme cases; therefore, under less severe disturbance conditions, the performance of the optimized VPP configuration is expected to be even more favorable. Since the highest penalty costs are associated with the commercial and industrial sectors, which also account for a significant share of the total demand, a strong positive correlation between unsupplied load and penalty cost is observed, as shown in Fig. 3. Consequently, any reduction in NEENS leads to a corresponding decrease in the CENS, indicating that improvements in technical resilience directly enhance economic performance.

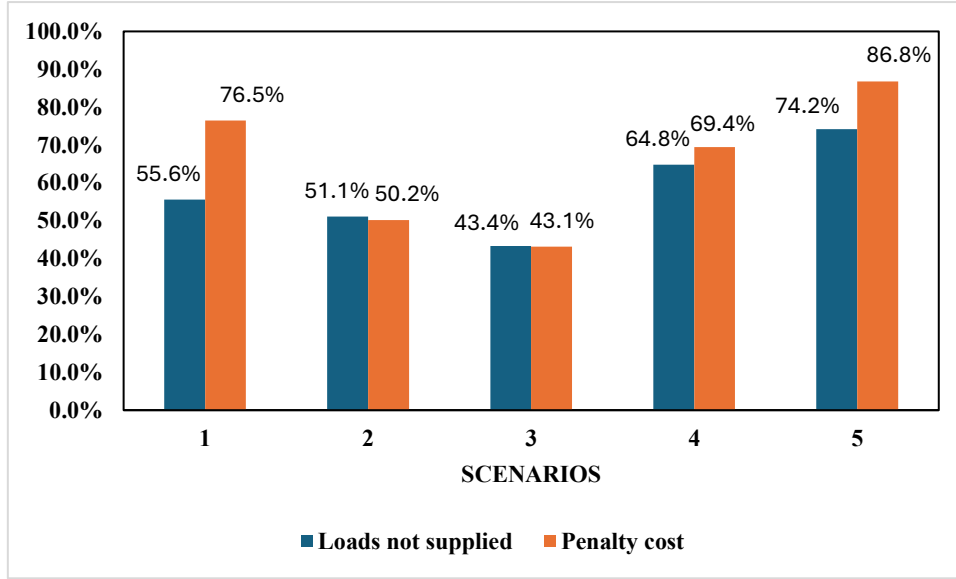


Fig. 3. Percentage of improvement for each scenario after the VPP implementation

4.3 Validation of NSGA-II convergence and repeatability

To verify the robustness of the adopted NSGA-II settings, an additional convergence and repeatability assessment was performed after the optimal solution had been obtained. The optimization was independently repeated five times using different random seeds while maintaining the same algorithm parameters.

The convergence behavior was evaluated by monitoring the best value of the primary objective function (NEENS) at each generation. Fig.4 illustrates the convergence histories for the five independent optimization runs. In all cases, the objective value decreased rapidly during the first generations and stabilized after approximately 10–15 generations, indicating that the selected number of generations is sufficient for convergence.

The repeatability of the optimization was assessed by comparing the selected compromise solutions obtained from the five independent runs. Only minor variations were observed in the objective values and VPP configurations. The best NEENS values ranged from 0.33 to 0.37, CENS ranged from 2.314 MNOK to 2.612 MNOK, while the installed VPP capacity ranged from 1.56 MW to 1.85 MW. Moreover, the selected VPP locations consistently converged to the same or neighboring candidate buses within each predefined cluster, indicating that the optimization results are not significantly affected by the stochastic initialization of the algorithm. These results confirm that the adopted NSGA-II parameter settings provide stable, repeatable, and computationally efficient optimization results.

