

Research Paper

Enhancing Gas Grid Robustness and Power System Reliability to Natural Disasters by Deploying Power-to-Gas and Coordinated Planning

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Abstract— Conventional power systems are designed for reliability under normal conditions but struggle during extreme events such as hurricanes. Most resilience studies either concentrate on transmission systems or fail to explicitly model gas-network failures that can disrupt electricity distribution. This oversight results in inadequate planning for interdependent power–gas distribution grids during floods and storms. We propose a two-stage stochastic Mixed-Integer Linear Programming (MILP) model that (i) strengthens and configures power distribution assets while simultaneously planning for the gas network, (ii) explicitly simulates gas pipeline failures caused by floods that hinder gas-fired generation, and (iii) incorporates gas storage and Power-to-gas (P2G) locations while adhering to gas flow and pressure constraints. The framework has been validated on a 33-bus power system, a 14-node gas system, an IEEE-118 system, and a 26-node gas case. Key findings indicate that, in the absence of gas storage, disruptions in fuel supply lead to significant unsupplied energy (ENS reaching 67.06 MWh) and reduced reliability (SAIDI reaching 38.6 minutes. However, including gas storage can decrease load-shedding costs by approximately 30% and improve reliability indices such as SAIFI, CAIDI, and ENS by 20–40%. Optimal strategies involve targeted fortification and the strategic placement of distributed energy resources and energy storage systems (e.g., seven fortified lines, three distributed generators, and four energy storage systems in the 33-bus scenario), balancing investment against recovery effectiveness across various failure scenarios. Integrating gas-network failure modeling with coordinated power–gas planning significantly enhances outage management and cost outcomes during flooding events.

Keywords—P2G, reliability, resilience, gas-network-natural disasters.

NOMENCLATURE

Parameters

χ_d^{dg}	Energy demand at generator level
χ_e^{es}	Energy stored in storage systems
χ_{ij}^h	Energy loss during the transmission process in the system
Δt	Time step, representing the time interval
$BigM$	A large constant used in modeling, often used in the Big- M method for optimization constraints
c_d^{dg}	Cost associated with generator installation
c_E^{es}	Investment cost for energy storage capacity
C_i^s	Removal cost of energy storage unit i
C_p^2	Constant coefficient related to gas flow characteristics, possibly representing resistance or a similar factor

c_p^{es}	Investment cost for the installation of energy storage capacity
c_{ij}^e	Cost of investment in the resistance of transmission lines
c_{ij}^h	Cost related to energy losses on specific lines between nodes
$E_{e,t}^{initial}$	Initial energy stored in the storage system
LTS_{ij}	Factor associated with long-term storage
ps^{max}	Maximum allowable pressure in the natural gas network
r	Interest rate
SOC^{max}	Maximum allowable state of charge for the storage system
SOC^{min}	Minimum allowable state of charge for the storage system
W_{ng}^{max}	Maximum power generation capacity of natural gas plants
x_i^{dg}	Energy demand at generator level
Y	Rate of return on investment
α_d	Coefficient of nonlinear gas-to-electric power output
$\chi_{ng,mg}$	A factor representing the maximum pressure ratio between network ng and grid segment mg
η^{ch}	Efficiency of the charging process
η^{dch}	Efficiency of the discharging process
η_{ch}	Charging efficiency of the storage system (fraction of input power that is converted to stored energy)
η_{dch}	Discharging efficiency of the storage system (fraction of stored energy delivered as useful output)

Received: 30 May 2025

Revised: 24 Oct. 2025

Accepted: 09 Nov. 2025

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DOI: 10.22098/joape.2025.17549.2372

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π_s	Probability of the emergency scenario
$\tau_{i,s}$	Repair/restoration time for component i in scenario s (drives restoration logic)
E^{ES}	Energy storage capacity
E^{max}	Maximum energy capacity of the storage system
$E_{C,s}$	Cost of energy supply for electrical energy
F^{max}	Maximum gas flow capacity for network ng
$G_{t,s}$	Upstream natural gas supply available to the system at time t in scenario s
$ICTC$	Investment cost at time t
N_{DG}	Number of distributed generators
$P^{dch,max}$	Maximum charging power capacity for the energy storage system
P^{ES}	Energy supply from storage
$R_{n,t,s}$	Renewable availability (or renewable generation ceiling) at node n , time t , in scenario s
$x^{e,s}$	Maximum energy capacity of the storage system
Sets and Indices	
DG	Number of distributed generators
E	Energy storage
i, j	Bus number
k	Index for the specific pipeline or grid segment
Ng, Mg	Gas network
s	Scenario index
t	Time
ω_s	Scenario vector
Variables	
$\beta_{lg,t,s,k}^{pipe}$	Binary variable indicating the active linearization interval k for pipeline segment lg at time t in scenario s
$\delta_{lg,t,s,k}^{pipe}$	Binary variable enforcing adjacency/logic at node lg (time t , scenario s) to ensure valid segment activation in the pipe-level PWL scheme
$\delta_{ng,t,s,k}^{node}$	Binary variable enforcing adjacency/logic at node ng (time t , scenario s) to ensure valid segment activation in the node-level PWL scheme
Δp_{ss}	Squared pressure-difference term used in the linearization of gas flow constraints
$\lambda_{ng,t,s,k}^{node}$	Binary selector that activates interval k (piecewise segment) for the node-level piecewise-linear (PWL) approximation at node ng , time t , scenario s
$\psi_{e,t}^{ch,s}$	Binary variable representing whether charging occurs in the storage system at time t
$\psi_{e,t}^{dch,s}$	Binary variable representing whether discharging occurs in the storage system at time t
ρ_{ij}^s	A binary variable representing whether charging or discharging happens at the energy storage system at time t
ρ_{ij}^s	Removal rate of energy storage unit i at time t
$E_{e,t}^s$	Energy stored in the storage system e at time t
$F_{ng,mg,t}^s$	Actual gas flow through pipeline (ng,mg) at time t in scenario s , derived from the PWL approximation of squared-pressure differences
p_d^{DGs}	Power generation from distributed generation d at time t
P_i^s	Power output of the energy storage unit i at time t
$P_{e,f}^{ch,s}$	Power input during the charging process of storage system e at time t
$P_{e,t}^{dch,s}$	Power output during the discharging process of storage system e at time t
p_{ef}^{dch}	Power output from the energy storage system e during discharging at time t
P_{ij}^s	Power generation at transmission line i, j at time t from storage system s
$p_{r,t}^{SUBS}$	Power supplied from renewable sources in region r at time t
$ps_{mg}^{s,2}$	Pressure at the gas grid segment mg at time t for scenario s
$ps_{ng,t}^s$	Squared gas pressure at node ng at time t in scenario s obtained from the PWL interpolation
ps_{ng}^s	Pressure of natural gas at time t for scenario s at gas

	network ng
$ps_{ng}^{s,2}$	Pressure at the gas network ng at time t for scenario s
ps^{min}	Pressure of natural gas at time t for scenario s at gas network ng
$SOC_{e,t}^s$	State of charge of the storage system e at time t , defined as the ratio of energy stored to maximum energy capacity
U_{ng}^s	Binary variable indicating whether a gas line between ng and mg is operational in scenario s at time t
$W_{CG,t}^s$	Gas consumption at time t for scenario s in the natural gas grid
$W_{DG,t}^s$	Power generation from distributed generation sources at time t for scenario s
W_{DG}^s	Distributed generation at time t for scenario s
$W_{L,t}^s$	Power loss at time t for scenario s in the grid
W_{ng}^s	Power output from natural gas plants ng at time t for scenario s
$W_{shed,t}^s$	Shed loads in the gas network
X_p	Storage capacity
$y_{lg,t,s}^{pipe}$	Auxiliary variable representing the absolute value of the difference in squared pressures across pipeline nodes (absolute-value linearization)
$D_{n,t,s}$	Electric demand at node n , time t , in scenario s (used in node-balance constraints)
$x_{p,k}$	Binary variable related to the use of emergency generators

1. INTRODUCTION

1.1. Motivation and incitement

Energy infrastructure resilience has become a critical concern as extreme natural events increasingly threaten the reliable supply of power and gas. Modern electricity and gas networks are deeply interdependent due to the widespread use of natural gas in power generation and the reliance of gas facilities (compressor stations, controls, etc.) on electricity [1]. This interdependence means that failures can propagate in both directions: an outage in the electric grid can disrupt gas operations (e.g., stopping electric-driven compressors), while a gas supply failure can cripple gas-fired power plants, creating a bilateral, looped failure propagation between the two systems. Such coupling is further intensified by emerging technologies like power-to-gas (P2G) and gas-to-power (G2P) units, which establish two-way energy flow links between the networks. As a result, integrated power-gas systems (IPGS) are particularly vulnerable to high-impact, low-probability events like natural disasters. Planners and regulators have historically focused on “credible” single contingencies, but recent climate-driven disasters underscore the need to design for extreme events beyond traditional reliability standards. Developing resilient multi-energy systems that can withstand and quickly recover from catastrophes has therefore become a key research imperative [2]. Among various natural threats, floods have emerged as a major hazard with the potential to devastate both power and gas infrastructures. Floodwaters can inundate electrical substations and knock out power lines, leading to widespread and prolonged outages. For example, a severe flood can disable multiple substations simultaneously, as occurred in past events, and cascade into blackouts across the grid. This loss of electricity supply in turn impairs gas network operations by cutting power to gas compressor stations and control systems, undermining gas pressure management and delivery. Conversely, floods can directly damage gas pipelines (through scour, buoyancy, or debris impact) and gate stations, causing gas supply interruptions—which then jeopardize electricity generation fuel supply for gas-fired plants. In essence, a flood in one network can induce a cascading failure in the other due to their interdependence. Recent studies emphasize the importance of addressing such coupled risks. Movahednia *et al.* (2021) demonstrated that proactive hardening measures (e.g., deploying temporary water barriers around critical substations) can significantly improve power grid resilience against flood hazards [2]. Their stochastic planning framework showed that targeted

protection of a few vulnerable substations yields outsized benefits in reducing outage severity. However, purely electrical hardening is not enough—coordinated, cross-network strategies are required so that the gas network can support the power system (and vice versa) during flood events. For instance, if portions of the electric grid are flooded, the gas network could help sustain critical power supply via distributed gas generators; likewise, if gas supply is disrupted by flooding, the electric system (with P2G units) might inject alternative fuel into the gas network to maintain service. This two-way support under flood conditions is a central motivation for integrating P2G technology and joint energy planning in resilience efforts. Prior Research on Integrated Power-gas Resilience: In the past few years, substantial research has been devoted to enhancing the resilience of interdependent electricity and natural gas systems under extreme events. Broadly, the literature can be categorized into preventive planning approaches and post-disaster operational strategies—often combined for maximum efficacy. On the planning side, many works propose hardening and expansion of infrastructure with a coordinated perspective. For example, Zou *et al.* (2020) developed a two-stage robust co-expansion planning model for integrated power and gas distribution networks. In their model, the first stage optimizes investments in hardening or adding power lines, gas pipelines, and distributed gas-fired generation under normal conditions, while the second stage evaluates those investments against a worst-case disaster scenario. This robust optimization ensures the integrated network can meet a target resilience level with minimal load shedding even under severe disturbances. The results showed that jointly planning the electric and gas network reinforcements yields a more resilient system than separate planning [3]. Similarly, Hasanzad *et al.* (2022) proposed a tri-level resilience optimization for interdependent power-gas systems, combining long-term preventive decisions with real-time post-event operations. Their framework hardens selected transmission components (both power lines and gas pipelines) and, in the aftermath of a disaster, leverages fast-response resources like gas-fired generators, gas storage units, and P2G facilities to minimize unserved load. Notably, they introduce an uncertainty modeling approach for disasters to capture the probabilistic damage of components, using robust optimization to account for worst-case impacts [4]. This reflects a wider trend: robust and stochastic optimization techniques are commonly employed to handle the unpredictability of natural disasters in planning models. Some studies adopt scenario-based stochastic programming, generating numerous disaster scenarios (e.g., flood or hurricane impact scenarios) to inform resilient investment decisions. Others use distributionally robust methods that hedge against a range of plausible probability distributions of extreme events. For instance, a recent work by Chuan He *et al.* (2025) formulates a distributionally robust expansion plan for integrated distribution systems, considering both “inherent” resilience (ability to withstand initial impact) and “dynamic” resilience (ability to recover) under decision-dependent uncertainty. These advanced models underscore the importance of integrated planning under uncertainty for critical infrastructures. On the operational side, researchers have explored how to coordinately manage power and gas networks during and after a disaster to expedite recovery. Chen *et al.* (2020) presented a comprehensive resilience assessment of coupled power-gas systems under hurricane conditions, using spatially correlated component failure models and Monte Carlo simulation. They introduced integrated operation metrics to quantify how quickly and effectively the combined system can restore service after widespread damage. Other works focus on optimal restoration strategies that leverage the interdependence between networks [5]. For example, Qin *et al.* (2025) propose a novel two-stage recovery scheme for an integrated electricity-gas system facing extreme weather. In the pre-disaster stage, their method optimally positions resources such as mobile natural gas compressors, configures gas pipeline linepack levels, and even reconfigures the power distribution network topology to maximize the system’s ability to