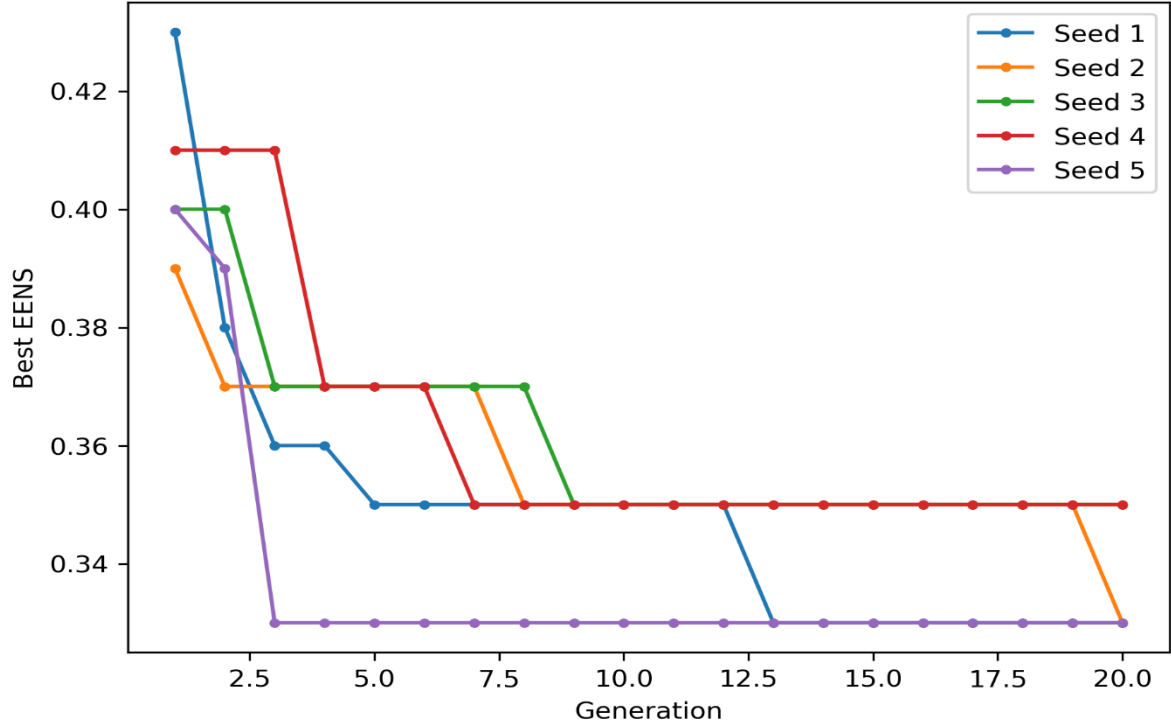


Fig. 4. Convergence history of the best NEENS value

4.4 Impacts of size and design of VPP

Based on the installed capacities presented in Table 7, the total integrated VPP capacity within the distribution network studied is 1.89 MW. This represents the minimum capacity required to satisfy the resiliency objectives while mitigating potential penalty costs associated with supply interruptions. The addition of VPPs to the system with such allocation and size resulted in reduction in power losses from 0.215 MW into 0.082 MW. Considering the geographical characteristics of the investigated region, Node 9 is identified as a suitable location for integrating a mini-hydropower unit, similar to the configuration demonstrated in [66] for a case study in northern Tanzania. The western Nordic region possesses favorable topographical and hydrological conditions, particularly abundant water resources and natural elevation differences that support small-scale hydropower development. Moreover, Node 9 is located in close proximity to a local stream, further supporting its technical feasibility for mini-hydropower integration within the proposed VPP configuration. Such a generation source can be complemented by battery energy storage systems to effectively balance the high-energy capacity characteristics of hydropower with the high-power response capability of batteries.

In addition to hydropower, small-scale wind turbines represent another potential renewable generation source that can be connected to other buses in the network. According to the wind speed data reported in [67], the average annual wind speed ranges between 10–20 km/h, indicating favorable wind availability for a large portion of the year. Alongside renewable generation, energy storage technologies play a crucial role in enhancing system flexibility and energy security in the region. The high penetration of electric vehicles (EVs) in Norway further supports this approach [68]. EV batteries can be considered as distributed energy storage resources and integrated within the remaining VPP units. In addition to EV-based storage,

stationary battery energy storage systems constitute another viable component of the proposed VPPs.

Demand response programs can further enhance system flexibility and help mitigate energy shortages during critical periods. Studies conducted in Norway indicate that households are capable of responding to variable hourly electricity prices, achieving approximately 11.4% energy savings during winter periods. The response is particularly significant among households that actively monitor real-time electricity prices and those utilizing smart EV charging systems, which enable load shifting from peak-price periods to low-price hours [69]. Collectively, the integration of renewable generation, distributed storage, and demand response form a comprehensive VPP framework that enhances the resilience and operational flexibility of the distribution network.

4.5 Sensitivity analysis for different solutions

The results presented above demonstrate that the selected optimal solution primarily favors system resilience. Nevertheless, several alternative solutions exist in addition to the configuration presented in Table 7. To investigate these alternatives, a sensitivity analysis was conducted by varying the weight assigned to each objective function, leading to different solutions as summarized in Table 9. The first solution corresponds to the main proposed configuration, where resilience is prioritized by assigning the highest weight (0.45) to the NEENS objective. In the second solution, greater importance is given to reducing the investment cost by assigning the highest weight (0.35) to the VPP installed capacity, while the second priority is given to resilience with an NEENS weight of 0.30. Although the resilience performance slightly decreases by approximately 7%, the total installed VPP capacity is reduced from 1.89 MW to 1.52 MW, which directly lowers the associated investment cost. The third solution focuses mainly on the economic aspect by reducing both the penalty cost and the VPP investment cost. This configuration results in a solution similar to Solution 1, but with a lower installed VPP capacity at bus 16. Consequently, the installed VPP capacity is reduced by approximately 330 kW compared to Solution 1, while maintaining satisfactory resilience performance. In addition, the resulting penalty cost lies between the values obtained in Solutions 1 and 2. The fourth solution assigns equal importance to all objective functions and results in a configuration identical to Solution 3.

Table 9. Sensitivity analysis for different solutions of pareto front

	Solution 1	Solution 2	Solution 3	Solution 4
NEENS weight	0.45	0.30	0.20	0.25
CENS weight	0.30	0.25	0.40	0.25
VPP size weight	0.10	0.35	0.35	0.25
P_{loss} weight	0.15	0.10	0.05	0.25
Allocation and size result	[16, 0.43, 9, 0.49, 32, 0.47, 27, 0.50]	[14, 0.31, 10, 0.23, 29, 0.48, 27, 0.50]	[16, 0.20, 9, 0.49, 32, 0.47, 27, 0.50]	[16, 0.20, 9, 0.49, 32, 0.47, 27, 0.50]
NEENS	0.33	0.40	0.36	0.36
CENS (NOK)	2,263,435	2,803,602	2,571,206	2,571,206
VPP size (MW)	1.89	1.52	1.66	1.66
P_{loss} (MW)	0.082	0.082	0.082	0.082

Vulnerability of network buses is also examined under the considered extreme scenarios. As illustrated in Fig. 5, buses 3, 8, and 24 experienced failures in more than one of the five scenarios studied, indicating higher vulnerability. Fortunately, most of the obtained solutions allocate VPP units at buses with relatively lower failure probabilities. Buses that failed once across the scenarios are marked in green in Fig. 5 and include buses 6, 14, 20, 21, 22, and 26. Although Solution 2 places one VPP at bus 14, the probability of failure at this location remains relatively low, while the remaining VPP units with the largest capacities are positioned at safer locations within the network.