absorb shocks. In the post-disaster stage, the mobile compressors are dynamically dispatched to connect gas wells or high-pressure zones to isolated “islands” of the gas network, effectively bypassing damaged pipeline sections. This coordinated operation between the power and gas subsystems (including switching of electricity network paths and rerouting of gas flows) substantially improves the speed of load restoration. Such innovative operational measures highlight that resilience is not only about robust infrastructure but also about flexible cross-network support and intelligent control in emergencies [6]. Role of Power-to-gas (P2G) Integration: A distinctive strategy for resilience enhancement is the integration of P2G technology into energy networks. P2G facilities convert electrical power (preferably excess renewable generation) into gaseous fuels like hydrogen or synthetic natural gas, which can be stored in the gas network. This provides additional emergency flexibility: during power outages, P2G units are inactive, but during gas shortages, stored gas or hydrogen can be used to generate power (via G2P) or supply gas demand, bridging one network’s shortfall with the other’s resources [7]. Recent studies confirm that P2G integration can significantly bolster resilience. For instance, Alasvand Javadi *et al.* (2022) investigated an integrated electricity-gas-heating network with energy hubs that include P2G units and gas storage. Using a scenario-based bi-level model (considering uncertainties in loads and renewables), they found that the presence of P2G and gas storage facilities markedly reduced the impact of gas supply disruptions. In simulations, adding these gas-electric coupling resources cut the forced load shedding by over 30% during a gas pipeline outage, as the P2G units provided an alternate gas supply to meet critical demand. This quantifiable benefit illustrates how multi-energy coupling improves survivability: the electric network’s flexibility (through P2G) can compensate for gas network weaknesses, and vice versa [8]. Likewise, Shabanian-Poodeh *et al.* (2024) specifically addressed flood scenarios and showed that strategic deployment of P2G and G2P units can enhance the resilience of power and gas distribution networks against flooding. They formulated a risk-constrained resilience planning model where investments in P2G/G2P facilities and network reinforcements are optimized under flood risk, combined with a distributed load restoration scheme [9]. Their results underscore that coordinated planning of P2G infrastructure alongside traditional network hardening yields a more robust interdependent system for flood scenarios. In summary, the integration of P2G creates a two-way emergency support mechanism: electricity can be converted to gas to supply heating or industry when gas infrastructure is compromised, and gas (via stored fuel or real-time production) can generate electricity to keep the lights on when the power grid is down. This bidirectional coupling is a powerful enabler of resilience in the face of natural disasters. Toward Coordinated Resilience Planning: Building on the insights above, it is clear that no single measure is sufficient—a holistic, coordinated planning approach is needed to truly enhance the resilience of interdependent gas and electric networks against natural disasters like floods. Such an approach involves (1) jointly planning infrastructure reinforcements in both networks with awareness of interdependencies, (2) incorporating P2G/G2P facilities and storage as part of the resource mix to provide cross-network support, and (3) developing operational strategies for disaster response that exploit network flexibility (e.g., network reconfiguration, mobile units, and demand response). Prior works have laid important groundwork: coordinated expansion planning models have demonstrated that integrating the planning of power and gas systems can achieve resilience more cost-effectively than separate plans. Operational schemes have shown the value of dynamically coordinating recovery actions across networks and P2G integration has proven its merit in reducing outage impacts. However, there is still a gap in fully addressing flood-specific impacts on coupled networks. Floods present unique challenges (e.g., spatially correlated substation and pipeline inundations, delayed access for repairs, etc.) that require specialized planning.

Few studies to date have explicitly focused on flooding in the context of integrated electricity-gas resilience, and those that do indicate significant room for further innovation in cross-sector mitigation strategies.

In this work, we aim to fill this gap by proposing a coordinated resilience enhancement framework for interdependent gas and electric networks against flood disasters, leveraging P2G integration and joint planning. The proposed approach will integrate long-term preventive measures (hardening and expansion of critical gas and power infrastructures and optimal allocation of P2G units) with operational measures (coordinated network reconfiguration, fast dispatch of gas-fired generators and P2G units, and prioritized load restoration) to minimize the impact of flood-induced failures on both networks. By planning the two energy carriers together and enabling them to support each other during emergencies, the overall system can maintain service continuity or recover much faster than isolated planning would allow. The following sections detail the methodology and demonstrate, through case studies, how power-to-gas integration and coordinated energy planning significantly improve the resilience of gas networks (and the coupled power grid) against severe flooding events.

A) Gas-power interdependence and recovery strategies

It is very important for system recovery that the natural gas and power distribution networks work together. For instance, gas-powered generators are necessary to get services back up and running after major events. Damage to gas distribution pipelines, on the other hand, can stop generators from working [10]. In [11], a two-stage stochastic programming method is suggested to help gas and power systems recover faster after these kinds of events. In addition, [12] talks about ways to improve emergency response by using repair teams that work on both gas and power lines. By combining resources from different energy systems, these repair strategies help the economy get back on its feet faster. Most of the research on making systems more resilient has been done on transmission-level systems or systems that combine power and gas. Studies show that making transmission systems more resilient is a big part of making sure they can get back to normal after a big event. Also, it's very important to think about power-gas dependency when planning for resilience [9, 13]. Fig. 1 shows how the different systems are linked to each other.

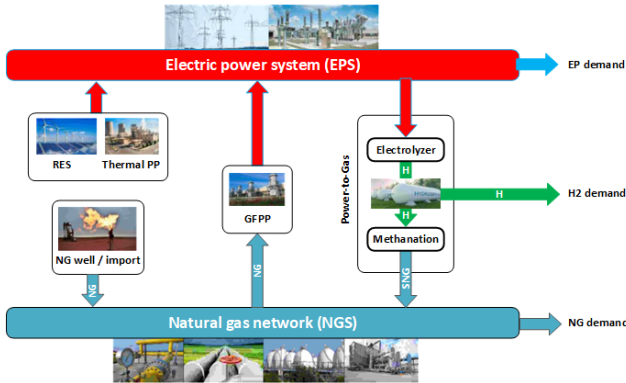


Fig. 1. Integrated electricity-gas-energy system framework with Power-to-gas technology.

B) Gas-power network interdependency

During events such as storms and floods, damage to gas pipelines can escalate failures in the power grid. Therefore, understanding the interdependency of gas and power systems during resilience planning is critical [14]. Neglecting this dependency may lead to power network deviations from optimal operation as shown in Fig. 2. The impacts of severe hurricanes on power and natural gas systems have been examined separately. According to this source, during Hurricane Katrina, 88% of natural gas production in the

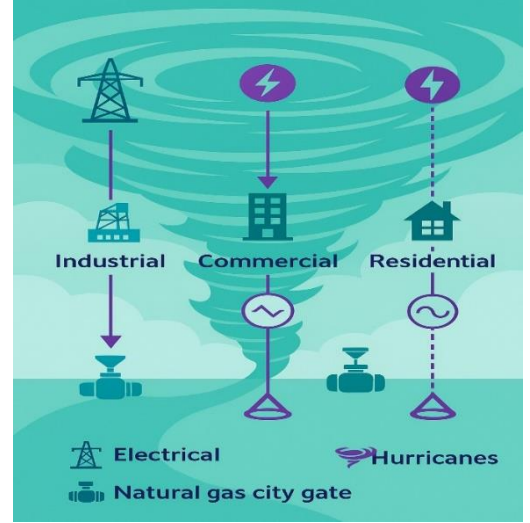


Fig. 2. Illustrates the interdependencies between gas and power infrastructures, demonstrating their vulnerabilities to natural disasters.

Gulf of Mexico was halted. Similarly, during Hurricane Rita, approximately 100% of gas production was suspended. By the end of 2005, 20% of natural gas production capacity in the Gulf remained offline. The number of failures in natural gas pipelines increased due to heavy rainfall and flooding, which made gas networks highly vulnerable. For example, during the hurricanes of 2005, pipeline failures increased significantly compared to other decades. It is evident that hurricanes primarily affect natural gas extraction and aerial transmission infrastructure. Heavy rainfall and flooding significantly contribute to pipeline failures in natural gas networks. As discussed earlier, the damage curve for natural gas pipelines indicates their vulnerability. Research on the vulnerability of distribution poles and guides during hurricanes has provided useful insights. However, the failure curve for gas pipelines has not yet been fully explored. In this study, it is assumed that gas pipelines are vulnerable during hurricanes and flooding. Gas pipelines located in flood-prone areas are assumed to experience failures. Unlike electrical distribution systems, the impact of natural gas failures is not easily mitigated. As such, proactive strategies for natural gas resilience during hurricanes are essential. The failure model for natural gas networks is shown in Fig. 3. This model demonstrates that pipeline failure probability increases if rainfall in each hour exceeds a certain threshold. In the power system domain, the concepts of reliability and resilience are two key factors that must be considered when designing new network structures. These two concepts are often perceived as identical, although they differ significantly in terms of event probability and impact. Despite extensive research on their distinction, the precise relationship between them has not yet been fully established [15]. The key difference between reliability and resilience lies in their ability to address events of high probability with low impact and low probability with high impact, respectively. This distinction is illustrated in Figs. 1-2, while other critical aspects are summarized in Table 1 [16].

Table 1. Comparison between reliability and resilience.

Attribute	Reliability	Resilience
Error probability	High	Low
Event impact	Low	High
Recovery time	Short	Long
Prediction level	Predictable	Unpredictable
Restoration targets	All network loads	Critical life loads
Outage duration	Short	Long
Event Type	Controllable faults, minor repairs	Storms, earthquakes, cyber-physical attacks
Performance metrics	Outage frequency and duration	System downtime and recovery speed

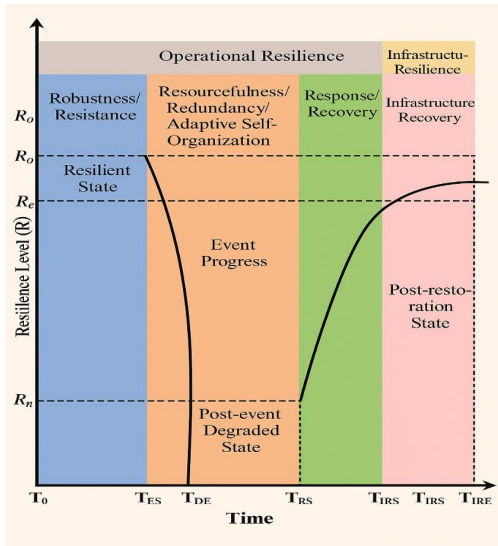


Fig. 3. Resilience curve: Operational and infrastructure resilience phases.

1.2. Literature review

Wang *et al.* (2025) – Developed a post-disaster repair and network reconfiguration strategy for integrated electric-gas systems with a focus on using natural gas pipeline line pack as a form of short-term energy storage. Their approach dynamically isolates damaged gas pipelines and releases stored gas (line pack) from intact pipeline sections to sustain gas supply and fuel gas turbines for power generation immediately after an earthquake. Simultaneously, the electric grid is reconfigured (closing tie switches to form “islands”) to deliver power to critical loads and to gas compressor stations, preventing cascading failures. They coordinate repair crews across both networks, prioritizing fixes that restore power to gas facilities (or vice versa) to break cross-system bottlenecks. In case studies, this integrated strategy maintained essential electricity and gas service in the first hours after a quake (using line pack as an energy bridge) and accelerated full recovery, reducing total load curtailment by $\sim 32.7\%$ compared to a non-integrated repair approach [17]. Shabani-Poodeh *et al.* (2023) – Provided a comprehensive review of resilience enhancement strategies for modern energy systems, especially integrated power and gas systems (IPGS). The review outlines how traditional grids are vulnerable to high-impact, low-probability events (natural disasters, cyberattacks) and emphasizes that coupling technologies like P2G and (G2P) create a bidirectional interface between electricity and gas networks, enabling new resilience tactics (each network can back up the other). It classifies long-term planning vs. short-term operational strategies and highlights emerging trends such as cross-sector infrastructure hardening, cybersecurity measures, and uncertainty modeling. A key conclusion is that coordinated multi-energy system planning (incorporating gas and power together) is crucial to fortify energy infrastructure against future calamities, filling the gaps left by siloed, single-network resilience approaches [18]. Han *et al.* (2023) – Explored hydrogen-powered smart grid resilience by examining how hydrogen technologies (like fuel cells and electrolyzers) can strengthen electrical grids. The paper discusses using hydrogen fuel cells as clean backup generators to maintain critical power during outages. It notes that hydrogen fuel cell systems offer high reliability and black-start capability (they can restart a grid without external power) with zero local emissions, making them attractive replacements for diesel gensets in emergency power supply. The authors present scenarios where surplus renewable electricity is converted via P2G into hydrogen, stored, and then used in fuel cells to support the

grid when a disaster strikes. This hydrogen-supported microgrid approach improves resilience by providing long-duration backup power, reducing dependence on diesel fuel logistics, and cutting emissions during recovery operations [19]. Gao *et al.* (2025) – Proposed a two-stage stochastic resilience planning for integrated electricity–gas systems under typhoon scenarios. In Stage 1, their model optimally invests in new assets—notably placing Hydrogen Refueling Stations (HRS) equipped with electrolyzers and hydrogen storage, as well as adding distributed gas-fired generators—to harden the system. Stage 2 simulates many possible typhoons damage scenarios (using Monte Carlo sampling of random line failures caused by storms) and determines the optimal operational response for each. The HRS act as decentralized energy hubs: during normal operation they produce and store hydrogen, and during a typhoon-induced outage they can supply hydrogen to fuel-cell generators or inject hydrogen into local gas pipelines to maintain gas pressure for customers. Simulation on a test system (based on Typhoon Saola) showed the integrated plan with HRS significantly reduced outage impacts compared to several baseline strategies. By considering a distribution of scenarios instead of a single worst-case, this approach yielded a cost-effective resilience upgrade—balancing investment cost and expected outage mitigation—and outperformed plans that focused on only one aspect (pure hardening, or only HRS, etc.). In summary, Gao *et al.* demonstrated that strategic siting of hydrogen stations and generators can provide critical backup energy during typhoons, markedly improving service continuity [20]. Chen *et al.* (2025) – Developed a two-stage planning model for district-level integrated energy systems under compound extreme weather uncertainty. They specifically considered correlated hazards like simultaneous typhoon winds and coastal flooding (using copula-based statistical models to capture the dependency between wind damage and flood damage). The first stage optimizes infrastructure investments (e.g., elevating or hardening substations, adding distributed generators, reinforcing gas pipelines), while the second stage simulates operations under numerous joint wind and flood scenarios. Their coordinated plan included measures such as relocating or flood-proofing critical electrical nodes, installing submersible distribution switchgear, and providing backup power to gas compressor stations in flood-prone areas. Results showed over a 50% reduction in expected unserved energy when planning for combined wind-and-flood events versus treating each hazard in isolation. This work highlights that multi-hazard resilience planning yields more robust solutions—by anticipating how one disaster (like a storm) can exacerbate another (flooding), planners can invest in complementary defenses that keep energy supply running during complex disasters [21]. Hasanazad and Rastegar (2022)—Introduced a tri-level robust optimization framework for hardening an interdependent electric-gas network against worst-case disasters. Their model uses a defender–attacker–defender structure: the upper level (“defender”) chooses a limited set of critical components to harden (e.g., key power lines, gas pipelines, compressors), an adversarial middle level (“attacker”) then simulates the worst-case damage to the system (within given disaster severity bounds), and the lower level (“defender” post-attack) optimizes emergency operations to minimize load shedding. Importantly, the model incorporates Power-to-gas units and gas storage as part of the defensive toolkit—meaning after a disaster hits, the system can convert whatever electricity is available into gas/hydrogen to support the gas network and use stored gas to fuel generators for power. In case studies, this robust plan achieved significant resilience gains: hardening only a few components (e.g., the 5 most critical links) reduced total outage losses by $\sim 40\%$, and utilizing P2G plus gas storage in the post-disaster operation cut load-shedding costs by over 20% relative to not using those resources. The downside noted is high conservatism and computational cost—because planning for the worst-case tends to over-invest in protections—but it guarantees that the integrated system can withstand the most severe credible