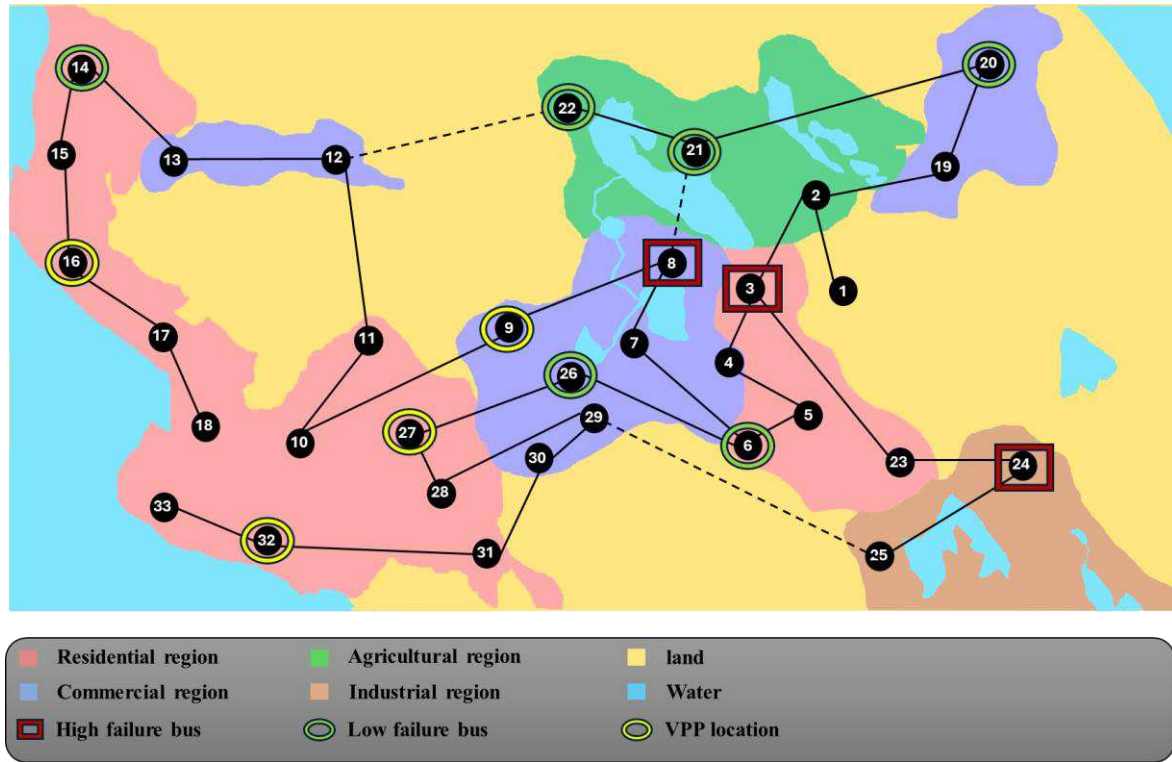


Fig. 5. Distribution power grid after implementation of optimal solution

4.6 Resilience index results

Solution 1 from the sensitivity analysis is applied to calculate the Level 3 redundancy-related resilience indicator, namely ION. ION is calculated for the filtered scenarios before and after VPP implementation. From the initial 100 scenarios, only those involving landslides are considered, resulting in a total of 79 scenarios. The results indicate that, prior to VPP deployment, 12.98% of the nodes were shed throughout the 79 scenarios. Following VPP implementation, this value decreases significantly to 2.16% across the same scenarios.

The resilience performance impact metrics presented in Table 10 are derived from the cumulative contribution of the different customer sectors to the total system demand and the cumulative number of buses belonging to each customer category. The customer priority adopted in the load shedding strategy follows the interruption cost characteristics presented in Table 5, where agricultural customers have the lowest interruption penalty, followed by residential, industrial, and commercial customers. Consequently, load shedding is applied according to this predefined priority (agricultural → residential → industrial → commercial), and the threshold values correspond to the remaining percentage of supplied demand and functioning buses after each customer category is shed. Therefore, the resilience performance

levels are based on the operational load-shedding priority derived from customer interruption costs rather than on arbitrary percentage intervals.

Prior to VPP implementation, the normalized NEENS and ION values were 0.7700 and 0.1298, corresponding to approximately 23% of the electricity demand being supplied and 87.02% of the buses remaining operational. These values are classified as Restoration (score = 1) for electricity supplied and Alert (score = 3) for functioning buses, resulting in an RRI of 2.