event [4]. Zhou *et al.* (2025) – Proposed a similar three-level defender–attacker–defender robust model for resilience of coupled electricity and gas networks. Their approach ensures the planning decisions are immune to worst-case disruptions in both networks. The upper level decides on investments like line and pipeline hardening or new redundancy, the middle level assumes an intelligent adversary causing maximal damage (within a budget of attacks), and the lower level restores the system optimally. Zhang *et al.* highlight that by co-optimizing power and gas restoration, the robust plan can handle contingencies such as a gas pipeline failure that would otherwise cripple gas-fired power plants. The model was validated on a test gas-electric system, showing it could maintain service to critical loads under worst-case simultaneous outages. However, like other robust methods, it tends to yield conservative (high-cost) solutions—for example, recommending extra backup generators and pipelines that might sit idle in normal times—as the price for worst-case resilience assurance [22]. He *et al.* (2025) – Developed a distributionally robust expansion planning approach for integrated electricity and gas distribution networks under seismic risk. A unique feature of their model is decision-dependent uncertainty: the act of reinforcing a component (like undergrounding a power line or using thicker-walled pipe) directly reduces its probability of failure in an earthquake, and the model accounts for this changing fragility. They formulate a two-stage expansion plan where the first stage chooses investments (new electric lines, gas pipelines, dual-fuel generators, energy storage, P2G units, etc.), and the second stage simulates earthquake damage and optimizes the post-quake operation. Instead of assuming a fixed probability distribution of earthquake damage, He *et al.* employ a distributionally robust optimization (DRO) with an ambiguity set (using a Kullback–Leibler divergence constraint)—this means the plan is hedged against a range of possible quake impact distributions, not just one. They define two metrics: inherent resilience (the network’s ability to supply load after the event) and dynamic resilience (the speed/extent of service restoration), and maximize both through a weighted objective. The resulting plan tends to invest in a mix of hardening and flexible resources: for instance, reinforcing a few critical pipelines and power lines, adding P2G units for alternative fuel supply, and installing dual-fuel or mobile generators that can be deployed if part of the network fails. Compared to a conventional plan, their DRO-based solution provided a better balance of cost and protection, avoiding over-conservatism while still guaranteeing robust performance under a variety of earthquake scenarios [23]. Wen *et al.* (2024) – Presented a data-driven stochastic-robust planning framework for a hydrogen-enhanced power system facing typhoons. They combined stochastic scenario planning with robust optimization in a tri-level model: the upper level invests in infrastructure (hardening key power lines and building hydrogen-to-power stations, i.e., fuel cell hubs), the middle level considers worst-case damage within each typhoon scenario, and the lower level optimizes operations (generator dispatch, load shedding) after the event. To generate realistic storm scenarios, they trained a Wasserstein GAN on historical typhoon data to produce many synthetic typhoon events, then used clustering to select representative scenarios. Using this, Wen *et al.* ensured their plan is effective over a broad distribution of possible typhoons rather than a single case. In simulation, the hydrogen-integrated system showed dramatic resilience improvements—load shedding was reduced by about 95.7% compared to a baseline with no hydrogen support. The hydrogen assets (electrolyzers, storage tanks, and fuel cells) provided long-duration backup power to critical loads when the main grid was down, essentially forming islanded microgrids that could run for days. This study demonstrated the potential of hydrogen fuel cells as emergency generators, outperforming conventional solutions in both reliability and environmental impact, albeit with the assumption that future hydrogen costs decline. It also introduced an efficient algorithm (nested column-and-constraint generation with progressive hedging) to solve the complex tri-level

problem faster. Overall, Wen *et al.* show that integrating hydrogen substantially boosts resilience against extreme wind events, albeit at some planning cost [24]. Ameli *et al.* (2025)—Investigated the role of hydrogen in a national-scale net-zero energy system (Great Britain) and its impact on system resilience. They found that large-scale deployment of renewables (wind/solar) coupled with P2G (electrolytic hydrogen) causes more energy supply variability to be absorbed by the gas network—requiring up to 83% more line-pack flexibility in gas pipelines to buffer these fluctuations. In effect, the gas network with hydrogen blending acts as a giant energy storage reservoir (a “gas battery”) that can smooth out renewable intermittency: when there is surplus renewable power, it’s converted to hydrogen and stored under pipeline pressure, then during low renewable periods, that hydrogen-rich gas is used to generate power or meet heating demand. Ameli *et al.* quantified resilience benefits of this integration: the combined system could better handle extreme scenarios like week-long wind lulls or cold spells because the hydrogen/line-pack provided a strategic reserve. They also discussed operational challenges – e.g., ensuring gas quality and safety with hydrogen blends and upgrading infrastructure to be hydrogen-compatible. The study’s key point is that hydrogen integration for decarbonization can simultaneously enhance resilience by adding multi-day storage capacity and fuel flexibility to the energy system. However, policy and market mechanisms will be needed to incentivize the extra line-pack usage and storage, as these are not traditionally valued in current markets [25]. Alizad *et al.* (2024) – Proposed a hybrid stochastic and Info-Gap decision theory (IGDT) planning model to improve resilience of a community multi-energy system under multiple hazards. They considered a community supplied by electricity and gas (and possibly heat), subject to threats like earthquakes, hurricanes, and extreme winter storms. The model allocates a limited “resilience budget” to various upgrades and new assets, including a Hydrogen Storage System (HSS) (e.g., hydrogen tanks or underground storage). Using IGDT, they assess robustness under deep uncertainty—i.e., they don’t assume exact probabilities for extreme events but ensure the plan can handle a range of event severities up to a certain confidence. The two-stage model first picks investments, then simulates the worst-case operational response given those investments. The results were notable: dedicating even a small fraction of total investment (say 5–10%) to resilience measures like HSS yielded a very large gain in resilience (they reported over 93% improvement in a resilience index with ~10% cost increase). In practice, this could mean that adding a modest hydrogen storage facility and some backup generation drastically shortened outage durations and served critical loads during all tested disaster scenarios. The HSS provided an on-demand energy buffer that could supply either power (via fuel cells) or gas (via injection) when the usual supply was cut—a versatility that pure battery storage or diesel gensets alone could not fully replicate. Alizad *et al.* conclude that strategic investment in hydrogen storage is highly cost-effective for multi-hazard resilience, though they also note the importance of optimizing its size/location and acknowledge current hydrogen cost uncertainties. Their planning approach helps decision-makers quantify the trade-offs, showing that a well-spent resilience budget can protect a community from a wide spectrum of disasters [26]. Huang *et al.* (2025)—Reviewed the use of Artificial Intelligence (AI) techniques to enhance power system resilience. This work surveys recent advances in AI-driven solutions for outage prediction, system monitoring, and adaptive control that can help prevent or mitigate disaster impacts. For example, AI models (like machine learning classifiers) can process weather forecasts and sensor data to predict which components are likely to fail in an impending storm, allowing utilities to pre-position crews or re-route power. AI-based controllers can also dynamically reconfigure grids or dispatch distributed energy resources in real-time during an emergency, beyond human-speed decision-making. Huang *et al.* discuss how reinforcement learning has been applied to optimize grid restoration and how image

recognition drones or robotics aid in damage assessment post-disaster. They also address challenges: AI systems themselves must be robust to bad data or cyberattacks, and operators need trust and interpretability for AI recommendations (black-box decisions are hard to accept for critical infrastructure). A notable point is the intersection of cybersecurity and resilience—as grids get “smarter” with AI and IoT devices, they must also withstand hacking or false data injection, or else the AI could be misled. The paper suggests a future where AI is an integral part of resilient grid architecture but calls for research on securing AI tools and ensuring they perform reliably under the extreme conditions when they are needed most [27]. Izadi *et al.* (2023)—Investigated distribution network operation under wildfire conditions using a multi-horizon Info-Gap Decision Theory framework. Wildfires pose a unique threat: they can progressively damage power lines and force preemptive shut-offs. Izadi *et al.* considered a distribution system in a wildfire-prone area and the uncertainty in how a fire spreads. They schedule both stationary and mobile resources (like battery energy storage systems and portable generators) over a planning horizon to minimize the worst-case load not served, without assuming precise probabilities of fire behavior. Their IGDT approach identifies a strategy that is robust against a wide range of fire intensities—for example, ensuring critical loads (hospitals, emergency centers) remain powered even if the fire causes more damage than expected. The plan might involve, say, dispatching mobile generators to threatened substations in advance and reconfiguring feeder lines to create self-sufficient islands if main lines must be de-energized. Compared to a deterministic or probabilistic approach, their resilience-oriented operation maintained higher service continuity in the worst-case fire scenario, at the expense of some extra cost (like repositioning resources that might prove unnecessary if the fire is mild). This study underlines the value of flexible, mobile assets and proactive operation in the face of unpredictable, spreading disasters like wildfires [28]. Shalaby *et al.* (2024) – Proposed a “self-proactive” distribution grid strategy to tackle approaching wildfires. Their method uses a dual rolling-horizon optimization: one horizon looks ahead to reconfigure the network and dispatch resources in the near term, while another schedules the movement of mobile battery units over a longer horizon as a wildfire front approaches the service territory. Essentially, as a wildfire is forecasted to hit certain areas, the grid preemptively isolates those high-risk zones (to prevent sparking new fires and protect equipment) and reroutes power to maintain supply to safer areas. Mobile energy storage (such as battery trucks or trailers) is repositioned to support critical loads that might otherwise be cut off. By continuously updating the plan as the fire spreads (rolling horizon), the grid “dodges” the threat in real time. In case studies, this proactive approach greatly reduced customer outages—the authors report over a 70% reduction in load shed compared to a reactive approach where the grid only responds after faults occur. This work demonstrates the next generation of resilience operations: not just reacting to damage, but anticipating disasters and taking action before components fail, using mobility and flexibility of resources [29]. Khatibi *et al.* (2023)—Delivered an extensive overview of integrated electricity and gas system planning and its new opportunities, with an emphasis on reliability and resilience benefits. This work systematically reviews the technical issues that arise when planning electric and natural gas infrastructures together (such as modeling their couplings, co-optimizing investments, and regulatory hurdles). One major point is that integrated planning allows planners to exploit synergies between the systems—for example, adding a P2G unit might defer the need for a new gas pipeline and simultaneously provide voltage support to the grid via the gas-fired generators it enables. From a resilience perspective, Khatibi *et al.* note that separate planning often ignores how failures propagate between systems (like electricity outages disabling gas compressors); integrated planning internalizes those interactions and thus identifies investments that improve joint

resilience. They highlight case studies where an investment in one network (e.g., a gas storage facility) significantly improved the resilience of the coupled system (by fueling generators during power outages), which would not be captured in siloed analysis. The paper also discusses trends such as the inclusion of environmental objectives (carbon reduction) alongside resilience and how multi-energy microgrids and demand response can be planned to enhance community-level resilience. In essence, this review solidifies that coordinated multi-energy planning is becoming essential, and it provides a foundation for researchers and practitioners to understand the benefits and challenges of planning power and gas systems as a unified whole [30]. Aslam *et al.* (2025) – Presented a critical review on the application of energy storage systems (ESS) for power system resilience. This paper catalogs various types of ESS (battery energy storage, pumped hydro, flywheels, thermal storage, etc.) and examines how each can help a grid resist and recover from outages. Key points include batteries provide near-instantaneous response and can supply critical loads for a few hours, pumped hydro offers large capacity but slower response and geographical limits, thermal storage can supply heat (or absorb surplus energy) to maintain energy services during crises (useful in integrated power-heat systems), and emerging solutions like mobile battery packs or electric vehicles can act as distributed backup sources. The review also discusses strategies for deploying storage for resilience, such as optimal sizing/location (ensuring batteries are placed at critical nodes) and control schemes that prioritize lifeline loads during an emergency. They highlight that while storage is crucial for bridging short gaps (seconds to hours) and providing grid stability, it typically cannot single-handedly address very long outages (multi-day blackouts) due to capacity limitations—this is where fuel-based storage (gas, hydrogen) might be needed. An important insight from Aslam *et al.* is on resilience metrics and valuation: they note that planners are increasingly evaluating investments in storage not just on normal operational benefits but also on how much outage cost reduction they provide in extreme events. This aligns with evolving regulatory attitudes to treat resilience as a quantifiable service. The review concludes by identifying research gaps, such as the need for better models to optimize hybrid storage (combining battery, thermal, and hydrogen storage) and for policies that incentivize storage deployment specifically for resilience (since market signals alone may undervalue it) [31]. Qiu and Li (2025)—Examined the potential impacts of a High-Altitude Electromagnetic Pulse (HEMP) attack on power systems and the related research challenges. A HEMP event (resulting from a nuclear detonation in the upper atmosphere) could induce very fast, high-voltage transients over a continental-scale area, simultaneously damaging a large number of electrical components (transformers, relay electronics, and communication equipment). This paper outlines the physics of HEMP and warns that modern grids, with extensive electronics and SCADA, are quite vulnerable. It calls attention to resilience measures like EMI shielding for critical control centers, hardening substation electronics, creating redundant communication paths, and having manual or analog backup controls in case digital systems are fried. The authors also highlight the need for planning restoration without telecom—since a HEMP could knock out communications, grid operators may have to rely on pre-set automated islanding schemes or local control to re-energize sections. The research prospects discussed include developing better HEMP threat models (to simulate which components would fail), coordinating with national defense for early warning, and designing “graceful degradation” strategies so that even if a large portion of the grid is lost, some islands can survive. While HEMP events are extremely rare, the consequences are so high that Qiu and Li argue the resilience community should treat them similarly to natural mega-disasters, ensuring that critical infrastructure (like nuclear plant controls or defense facilities) has extra layers of protection and backup against such pulses [32]. Rezaee Jordehi *et al.* (2024)—Investigated resilience

in the context of industrial energy hubs that supply electricity, heat, and hydrogen to industrial facilities, focusing on the use of mobile storage for resilience. Industrial sites often have high energy demands and can't afford long downtimes (for safety and economic reasons). This paper considers an energy hub with on-site generation (possibly solar, CHP, etc.), hydrogen production for industrial processes, and thermal systems, connected to the wider grid. The authors propose using mobile battery units and mobile hydrogen storage or fuel cell units that can be relocated to the site during emergencies. They formulate an optimization that decides how to deploy these mobile resources when an outage is anticipated or occurs—for example, sending a battery truck to an industrial park before a predicted hurricane or having a hydrogen tanker ready to fuel generators if gas supply is disrupted. Their results indicate that such mobile assets can significantly reduce unserved energy for critical industrial loads, essentially by temporarily converting the industrial hub into an islanded microgrid that can run independently of the main grid. They also address coordination: since multiple industrial hubs might need support simultaneously, strategies like priority ranking or shared mobile fleets are discussed. This study adds to resilience literature by extending it to multi-vector industrial systems and highlighting the value of mobility and cross-usage of energy carriers (hydrogen as backup fuel) in keeping essential industries running through disasters [33]. Wu *et al.* (2024) – Proposed a novel resilience assessment framework for multi-component critical infrastructure, which can be applied to systems like integrated power and gas networks. Traditional reliability metrics (SAIDI, N-1 security) fall short in measuring resilience for complex, interdependent systems. Wu *et al.* developed a framework that models the infrastructure as a graph of interdependent components and introduced metrics capturing not only the frequency of failures but also the duration of service interruption and the effectiveness of recovery efforts. They integrate concepts like the “resilience trapezoid” (graphical representation of system performance drop and recovery) and define composite indices that combine the extent of disruption, the time to recover, and the resources expended in recovery. Their framework can incorporate multiple infrastructure layers—for example, evaluating how quickly power can be restored and gas pressure stabilized in a region, given repair crew allocations and available backups. By simulating various hazard scenarios, they can output a resilience score that helps identify which investments yield the biggest improvement. An important contribution is a method to account for cross-sector interdependencies in the metric; e.g., a power outage that also causes a water supply failure would count more heavily. The authors demonstrate the framework on a notional system and show how it can guide decision-makers—for instance, revealing that investing in a certain substation and the adjacent gas compressor station provides more resilience benefit than treating either alone. This work pushes the field toward more holistic resilience quantification, enabling better comparison of strategies across different types of infrastructure [34]. Pan *et al.* (2023) – formulated a multi-objective two-stage optimization for an integrated energy system, incorporating Power-to-gas (P2G) and demand response, to achieve both economic efficiency and resilience. In the first stage, they optimize the day-to-day operation of the system (economic dispatch), and in the second stage, they simulate the system under an extreme event and optimize the response (islanding, load shedding, etc.). The objectives considered include minimizing cost (or emissions) and minimizing outage impact, yielding a Pareto front of solutions that trade off between cost and resilience. Including P2G in the model allows excess renewable electricity to be converted to gas, which can either generate power later or serve gas loads—this adds flexibility. Integrated demand response means that controllable loads (electric or gas heating loads, for example) can be curtailed or shifted in an emergency to support the system. Their results show that certain strategies—like using P2G to maintain gas supply for peaking generators and calling upon industrial demand response to drop

non-critical load—lead to a much more resilient system with only a small cost increase. The multi-objective analysis helps illustrate the diminishing returns: beyond a point, achieving higher resilience causes a sharp rise in cost. This kind of study provides practical insight: for instance, one might choose a solution that increases annual operating cost by, say, 5% but can reduce expected load shed in disasters by 50%, which is likely a worthwhile trade-off. Pan *et al.* thus demonstrate the value of co-optimizing economic and resilience objectives and show that P2G plus demand flexibility are key enablers of a resilient, low-carbon energy system [35]. Ren *et al.* (2023)—Focused on planning a district-level integrated energy system (electricity, heating, and gas) that is both economic and resilient against natural disasters. They model a city district with distributed renewable generation, CHP units, electric boilers, and gas boilers—a typical integrated energy system—and consider investments like additional distributed generators, network ties, or energy storage. They also incorporate demand response programs (both electrical and thermal load shifting) as a soft resource. The planning optimization minimizes cost while constraining a resilience metric (or vice versa). One highlight is analyzing a scenario of a severe earthquake followed by a cold wave: the earthquake can damage power lines and gas pipes, then a cold spell sharply raises heating demand when some infrastructure is down. Ren *et al.* found that a coordinated strategy—e.g., investing in a dual-fuel CHP that can switch to oil if gas is out, plus implementing a demand response that lowers thermostat setpoints to reduce load during emergencies—kept the district functioning much better than a business-as-usual plan. Combining infrastructure upgrades with demand-side management yielded a synergistic effect: the physical upgrades provided alternative supply paths, and demand response shaved peak loads to manageable levels when supply was constrained. The outcome was a resilient design that could supply essential heat and power services through the modeled disasters, at an incremental cost that was justified by the avoided outage losses. This work underscores the importance of including customer-side flexibility and multi-energy coordination in resilience planning for local energy networks [36]. Li *et al.* (2022)—Studied a 100% renewable island energy system and how P2G technology could help it withstand extreme weather. The island is assumed to rely solely on renewables (solar, wind) for power, with P2G used to convert surplus power to hydrogen (or synthetic methane), which is stored for backup. They use a combination of multi-objective optimization and agent-based simulation to design the system and test its performance under scenarios like prolonged cloudy, windless periods or storms that disrupt generation. One key finding is that P2G (with hydrogen storage) greatly improves reliability: during a long calm period when wind turbines produce little, the stored hydrogen can be used in fuel cells or generators to keep the lights on, whereas without P2G the island would experience blackouts once battery storage is exhausted. They also examined the effect of extreme weather events (e.g., a typhoon that damages some solar panels): the agent-based model simulates how individual components fail and repair over time. The system with P2G had higher survivability, as it could island sections of the grid powered by hydrogen generators while repairs were underway. However, efficiency and cost were challenges—hydrogen storage required oversizing generation capacity and still had round-trip losses. The multi-objective analysis showed the trade-off between more hydrogen storage (for resilience) versus curtailment or load shedding in rare events. Overall, Li *et al.* demonstrate that for an isolated renewable-based system, P2G is a key to handling long-duration gaps in energy supply, effectively acting as seasonal storage and emergency fuel, thereby ensuring energy security under extreme conditions [37]. Chen *et al.* (2024) – Proposed a triple-level adaptive restoration optimization for coupled transmission and distribution power systems after a wide-area disaster. This model coordinates high-voltage transmission grid restoration with local distribution and microgrid restoration, recognizing that the two levels interact (e.g., a distribution feeder can't be re-energized until

its upstream transmission line is back, but conversely, transmission may depend on distributed generation in some areas for black start). Level 1 of the model assigns repair crews to transmission and major distribution outages (deciding which lines or substations to fix first), Level 2 optimally reconfigures the distribution network and dispatches distributed generators (including microgrids) to serve as many customers as possible with the partially available network, and Level 3 checks system security constraints (ensuring that as we restore, we don't overload lines or cause instability). By iterating these levels, the approach adapts the restoration plan as repairs progress—for instance, once a substation is repaired, it might shift the priority of the next repair or reconfiguration. Chen *et al.* also incorporate restoration security constraints, meaning they avoid intermediate steps that could risk operator safety or system integrity (like avoiding closing a switch that would create an unintentional power loop). Tested on a benchmark system, the tri-level optimization restored service faster than conventional methods—it leveraged temporary microgrid islands to support critical loads within the first few hours and ensured a smoother transition as the bulk system came back. This work exemplifies advanced operational resilience: instead of treating transmission and distribution separately, it uses a unified optimization to maximize overall load restoration, acknowledging modern grids' ability to self-heal via distributed resources [38]. Hafezparast *et al.* (2023)—Addressed resilience against cyberattacks in integrated energy systems by proposing an attack-resilient distributed energy management strategy. Modern integrated systems (electricity, gas, etc.) rely on communication networks for monitoring and control, which opens the door to cyber threats. This study models scenarios where an attacker tries to disrupt the system by targeting control signals—for instance, falsifying the status of a gas compressor or tripping an electrical substation remotely. The authors introduce a distributed control scheme that can detect anomalies and reconfigure the system's operation to mitigate the impact of attacks. It uses redundant measurements and peer-to-peer agent communication (so if one control center is compromised, local controllers can still make decisions). In effect, the system can island itself in cyberspace—isolating attacked segments of the control network to prevent spread—analogue to islanding in the physical grid. They tested the strategy on a small integrated power-gas network model under a cyberattack that tried to shut down a gas compressor and a power generator. The resilient controller detected the inconsistencies (e.g., power flow readings not matching the commands) and responded by switching control to backup schemes: activating an alternate gas route and adjusting generator outputs to keep the system balanced. This kept the energy supply largely uninterrupted despite the attack, whereas a standard centralized control would have caused significant load drops. Hafezparast *et al.* highlight that cyber resilience must complement physical resilience; tools like distributed ledgers, encryption, and anomaly detection are becoming as important as spare transformers. Their strategy contributes to making integrated systems “gracefully degrade” under cyberattacks, ensuring energy delivery is maintained as much as possible even if some control functions are compromised [39]. Nazemi and Dehghanian (2022) focused on power grid resilience during wildfires, introducing an integrated solution that combines dynamic line rating (DLR) and adaptive microgrid islanding. In wildfire conditions, high temperatures and smoke can reduce the current-carrying capacity of overhead lines (due to sag and cooling effects), and utilities often de-energize lines preemptively to avoid igniting fires. This work proposes using real-time sensor data (temperature, line sag, etc.) to dynamically adjust line ratings instead of fixed conservative limits—thereby maximizing the power throughput of lines that are still safe, which can be crucial when other lines are shut off. At the same time, they implement a self-healing algorithm that forms microgrids in areas at risk: if a line must be opened due to fire risk, the downstream section can disconnect and rely on local distributed energy resources (like diesel gensets and solar+battery) to supply

critical loads. A case study on a California region showed that with DLR, some lines could carry, say, 10–20% more power than static limits would allow during a heat event, which helped reroute power to evacuation centers and water pumping stations. And where lines had to be cut, the preformed microgrids kept those local areas powered, whereas traditionally they would suffer an outage. This integrated approach improved both safety (by preventing faults that cause fires) and resilience (by maintaining service to key loads). The authors note the importance of coordination with firefighters and using forecast data: if a fire is moving towards a corridor, the system can proactively reconfigure such that when that corridor is cut off, as few customers as possible are impacted and alternatives are already supplying them [40]. Zhao *et al.* (2023) provide a comprehensive review of power system resilience concepts, metrics, and enhancement strategies. This work serves as a foundational reference in the resilience field. It clarifies the definition of resilience (distinguishing it from reliability), breaking it down into aspects like robustness, resourcefulness, rapid recovery, and adaptability. The review compiles metrics used in literature—for example, Expected Energy Not Served (EENS), Value of Lost Load, resilience trapezoid area, time to recovery, etc.—and discusses their pros/cons in quantifying resilience. It also surveys a wide range of enhancement strategies: hardening infrastructure (physical strengthening of components), operational strategies (network reconfiguration, microgrids, demand response), and emerging technologies (energy storage, P2G, EVs as backup, etc.). Zhao *et al.* emphasize the need for multi-dimensional approaches, as no single solution (like just adding backup generators) is sufficient for all scenarios. They highlight case studies of recent disasters (hurricanes, earthquakes, and winter storms) and what worked or failed in those events as lessons learned. One trend noted is the move from single-system analysis to interdependent network resilience—modern studies (2020s onward) often consider coupled infrastructures, as this yields more accurate assessments of how outages propagate. The review concludes by identifying challenges such as modeling complex interdependencies, valuing resilience investments economically, and incorporating climate change projections into planning. In short, Zhao *et al.* (2023) is an authoritative summary that grounds researchers in the state of resilience research up to 2023, making clear that enhancing resilience is a multi-faceted problem requiring coordinated planning, advanced technology adoption, and supportive policy frameworks [41].

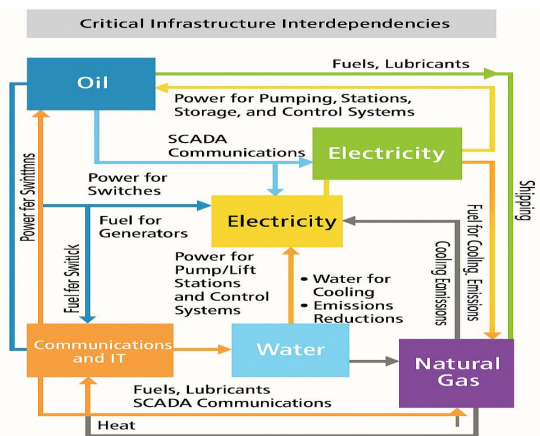


Fig. 4. Relationship between the electricity and gas sectors, energy carriers, and consumers.