Based on the optimization results, the normalized NEENS and ION values are 0.33 and 0.0216, respectively. These correspond to approximately 67% of the total electricity demand being supplied and 97.84% of the buses remaining operational following the landslide scenarios. According to the resilience performance levels defined in Table 10, the electricity supplied falls within the Alert state (score = 3), while the percentage of functioning buses corresponds to the Normal state (score = 4). Consequently, the Redundancy Resilience Index (RRI) is calculated as 3.5 on a scale ranging from 0 to 4. Following the installation of 1.89 MW of VPP capacity, the RRI increases from 2.0 to 3.5, corresponding to a 75% improvement in the redundancy-related resilience of the distribution system.

Table 10. Impact metrics for redundancy resilience index

Impact metrics	Adapted operational state	Indicator 1 (Electricity supplied)	Indicator 2 (Functioning nodes)	Operational meaning
4	Normal	> 92.5% of grid is operational	> 93.5% of nodes are functioning	All sectors served; agricultural nodes at most partially affected.
3	Alert	> 56.6% - 92.5% of grid is operational	> 41.9% - 93.5% of nodes are functioning	Agricultural fully shed; residential progressively shed.
2	Emergency	> 34% - 56.6% of grid is operational	> 35.4% - 41.9% of nodes are functioning	Agricultural and residential are fully shed; industrial being shed.
1	Restoration	> 0% - 34% of grid is operational	> 0% - 35.4% of nodes are functioning	Agricultural, residential, and industrial are shed; only commercial partially served.
0	Total blackout	0% of grid is operational	0% of nodes are functioning	Complete outage

The reported resilience improvements represent model-based performance under the assumptions of the proposed framework. Practical implementation would additionally require appropriate regulatory, operational, communication, and cybersecurity arrangements. Therefore, the proposed methodology is intended as a decision-support tool for resilience planning rather than a complete implementation framework.

5 Conclusions

This paper presents the RECINAT framework as a unified and structured methodology for assessing and enhancing the technical and economic resilience of critical infrastructures exposed to Natech events. The proposed framework bridges analyses of natural hazards and CI performance, as well as qualitative resilience concepts with quantitative engineering metrics through a four-level indicator hierarchy. By integrating multi-objective optimization using NSGA-II into the assessment process, the framework systematically evaluates the interactions between technical performance, economic consequences, and system redundancy under hazard-dependent failure scenarios.

The RECINAT framework is then applied to an enhanced IEEE 33-bus distribution test system adapted to represent a Nordic distribution power network exposed to rainfall-induced landslide hazards. The results demonstrate the potential of strategically allocated VPPs to enhance the resilience of the distribution system studied. Under the modelling assumptions adopted in this study, the optimized VPP deployment increased the RRI by 75% while reducing the CENS by approximately 65%. For grid operators and policymakers, the proposed methodology provides a decision-support tool for short-term emergency response planning and long-term resilience investment planning. The results highlight the potential of strategically deployed decentralized generation to improve service continuity for critical industrial and commercial sectors during major network disruptions.

For future studies, the complexities of compound hazards should be addressed. This is because multiple natural events, such as windstorms, floods, and landslides, may happen in a short time and interact to create even more severe disruption patterns. Future models should also incorporate secondary infrastructure failures, such as hazard-induced dam breaches, together with more comprehensive geotechnical information, infrastructure vulnerability data, and anthropogenic influences to improve the predictive capability of the hazard-dependent failure model. Furthermore, given that electric vehicles account for over 95% of new passenger car sales in Norway, future implementations should investigate the integration of EV batteries as mobile energy storage resources within VPPs. Finally, the present study focuses on the physical resilience of the distribution network under Natech events. Future extensions should incorporate cyber-physical aspects, including communication failures, cyberattacks, secure control, resilient state estimation, and coordinated cyber-physical risk management, to provide a more comprehensive resilience assessment of modern power systems.

Author Contributions

R. Nasser: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization.

Y. Liu: Writing – Review & editing, Supervision, Funding acquisition, Conceptualization.

All authors contributed to the study conception and design. The first draft of the manuscript was written by Reem Nasser and all authors commented on previous versions of the manuscript. All authors have read and approved the final manuscript.

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