Fig. 4 depicts a tightly coupled network linking electricity, natural gas, oil, water, and communications/IT: fuels and lubricants flow from oil/gas, while electricity powers pumps, compressors, switching, and SCADA/control systems. Disruptions cascade—loss of gas supply quickly reduces dispatchable

generation, and power outages immediately halt gas compression, water cooling, and communications. Hence, resilience cannot be assessed in isolation; operational loads at the interfaces (pumps/compressors/SCADA/cooling) must be modeled explicitly. Within this dependency web, gas storage and battery ESS act as temporal buffers and flexibility resources that break propagation paths during crises. This systems view motivates our integrated stochastic MILP and the scenario-based evaluation of investment and restoration options.

The taxonomy in Table 2 situates our work within the prior literature by classifying studies along consistent dimensions: hazard type, modeling scope (power, gas, or integrated IPGS), decision layer (planning vs. operations/recovery), optimization paradigm, resilience levers, uncertainty treatment, test scale, reported metrics, and core findings. Across floods, typhoons, seismic events, and generic extremes, most papers emphasize planning-only models and handle uncertainty with scenario sampling or robust/DRO sets, typically reporting ENS and reliability indices. Few works explicitly model gas-network outages that throttle gas-fired generation within an integrated power–gas formulation, leaving cross-sector dependencies underexplored. Our study fills this gap: an IPGS, a two-stage stochastic MILP with spatially correlated, flood-driven fragility and physics-aware (PWL/Weymouth) gas constraints, evaluated on realistic test systems. Compared with prior approaches, we quantify the value of storage—gas storage consistently lowers risk and cost, while adding ESS yields additional but smaller savings—and show that integrated co-planning and explicit gas→power coupling materially change investment priorities. Overall, Table 2 clarifies coverage, exposes gaps, and positions our contribution as advancing both the modeling fidelity and the evidence base for resilient, cross-sector planning.

1.3. Contribution

In this work, we propose a coordinated resilience enhancement framework for interdependent gas and electric networks to address flood disasters, utilizing power-to-gas (P2G) integration and joint planning. This approach integrates long-term preventive measures—such as hardening and expanding critical gas and power infrastructures and optimally placing P2G units—with operational measures, including coordinated network reconfiguration, rapid deployment of gas-fired generators and P2G units, and prioritized load restoration. The goal is to minimize the impact of flood-induced failures on both networks. By planning the two energy carriers together and allowing them to support each other during emergencies, the overall system can maintain service continuity or recover more quickly than if planned in isolation. The subsequent sections detail the methodology and demonstrate through case studies how P2G integration and coordinated energy planning can significantly enhance the resilience of gas networks and the interconnected power grid in the face of severe flooding events.

1. A novel aspect of this work is the explicit modeling of gas infrastructure vulnerabilities during extreme weather events, such as pipeline ruptures, compressor station failures, or submersion during floods. These vulnerabilities can directly disrupt fuel supply to gas-fired power plants. The framework identifies critical gas flow paths and introduces adaptive control strategies aimed at minimizing cascading failures in the electricity network that are caused by gas outages.

2. We develop a three-phase resilience strategy that incorporates resilient design, uncertainty modeling, and coordinated recovery planning across electric and gas networks. This dual-layered approach allows for proactive planning and efficient restoration under hurricane-induced conditions.

3. In addition, the study employs a gas network-aware optimization framework to determine the optimal placement of P2G units. By considering gas flow dynamics, pressure limits, and node demands, the model ensures that P2G units are positioned

where they can most effectively support the system during disturbances, enhance gas supply reliability, and improve the flexibility of both gas and power networks.

2. MODELLING

2.1. First stage problem

The proposed framework for resilience planning of power distribution systems, considering dependency on the natural gas distribution network, is presented in Fig. 5. The objective function of the first stage is given as follows:

$$OF = \min [\gamma \cdot I_{CTC} + EC_s] \quad (1)$$

$$\begin{aligned} I_{CTC} = & \sum_{(i,j) \in B} \chi_{ij}^h \cdot c_{ij}^h + \sum_{d \in D} \chi_d^{dg} \cdot c_d^{dg} + \\ & \sum_{(i,j) \in SW} \chi_{ij}^1 (c_{ij}^{sw} + LTS_{ij} \cdot c_{ij}^c) + \\ & \sum_{e \in E} \chi_e^{es} (c_p^{es} \cdot P^{ES} + c_E^{es} \cdot E^{ES}) \end{aligned} \quad (2)$$

$$\gamma = \frac{r(1+r)^Y}{(1+r)^Y - 1} \quad (3)$$

$$\sum_{i \in D} x_i^{dg} \leq N_{DG} \quad (4)$$

$$\sum_{k \in K} x_{p,k} \leq X_p, \quad \forall p \quad (5)$$

The objective function (1) represents the total costs, including investment costs and operational costs under emergency conditions.

2.2. Constraints

Eqs. (2), (4), (5), and (6) from include constraints related to interest rate, planning horizon, and limitations on the installation of distributed generation units and switches. These constraints are also used in this section.

2.3. Second stage problem

After accounting for power line failures, load demand, and natural gas pipeline failures, the system operator must make decisions to minimize load shedding costs while restoring the system. In this phase, the priority of load supply is determined.

The objective function for the second stage is defined as Eq. (6):

$$\min EC_s = \sum_{s \in S} \pi_s \sum_{t \in T} \sum_{i \in L} \rho_{ij}^s C_i^s P_i^s \quad (6)$$

Constraints for electrical energy storage systems

Another key element introduced in this study as an effective method for network resilience against severe water and weather events is the use of electrical energy storage systems. The operational constraints of storage systems are defined as follows:

Fig. 6 presents a threshold-based fragility model for a pipeline under heavy rainfall. The horizontal axis is rainfall rate (in/hr.) and the vertical axis is failure probability (0–1). A marked point (W_{CR}) denotes the critical rainfall rate. For rainfall below (W_{CR}), the failure probability is zero—the pipeline is assumed to remain functional. Once rainfall reaches or exceeds (W_{CR}), the curve jumps to one, meaning failure is treated as certain.

Table 2. Pseudo code for shuffled bat optimization algorithm.

Study (year)	Hazard focus	Scope (P/G/IPGS)	Decision layer	Optimization	Key resilience levers	Uncertainty model	Typical test scale	Metrics reported	Core finding
Movahednia <i>et al.</i> (2021)	Flood	P	Planning	Stochastic (2-stage)	Substation hardening	Scenario sampling	Feeder-level	ENS, SAIDI	Targeted flood hardening cuts outages disproportionately
Zou <i>et al.</i> (2020)	Natural disasters (generic)	IPGS	Planning	Robust (co-expansion)	Joint P+G reinforcements	Worst-case set	DN-scale	Load shed	Co-planning beats siloed plans under extremes
Hasanzad and Rastegar (2022)	Generic extremes	IPGS	Planning+Ops	Tri-level robust	Gas storage, P2G	Adversarial budget	DN-scale	Cost, load shed	Storage+P2G reduce post-event loss > 20%
Shabani-Poodeh <i>et al.</i> (2024)	Flood	IPGS	Planning+Ops	Risk-constrained	G2P/P2G, restoration	Probabilistic risk	DN-scale	ENS, cost	G2P/P2G planning improves flood resilience
Javadi <i>et al.</i> (2022)	Load/RES variability	IPGS	Planning	Scenario-based	ESS, flexible loads	Stochastic	City-hub	ENS, cost	Storage + fast flexibility reduce curtailment
Qin <i>et al.</i> (2025)	Extreme weather	IPGS	Ops (recovery)	2-stage ops	Linepack, mobile compressors	Scenario ops	DN-scale	Served load	Mobile gas support speeds recovery
He <i>et al.</i> (2025)	Seismic	IPGS	Planning	DRO	Hardening, P2G, dual-fuel	KL ambiguity set	DN-scale	Inherent/dynamic resilience	Balanced investments hedge model error
Wen <i>et al.</i> (2024)	Typhoon	Power+H2	Planning	Stochastic-robust (tri-level)	H2 hubs (electrolyzer, FC)	Data-driven + robust	System-level	Load shed	Hydrogen assets cut load shed ≈ 96%
Gao <i>et al.</i> (2025)	Typhoon	IPGS	Planning+Ops	2-stage	HRS siting, DG	Monte-Carlo storms	Regional	Cost, load shed	Decentralized H2 hubs enhance continuity
Chen <i>et al.</i> (2025)	Compound wind+flood	IES	Planning+Ops	2-stage	Hardening, backup power to compressors	Copula-based joint hazards	District	EENS	Joint-hazard planning halves EENS
This work	Flood (gas→power coupling)	IPGS	Planning Stage-2 ops +	2-stage stochastic MILP	Gas storage, ESS, DG, switching; explicit gas failures; gas-flow	Scenario vector ω_s with p_s; spatially correlated fragility; scenario reduction	33-bus + 14-node; IEEE-118 + 26-node	SAIDI/SAIFI/CAIDI, ENS, cost	Gas storage trims shedding cost ≈ 30%; ESS adds ≈ 3% and flexibility

Legend: P = power; G = gas; IPGS = integrated power–gas system; IES = integrated energy system.

This step-function idealizes the system as perfectly safe up to a threshold and guaranteed to fail beyond it.

$$E_{e,f}^s = E_{e,f}^{initial} + \eta^{ch} \times P_{e,f}^{ch,s} \times \Delta t - \frac{1}{\eta^{dch}} \times P_{e,f}^{dch,s} \times \Delta t, \quad (7)$$

$$\forall e \in E, t = 1, \forall s$$

$$E_{e,f}^s = E_{e,f-1}^s + \eta^{ch} \times P_{e,f}^{ch,s} \times \Delta t - \frac{1}{\eta^{dch}} \times P_{e,f}^{dch,s} \times \Delta t, \quad (8)$$

$$\forall e \in E, t = 1, \forall s$$

$$SOC_{e,f}^s = \frac{E_{e,f}^s}{E_{max}^s}, \quad (9)$$

$$\forall e \in E, \forall t, \forall s$$

$$SOC^{min} \leq SOC_{e,f}^s \leq SOC^{max}, \quad (10)$$

$$\forall e \in E, \forall t, \forall s$$

$$0 \leq P_{e,f}^{ch,s} \leq P_{e,f}^{ch,max} \times (1 - SOC_{e,f}^s), \quad (11)$$

$$\forall e \in E, \forall t, \forall s$$

$$0 \leq P_{e,f}^{dch,s} \leq P_{e,f}^{dch,max} \times SOC_{e,f}^s, \quad (12)$$

$$\forall e \in E, \forall t, \forall s$$

$$P_{e,f}^{ch,s} \leq BigM \times \psi_{e,f}^{ch,s}, \quad (13)$$

$$\forall e \in E, \forall t, \forall s$$

$$P_{e,f}^{dch,s} \leq BigM \times \psi_{e,f}^{dch,s}, \quad (14)$$

$$\forall e \in E, \forall t, \forall s$$

$$\psi_{e,f}^{ch,s} \leq \psi_{e,f}^{dch,s} \leq x_{e,f}^{e,s}, \quad (15)$$

$$\forall e \in E, \forall t, \forall s$$

Eqs. (7) and (8) describe the energy levels of storage systems based on the charging efficiency and discharging efficiency along with their initial charge at $t=1$. In Eq. (9), the energy level of the storage system is provided in a predictive format based on its capacity limits. Eq. (10) indicates the upper and lower limits of the storage charging capacity. Eqs. (11) and (12) specify the constraints on charging and discharging power within the allowed minimum and maximum values of storage capacity. These constraints ensure that the charging rate does not exceed the maximum allowable value. According to this relationship, the higher the energy level of the storage system, the slower the charging rate, while the discharging rate increases. Similarly, when the energy level of the storage system decreases, the discharging speed reduces, and the charging rate increases. Additionally, the simultaneous charging and discharging of the storage system is prevented using constraints Eqs. (13), (14), and (15).

2.4. Power balance constraint in each node

The power balance constraint for each node is applied, ensuring that power generation, storage, and load demand are dynamically balanced during system restoration in Eq. (16).

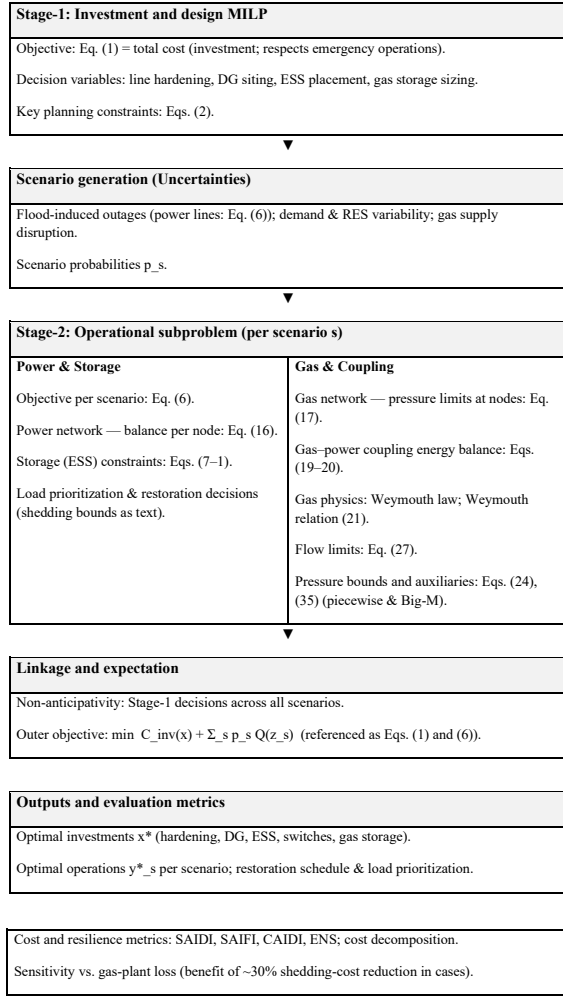


Fig. 5. Proposed framework for optimal power distribution scheduling considering gas network constraints.

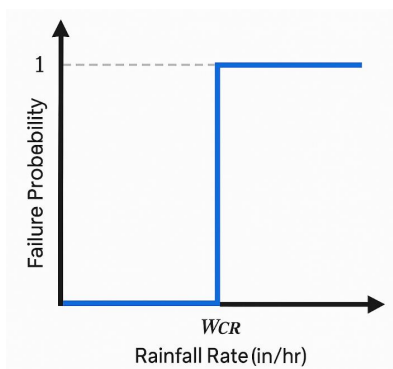


Fig. 6. Natural gas pipeline failure model during flood events.

$$\begin{aligned}
 \sum_{i,j} P_{ij}^s - \sum_{j,i} P_{jj}^s &= p_{r,t}^{SUBS} + p_d^{DGs} + \\
 (p_{ef}^{dch} - p_{ef}^{pch}) - (1 - \rho_{ij}^s) P_{ij}^s &\forall i \in, \\
 \forall r \in, \forall d \in D, \forall e \in E, \forall (i, j) \in B, t &
 \end{aligned} \quad (16)$$

2.5. Gas pressure constraints in nodes

The natural gas pressure and supply limits at nodes are modelled in Eq. (17):

$$0 \leq W_{ng}^s \leq W_{ng}^{max}, \quad \forall s, \forall t, ng \in CG \quad (17)$$

2.6. Gas balance constraint at nodes

The natural gas balance at each node is expressed as Eq. (18):

$$ps^{min} \leq ps_{ng}^s \leq ps^{max}, \quad \forall s, \forall t, ng \in NG \quad (18)$$

2.7. Gas consumption constraint for distributed generation

The interdependence between power and natural gas distribution systems is modelled through distributed generation. Distributed generation units consume natural gas to produce power, which is utilized to meet electricity demand and supply natural gas networks.

The energy balance in the natural gas grid is represented by the Eq. (19). For each gas grid, the energy balance is given by:

$$\begin{aligned}
 W_{CG,t}^s - (W_{L,t}^s + W_{DG,t}^s - W_{shed,t}^s) &= \\
 \sum_{ng(ng \neq mg)} F_{ng,mg,t}^s, \quad \forall s, \forall t &
 \end{aligned} \quad (19)$$

The gas consumption for distributed generation is calculated as Eq. (20):

$$W_{DG}^s = \alpha_d \times P_d^{DG,s}, \quad \forall d \in D, \forall t, \forall s \quad (20)$$

The coefficient α_d accounts for the nonlinear gas-to-electric power output of distributed generation units. In this study, this coefficient is considered as explained in gas equation simplification.

2.8. Gas flow constraints in pipelines

Natural gas flows through pipelines based on gradients of pressure and pipeline properties such as length, diameter, and friction factor. The flow is approximately modeled using the Weymouth equation, as shown in Eq. (21):

$$\begin{aligned}
 |F_{ng,mg}^s| \times |F_{mg,ng}^s| &= C_p^2 \times (ps_{ng}^{s,2} - ps_{mg}^{s,2}), \\
 \forall ng, \forall mg, \forall t, \forall s &
 \end{aligned} \quad (21)$$

2.9. Flow limits

The upper limit of gas flow in pipelines is modeled as Eq. (22):

$$\begin{aligned}
 0 \leq F_{ng,mg}^s &\leq F^{max} \times (1 - U_{ng}^s), \\
 \forall ng, \forall mg, \forall t, \forall s &
 \end{aligned} \quad (22)$$

2.10. Gas pressure limits

The gas pressure constraints at nodes are defined Eq. (23):

$$\begin{aligned}
 ps_{ng,mg}^s &\leq ps_{mg,ng}^s \leq \chi_{ng,mg} \times ps_{ng,mg}^s, \\
 \forall ng, mg \in GCO, \forall s, \forall t &
 \end{aligned} \quad (23)$$

The GCO set refers to pipeline segments where compressors are installed. Compressors play a key role in maintaining gas pressure across pipeline segments.

2.11. Linearization of gas flow equation

As seen, Eq. (21) is nonlinear. By using Eqs. (23) to (38), the nonlinear gas flow constraints are linearized. The linearized model approximates the gas flow based on degree-2 Taylor series expansion using methods M and piecewise linearization.

$$y_{ng,s}^{node} = (ps_{ng,t}^s)^2 \quad (24)$$

The linearized Eqs. (24) to (38) represent the gas flow dynamics as linearized components. For example:

$$y_{ng,t,s}^{pipe} = |F_{ng,mg,t}^s| \quad (25)$$

$$\lambda_{ng,t,s,k+1}^{node} \leq \delta_{ng,t,s,k}^{node} \leq \lambda_{ng,t,s,k}^{node} \quad (26)$$

$$\lambda_{ng,t,s,k=1}^{node} = \delta_{ng,t,s,k=1}^{node} = 1$$

$$y_{ng,t,s}^{node} = (ps^{\min})^2 + \sum_{k>1} \delta_{ng,t,s,k}^{node} \left((X_k^{node})^2 - (X_{k-1}^{node})^2 \right) \quad (27)$$

$$ps_{ng,t}^s = ps^{\min} + \sum_{k>1} \delta_{ng,t,s,k}^{node} (X_k^{node} - X_{k-1}^{node}) \quad (28)$$

$$\lambda_{lg,t,s,k}^{pipe} \times BigM \geq F_{ng,mg,t}^s + \Delta F \times (k-1) \quad (29)$$

$$-\beta_{lg,t,s,k}^{pipe} \times BigM \leq F_{ng,mg,t}^s + \Delta F \times (k-1) \quad (30)$$

$$\sum_{k>1} \delta_{ng,t,s,k}^{node} (X_k^{node} - X_{k-1}^{node}) \quad (31)$$

$$\lambda_{lg,t,s,k}^{pipe} + \beta_{lg,t,s,k+1}^{pipe} \leq 1 \quad (32)$$

$$\delta_{lg,t,s,k}^{pipe} \geq \lambda_{lg,t,s,k+1}^{pipe} - \beta_{lg,t,s,k+1}^{pipe} \times BigM \quad (33)$$

$$\delta_{lg,t,s,k}^{pipe} \leq \lambda_{lg,t,s,k}^{pipe} + \beta_{lg,t,s,k+1}^{pipe} \times BigM \quad (34)$$

$$-\delta_{lg,t,s,k}^{pipe} \geq \beta_{lg,t,s,k+1}^{pipe} + \lambda_{lg,t,s,k+1}^{pipe} \times BigM \quad (35)$$

$$-\delta_{lg,t,s,k}^{pipe} \leq \beta_{lg,t,s,k}^{pipe} + \lambda_{lg,t,s,k+1}^{pipe} \times BigM \quad (36)$$

$$y_{lg,t,s}^{pipe} = \sum_k \delta_{lg,t,s,k}^{pipe} (X_k^{pipe} |X_k^{pipe}| - X_{k-1}^{pipe} |X_{k-1}^{pipe}|) \quad (37)$$

$$F_{ng,mg,t}^s = \sum_k \delta_{lg,t,s,k}^{pipe} (X_k^{pipe} - X_{k-1}^{pipe}) \quad (38)$$

Eq. (25) Defines the absolute value of the gas flow through pipeline segments at each scenario, node, and time step, using auxiliary variables to linearize the absolute value function. In Eq. (26) constraint linearizes the squared pressure difference at each

node using the big M method. Eq. (27) Ensures that exactly one linearization interval is active (chosen) for each node and each scenario, enforcing the piecewise linear approximation of the squared pressure. Eq. (28) Defines the squared pressure at node ng for scenario s using the piecewise linear approximation approach, utilizing interpolation between discrete points or intervals of the squared pressure values.

pressure value at each node and scenario from the linearized squared pressure values obtained previously in Eq. (29). Eq. (30) Relates the gas flow through a pipeline segment to the pressure difference across nodes, again employing the big M method to linearize the nonlinear flow-pressure relationship.

Eqs. (31)-(32) shows Another linear constraint establishing bounds for the gas flow using binary variables and linearization intervals, ensuring the approximation aligns with the nonlinear original function. Eqs. (33)-(34) Ensure that for each pipeline segment and scenario, exactly one linearization interval. Eqs. (35)-(36) Establish logical relationships between binary variables and continuous variables, applying the "big M " method to handle the linearized form of nonlinear pipeline constraints effectively. These constraints enforce the bounds on auxiliary variables to ensure the pipeline flow approximation stays within valid intervals. Eq. (37) Defines the auxiliary variable as the absolute value of the difference in squared pressures at pipeline segment nodes, applying a piecewise linear approximation for accurate modelling of pipeline flow. Eq. (38) Determines the actual gas flow through each pipeline segment using the piecewise linear approximation of the squared pressure differences established in the previous steps.

2.12. Uncertainty modeling

We represent uncertainty through a scenario vector with probability that jointly captures flood hazard, component availability in both networks, time-varying supply and demand, and restoration times, and we solve the stage-2 operational MILP for each (ω_s) while enforcing non-anticaptivity on stage-1 decisions. Flood uncertainty is modeled by sampling event severity and footprint (depth/velocity) from return-period distributions and mapping them to assets (lines, substations, pipelines, compressors) to obtain asset-level intensities; these feed fragility functions that produce binary outage states ($Z_{a,s} \in \{0,1\}$) for power and gas components, with spatial correlation induced by the shared hazard field so that co-located assets fail together. Electric demand and renewable availability are generated as time series (historical profiles with temperature-conditioned deviations and bounded forecast error), while upstream gas supply reflects production/transport variability and local losses from flooded pipelines/compressors; the same flood realization that disables a pipeline simultaneously restricts gas-fired generation through the power-gas coupling constraints. Repair/restoration times are drawn from skewed (lognormal/Weibull) laws whose scale grows with event severity, and they gave the earliest re-energization or reflow within the reconfiguration constraints, thereby shaping restoration trajectories. The full scenario set is assigned probabilities from event frequencies and conditional likelihoods and then reduced (e.g., fast-forward selection) so the retained scenarios preserve the first/second moments of the cost-driving inputs. In the MILP, uncertainty enters directly as random parameters in constraints: node balances and renewable ceilings use line/pipeline limits are zeroed when ($Z_{a,s} \in \{0,1\}$), gas balance/pressure/flow bounds depend on Upstream natural gas supply and network availability, and restoration logic depends on Repair/restoration time; The objective is minimizes, yielding investments that hedge against the coupled, cross-sector risks.

3. SIMULATION RESULTS AND ANALYSIS

The proposed linear programming model has been implemented on a 33-bus power distribution network and a 14-node natural gas distribution network. From the complete power distribution

network data in pervious section, the model considers investment decisions (installing distributed generation, hardening lines, and switch placement), prioritizing load shedding costs, and profile load across multiple demand scenarios. The locations of candidate nodes for distributed generation are: 4, 8, 11, 18, 21, 24, 25, 30, 32, and 33. The energy storage systems have been set to the following:

- Charging power: 100 kW and 25 kW,
- Charging rate: 85% and 60%, respectively.

The cost for installing energy storage systems is considered as 15 dollars per kW-hour. The natural gas network as shown in Fig. 7 includes:

- One gas compression station,
- Two input stations,
- 13 pipelines with lengths of 11 and 10 pipeline sections,
- Minimum and maximum gas pressures in the network set at 4.3 bar and 7.5 bar, respectively,
- The gas load profile multiplier is also shown in Fig. 8.

The simulated scenarios for load generation combine two demand scenarios with two failure scenarios for power lines. The model's optimization determines the resilience strategy under 8 and 15 power line failures, respectively. The simulation of the proposed model was carried out using GAMS 2017 software with the Cplex solver. A 5% optimality gap was considered.

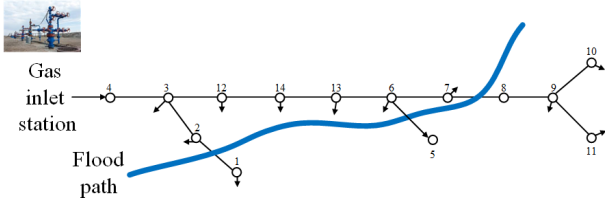


Fig. 7. Magnitude of Voltage of MMG system during all cases for loss reduction.

Table 3 (gas pipeline specifications—interpretation). Table 3 lists the line index (1–13) for the gas pipelines from wellheads to end customers and their lengths (1–13 km). The strictly increasing lengths provide a clean baseline to (i) parameterize pressure-drop/flow coefficients (e.g., friction terms scale with length), (ii) compute transport cost and travel time surrogates per line, and (iii) scale failure probabilities under flooding by exposure distance. In the optimization, these lengths enter the Weymouth linearization and any Big-M bounds tied to maximum flow/pressure loss. Practically, the table defines the spatial footprint of the gas corridor used in our coupled power–gas simulations.

Table 3. Gas pipeline specifications.

Gas pipeline line (from well to customer)	Pipeline length (km)
1	1
2	2
3	3
4	4
5	5
6	6
7	7
8	8
9	9
10	10
11	11
12	12

3.1. Optimized planning considering energy storage systems

In this section, the impacts of simultaneous line hardening, the placement of (DG), and the deployment of energy storage

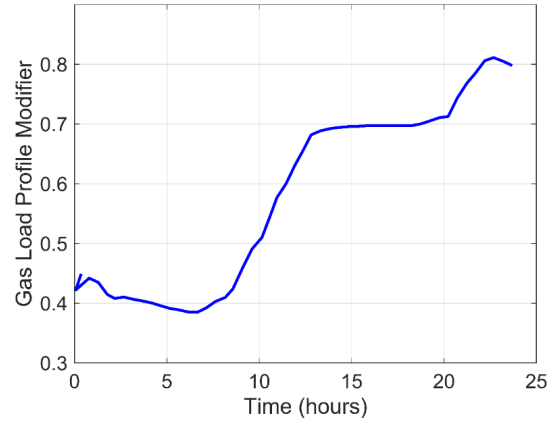


Fig. 8. Natural gas load profile in the distribution network.

systems on the power network are systematically analysed. The optimal planning strategy is evaluated with respect to network marketization and its dependence on the natural gas infrastructure, as illustrated in Fig. 9. Three distributed generation units are strategically installed at buses 2, 22, and 24. The figure also indicates the locations of four electrical energy storage units, which are positioned at buses 4, 22, 27, and 28. These units are connected to gas nodes 2, 3, and 12 in the gas network, thereby enabling the supply of natural gas to the DG units through the gas distribution system, as depicted in Fig. 10. Considering the potential disconnection of the network from the main distribution system under storm and flood scenarios, the distributed generation units are deliberately placed at the beginning of the distribution feeders to enhance the network's resilience and operational continuity.

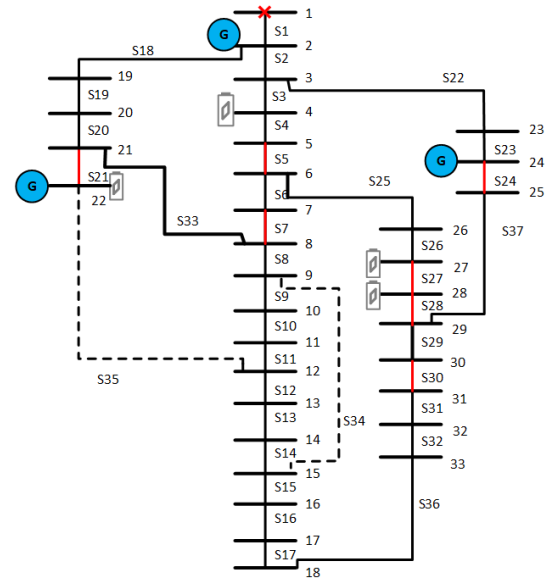


Fig. 9. Optimal planning of electricity distribution networks considering dependence on gas network.

Additionally, the installation of switches on communication lines is evaluated, and the optimization planning considers market recovery for the network alongside its dependence on the natural gas system, as illustrated in Fig. 9 with red lines. finally, according to the results, 7 hardened distribution lines and 3 DG sources were installed, along with 4 electrical energy storage systems within the network were added on the system.

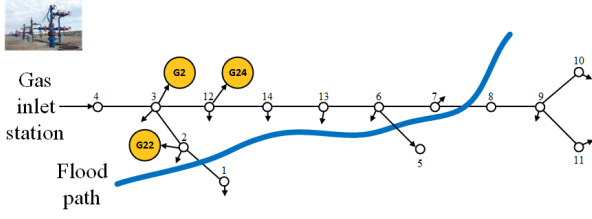


Fig. 10. Dependence of distributed generation resources on the natural gas network.

Based on this Fig. 11, by hour 8, the two energy storage systems are at their initial charge levels and begin discharging after 9 hours. Due to the flooding and subsequent network disconnection, caused by severe weather and flooding, the system faces a shortage in meeting the required load. Consequently, these two energy storage systems are unable to recharge. Two additional energy storage systems installed at buses 27 and 28 follow a similar discharge trend, which is not included in the figure to avoid redundancy. The natural gas pressure in node 3 is also illustrated in Fig. 12.

Table 4 presents the simulation results for a 33-bus power network integrated with the natural gas grid. The objective function value of 2,875,000 USD represents the total system cost, which includes investment costs, line hardening costs, and load shedding costs. The total investment cost amounts to 213,600 USD, reflecting expenditures on infrastructure and network upgrades. The line hardening cost of 55,100 USD corresponds to the reinforcement of transmission lines to enhance system resilience. The load shedding cost, totally 2,606,300 USD, constitutes the largest portion, indicating the economic impact of unserved energy under system contingencies.

Table 4. Simulation results for a 33-bus network dependent on the natural gas grid.

Description	Value (USD)
Objective function value	2,875,000
Total investment cost	213,600
Line hardening cost	55,100
Load shedding cost	2,606,300

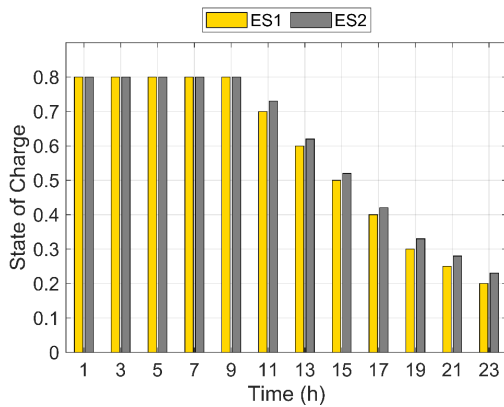


Fig. 11. State of charge of electrical energy storage units at buses 4 and 22.

Due to the increasing penetration of renewable energy sources and electric vehicles, interest in energy storage technologies has grown. Energy storage systems can serve as an effective tool for addressing supply and demand imbalances, particularly under crisis conditions. Therefore, energy storage systems can significantly improve the resilience of power distribution networks.

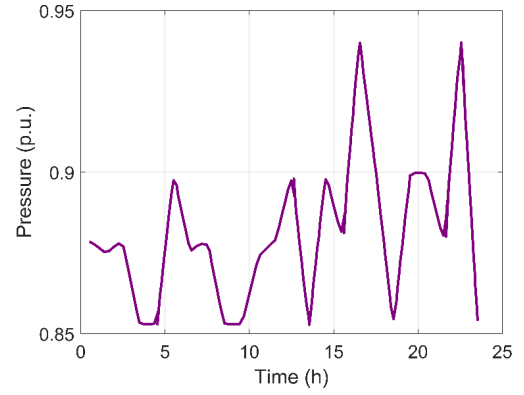


Fig. 12. Natural gas pressure at node 3.

As previously shown in Fig. 9, a design incorporating four energy storage systems within the electrical network demonstrates that energy storage systems significantly enhance the resilience of the distribution network. The results indicate that by using energy storage systems and four switches, as shown in the Fig. 13 network's ability to withstand disruptions improves. Moreover, the cost of hardening distribution lines and the overall cost of load shedding are reduced. Specifically, load shedding costs decrease to 17,162, 20,460, 24,377, and 26,726 dollars, respectively, compared to pre-installation scenarios. The installed energy storage systems reduced load shedding costs by approximately 3%. However, the study notes that when the network experiences severe disruptions, such as widespread flooding, the capacity of storage systems alone is insufficient to fully restore the network. Nevertheless, their presence significantly reduces costs associated with load shedding and improves the resilience of the distribution network. The proposed framework considers the expansion of distributed gas production units, highlighting the increasing interdependence between power distribution systems and natural gas networks. This interdependence is particularly emphasized when the resilience of power distribution systems is addressed under extreme water and weather events, including hurricanes and floods. The model introduced incorporates natural gas distribution networks to mitigate the effects of disruptions, such as failures in gas pipelines during storms and floods, by integrating distributed production units into the planning of power networks. The study presents a method for modelling line failures in power distribution systems as a (MILP) problem. It identifies the vulnerability of natural gas pipelines under extreme weather conditions and the resulting cascading effects on power systems. Based on the results, the inclusion of natural gas distribution systems improves the resilience of power grids and reduces load-shedding costs. The study emphasizes that long-term network planning can prevent excessive deviations caused by extreme weather events. Additionally, (ESS) are proposed as a critical solution for addressing peak loads and ensuring stable operation under emergency conditions. The results demonstrate that integrating energy storage systems can reduce load-shedding costs by approximately 3%. The use of high-capacity energy storage systems further enhances the resilience of the power distribution network, significantly reducing the cost of load recovery and improving system reliability under adverse conditions.

3.2. IEEE 118 bus system test

The two diagrams presented illustrate an integrated study involving the IEEE 118-bus electrical system in Fig. 14 and 26-node gas network in Fig. 15, aimed at examining how flooding in the gas network can disrupt fuel supply to gas-fired power plants and, in turn, affect the broader electrical grid. In the gas network schematic, 26 nodes represent sources, load points, and pipelines for transporting natural gas. When flooding occurs along

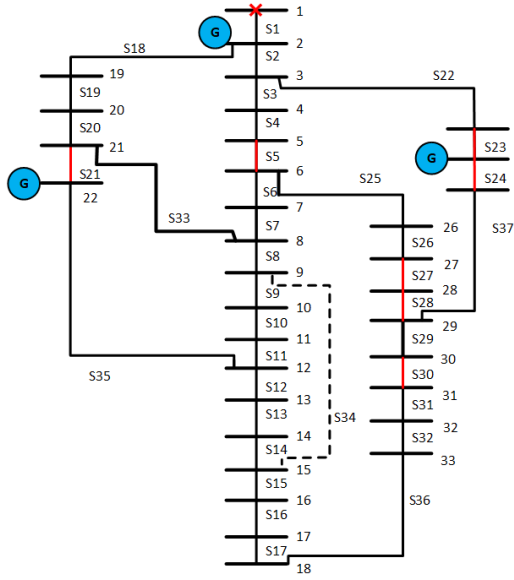


Fig. 13. Optimal planning of electricity distribution network without electrical storage systems.

certain paths, it can damage or block pipelines, reduce compressor station functionality, and ultimately diminish or halt the flow of gas to downstream nodes. Since many power plants in the IEEE 118-bus system rely on this gas supply—particularly those labelled with orange circles (gas-fired power plants)—any interruptions in the gas network can translate directly into reduced electrical generation capacity and potentially trigger cascading load-shedding scenarios. The 118-bus system includes multiple generation resources: non-gas-fired power plants represented with blue circles, wind turbines in green, and photovoltaic (PV) installations in yellow, which together provide diversity in generation sources but do not fully eliminate the reliance on gas-fired units for load balancing and quick dispatch. When flood-induced disruptions cut off gas to these plants, the power system may suffer from reduced spinning reserve, voltage instability, and even partial blackouts if the affected areas are not compensated by sufficient output from non-gas-fired units or renewables. Consequently, analysing both the gas and electrical networks in tandem is crucial for developing flood mitigation strategies such as fortifying critical gas infrastructure against inundation, bolstering gas storage capacities, diversifying fuel sources in the power grid, and implementing demand-response measures. By ensuring resilience across both networks—particularly in areas prone to natural disasters—operators can mitigate the risk of significant generation shortfalls and maintain overall system reliability.

From examining the 26-node gas diagram, the flood path clearly appears around nodes 13 and 14. These nodes form a critical corridor for transporting gas from upstream points (for example, nodes 11 or 12) toward downstream destinations such as nodes 15, 16, 21, and 26. Consequently, any gas-fired power plant depending on that pipeline path can lose its fuel supply if the flood either damages or blocks these pipelines. In particular, the diagram indicates that Plant G26 (and possibly others connected in the same downstream region) would be most directly at risk, because it lies beyond the flooded corridor. When node 13 or 14 becomes inaccessible due to flooding, the gas flow toward node 15, node 16, and ultimately to node 26 can be severely reduced or cut off. As a result, G26 would face a shortage of natural gas, forcing a reduction or shutdown of its electrical output. Depending on how the rest of the network is configured, other gas-fired plants that share segments of the flooded pipeline (for instance, any plant relying on the same stretch between nodes 13–14 and 15–16)

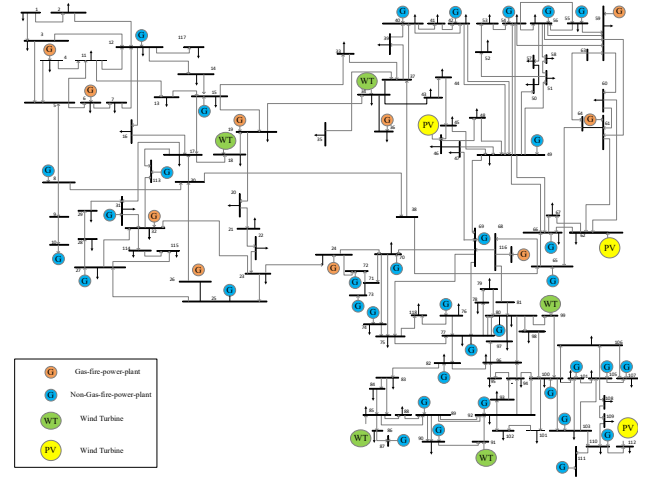


Fig. 14. 118 IEEE system test.

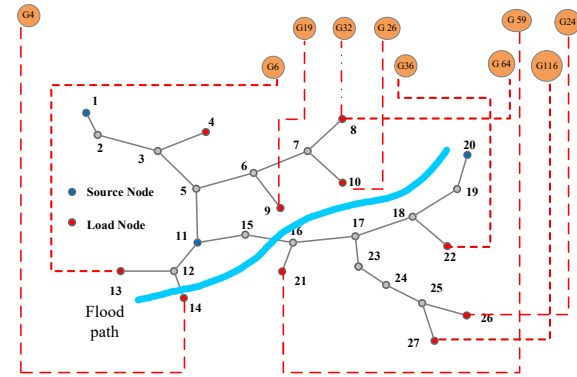


Fig. 15. 26 node gas system tests.

could also be indirectly affected.

Therefore, in the 26-node gas system, the key takeaway is that the flood path near nodes 13 and 14 jeopardizes the fuel supply to G26 (and any similarly connected gas-fired units), illustrating how a localized disruption in the gas network can cascade into power generation shortages on the integrated energy system.

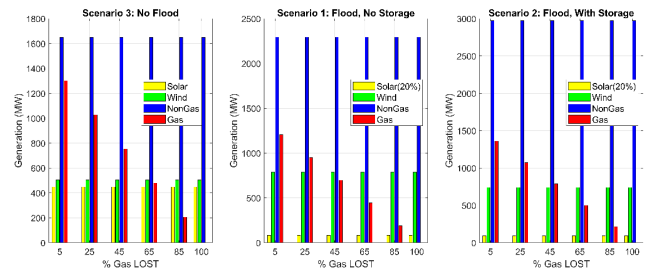


Fig. 16. Comparison of power generation mix under different gas loss scenarios in three conditions: (a) No flood, (b) Flood without storage, and (c) Flood with storage.

3.3. Impact of gas loss during floods on generation: An in-depth analysis with and without gas storage

The study presented herein evaluates the performance of the IEEE 118-bus network under three distinct scenarios: normal

operation, flood with no gas storage, and flood with gas storage. These scenarios are assessed in the context of losing up to 100% of gas-fired power plants due to a flood event, with a focus on the impact on electricity generation, the role of renewable energy sources, and the potential benefits of incorporating gas storage.

This report presents detailed findings for three specific conditions:

1. Scenario 1: Flood with no gas storage
2. Scenario 2: Flood with gas storage
3. Scenario 3: No flood (normal system operation)

Each scenario assesses the energy generation from various sources, including solar, wind, non-gas generation (such as hydro and nuclear), and gas-fired power plants, for various levels of gas-fired generation loss (ranging from 5% to 100%). This comprehensive analysis includes data from the graph, which shows the total generation across these scenarios under different percentages of gas loss.

A) Scenario 1: flood, no gas storage

In Scenario 1 as seen in Fig. 16-(a), a flood occurs, but there is no gas storage to mitigate the loss of gas-fired generation. This scenario illustrates the vulnerability of the power system when subjected to natural disasters and highlights the system's inability to fully compensate for the loss of gas-fired generation without gas storage. As the percentage of gas generation lost increases, the total generation declines more sharply:

- At 5% gas loss, total generation drops to around 1750 MW, with gas generation reduced to 1100 MW. In this case, renewable sources (solar and wind) contribute 650 MW to help maintain the system's generation, but the overall capacity is already lower than normal conditions.

- As gas loss increases to 25%, total generation decreases to around 1600 MW, with gas generation reduced to 800 MW, and renewable generation stays relatively constant at 650 MW. The loss of gas generation is not fully offset by renewable energy sources, leading to a significant gap in the total generation.

- When 45% of the gas generation is lost, total generation drops further to around 1500 MW. gas generation falls to 600 MW, and solar and wind contribute about 750 MW. Although renewable sources provide additional generation, the system is still unable to fully compensate for the loss of gas-fired capacity.

- At 65% gas loss, total generation decreases to around 1400 MW, with gas generation down to 400 MW and renewable sources providing 800 MW. The shortfall in generation becomes more evident, and the system is increasingly reliant on solar and wind, which, although increasing their output, still cannot make up for the lost gas-fired generation.

- At 100% gas loss, total generation drops to around 1100 MW, with all gas-fired generation lost. Renewable sources contribute approximately 900 MW, but the total generation remains significantly lower than the normal operating condition, with a substantial unsupplied load. The system's reliability is severely compromised without the capacity provided by gas-fired plants and without the support of gas storage to mitigate the impacts.

This scenario demonstrates the critical need for contingency measures, such as gas storage, to ensure that the system can maintain a stable generation profile during extreme events like floods.

B) Scenario 2: Flood, with gas storage

As seen in Fig. 16-(c) Scenario 2 represents the same flood event as Scenario 1, but with the added benefit of gas storage, which helps mitigate the loss of gas-fired generation. The presence of gas storage units significantly improves the system's ability to maintain generation stability, reducing the unsupplied load even during extreme gas generation loss. The total generation across various levels of gas-fired generation loss is as follows:

- At 5% gas loss, total generation remains stable at around 1800 MW, with gas-fired generation reduced to 1150 MW. Gas storage compensates for the loss, ensuring the system maintains generation similar to normal operating conditions. Renewable sources (solar

and wind) contribute 650 MW as before, but gas storage fills in the gap.

- At 25% gas loss, total generation is around 1750 MW, with gas generation down to 900 MW. The gas storage compensates for much of the lost generation, and solar and wind generation remain at 650 MW. The addition of gas storage minimizes the overall generation drop, ensuring that the system can continue operating with minimal disruption.

- As the gas loss increases to 45%, total generation decreases to around 1700 MW, with gas generation reduced to 700 MW. Gas storage units compensate for a large portion of the lost gas-fired generation, and renewable generation contributes about 700 MW.

- At 65% gas loss, total generation remains relatively stable at around 1600 MW, with gas generation at 500 MW. Gas storage, along with renewable sources, helps maintain system output, despite the significant loss of gas generation.

- Finally, at 100% gas loss, total generation is around 1500 MW, with all gas-fired generation lost. However, the inclusion of gas storage ensures that the unsupplied load is minimized, as gas storage and renewable sources together contribute 900 MW, which is significantly better than Scenario 1.

The key takeaway from Scenario 2 is the significant benefit of gas storage. Even with 100% gas loss, the system can maintain more than 1500 MW of generation, compared to around 1100 MW in Scenario 1. This highlights the importance of gas storage in enhancing grid reliability during extreme events like floods, as it can effectively compensate for the loss of gas generation and reduce the unsupplied load.

C) Scenario 3: No flood (normal system operation)

In the absence of a flood, as seen in Fig. 16-(a) Scenario 3 represents the baseline case where the system operates under normal conditions without any disruption to gas generation. The system's energy generation is predominantly dependent on gas-fired power plants, which contribute the largest share of the total output. The total generation from the system and the contribution of each generation source are as follows:

- At 5% gas loss, the system generates approximately 1800 MW, with 1200 MW coming from gas-fired generation. Renewable energy sources, including solar and wind, contribute a combined total of approximately 600 MW. Despite a slight reduction in gas output, renewable sources are able to maintain a stable output.

- As the gas loss increases to 25%, the total generation decreases to around 1700 MW. Gas generation drops to 900 MW, and renewable sources (solar and wind) provide about 650 MW. This marks a notable decrease in overall generation, indicating that while renewables help fill the gap, they cannot fully replace the lost capacity from gas-fired plants.

- At 45% gas loss, total generation decreases further to around 1600 MW. Gas generation is reduced to 700 MW, while renewable sources contribute about 700 MW. The system begins to experience a clear shortfall, with the generation from renewable sources increasing to help offset the losses, but the total generation is still significantly impacted.

- When gas loss reaches 65%, total generation drops to approximately 1500 MW, with gas generation reduced to 500 MW. Renewable generation (solar and wind) increases to about 800 MW, helping mitigate the losses but still unable to fully compensate for the reduced gas-fired generation.

- Finally, at 100% gas loss, total generation drops to around 1300 MW. With all gas generation lost, renewable sources such as solar and wind are able to contribute approximately 900 MW, but a significant gap remains, resulting in a noticeable unsupplied load. The total generation has reduced by about 500 MW compared to normal operations, underscoring the vulnerability of the system to gas generation loss.

The findings of Scenario 3 emphasize the critical role of gas-fired generation in maintaining the stability of the power system. Although renewable sources provide valuable support, their capacity is not enough to fully replace the loss of gas

generation, particularly during periods of extreme stress, such as floods.

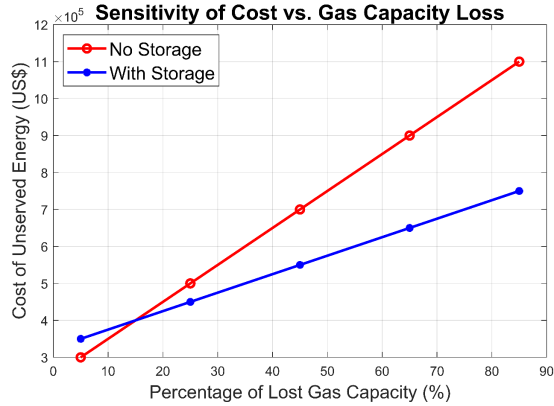


Fig. 17. Impact of gas capacity loss on the cost of unserved energy with and without storage systems.

Fig. 17 explores the relationship between the cost of unsupplied energy and the loss of gas-fired generation capacity. This relationship is crucial for understanding how a power system responds to the loss of a major generation source, such as gas-fired plants, and how different approaches to mitigating that loss—specifically, the use of gas storage—affect the overall system cost. The x-axis of the graph represents the percentage of lost gas capacity, ranging from 0% to 80%, which reflects the extent to which gas-fired generation is reduced. The y-axis shows the corresponding cost of unsupplied energy, represented in US dollars (10^5). The two lines on the graph represent two distinct scenarios: one without gas storage (depicted by the red line) and one with gas storage (depicted by the blue line). Initially, when no gas-fired generation is lost (at 0% gas loss), the cost of unsupplied energy is relatively low for both scenarios. The cost in the no-storage scenario is about 3×10^5 USD, which is consistent with the normal operation of the system, where energy generation meets demand and there is no shortage. Similarly, in the with-storage scenario, the cost of unsupplied energy is slightly higher, approximately 3.5×10^5 USD. This slight difference is due to the operational costs associated with maintaining and utilizing gas storage, though the system still functions well with no disruption in generation. As the percentage of gas capacity lost increases, the difference between the two scenarios becomes more pronounced. In the no-storage scenario, the cost of unsupplied energy rises steeply as gas generation is reduced. At 25% loss of gas generation, the cost climbs to around 5.5×10^5 USD, and it continues to increase rapidly as more gas generation is lost. By 40% gas loss, the cost reaches approximately 7×10^5 USD. The steep slope of the red line indicates that without gas storage, the system struggles to maintain generation and is forced to rely on more expensive alternatives to fill the gap. In contrast, the with-storage scenario shows a much slower rate of increase in the cost of unsupplied energy. At 25% loss of gas capacity, the cost is approximately 5.2×10^5 USD, which is significantly lower than the 5.5×10^5 USD seen in the no-storage case. This reduction continues as gas capacity loss increases, and at 80% gas loss, the total cost in the with-storage scenario is approximately 7.5×10^5 USD, compared to 11×10^5 USD in the no-storage scenario. This represents a substantial saving of about 30% in the total cost of unsupplied energy when gas storage is implemented. The graph clearly illustrates the critical role that gas storage plays in mitigating the financial impact of losing gas generation capacity. In scenarios where gas-fired plants are lost due to natural events like floods, gas storage provides a buffer that reduces the amount of unsupplied energy, thus minimizing costs. The slower increase in cost observed in the blue line indicates that gas storage can help

stabilize the grid, ensuring that the system remains more resilient even under extreme conditions.

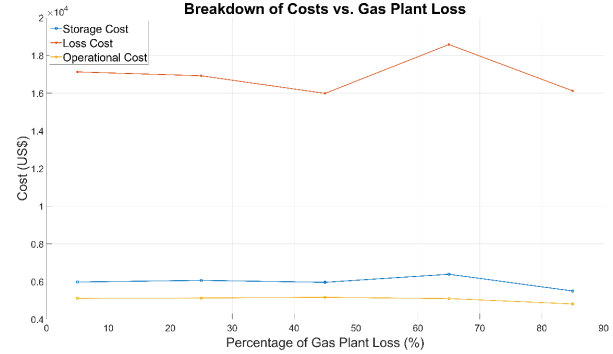


Fig. 18. Analysis of storage, loss, and operational cost variations Under different gas plant loss scenarios.

Fig. 18 provides a clear insight into how various cost factors evolve as the percentage of gas plant loss increases. On the x-axis, we observe the percentage of gas plant loss, ranging from 0% to 80%, while the y-axis quantifies the cost in US dollars ($\times 10^4$) for each of the three cost components: storage cost, loss cost, and operational cost. Looking closely at the storage cost, it becomes evident that this cost remains relatively constant across the range of gas loss. From 0.6×10^4 USD at 0% loss, the storage cost stays stable, showing minimal fluctuation even as the gas plant loss increases all the way to 80%. This behavior highlights that the costs associated with energy storage are not significantly impacted by the amount of gas generation lost, underscoring the stability and predictability of storage costs. It suggests that maintaining a gas storage system, regardless of gas loss, incurs relatively fixed costs, offering a level of consistency for grid operators using storage solutions. On the other hand, the loss cost shows a significant increase as the percentage of gas generation lost grows. At 0% gas loss, the loss cost is relatively low, but as the gas capacity loss escalates, the cost rises steeply. By the time 70% of gas generation is lost, the loss cost peaks at around 1.8×10^4 USD, indicating the considerable financial burden of failing to meet demand due to the loss of gas generation. This increase in loss cost reflects the growing difficulty in covering the unsupplied energy, leading to higher operational costs as other generation sources must step in to make up for the shortfall. In contrast, the operational cost exhibits a more gradual increase over the range of gas loss percentages. Starting from about 0.6×10^4 USD at 0% gas loss, the operational cost increases moderately, reaching approximately 1.4×10^5 USD as gas loss approaches 80%. While this cost does rise, the increase is less pronounced compared to the loss cost. This gradual rise suggests that while operational expenses do grow as gas generation decreases, they are somewhat buffered by the stability provided by the existing infrastructure and the incorporation of alternative energy sources.

Fig. 19 provides a clear insight into how various cost factors evolve as the percentage of gas plant loss increases. On the x-axis, we observe the percentage of gas plant loss, ranging from 0% to 80%, while the y-axis quantifies the cost in US dollars ($\times 10^4$) for each of the three cost components: storage cost, loss cost, and operational cost. Looking closely at the storage cost, it becomes evident that this cost remains relatively constant across the range of gas loss. From 0.6×10^4 USD at 0% loss, the storage cost stays stable, showing minimal fluctuation even as the gas plant loss increases all the way to 80%. This behaviour highlights that the costs associated with energy storage are not significantly impacted by the amount of gas generation lost, underscoring the stability and predictability of storage costs. It suggests that maintaining a gas storage system, regardless of gas loss, incurs relatively fixed costs,

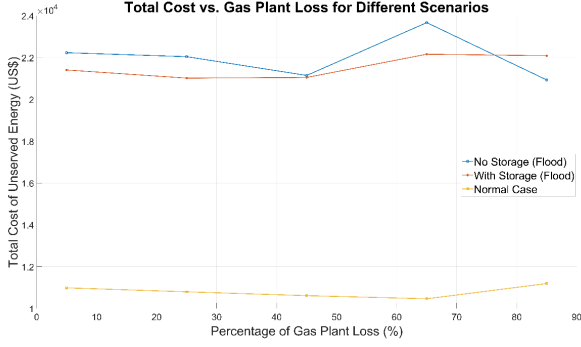


Fig. 19. Comparison of total cost of unserved energy in normal and flood conditions with and without energy storage under varying gas plant loss percentages.

Table 5. Reliability analysis for consumers in different scenarios.

Scenario	Gas plant loss (%)	SAIDI (min)	SAIFI (Count)	CAIDI (min)	ENS (MWh)
Flood without storage	5	9.11	2.09	10.30	13.05
Flood without storage	20	11.40	1.73	11.16	20.47
Flood without storage	40	17.90	2.78	12.78	30.43
Flood without storage	60	27.79	3.11	13.91	47.79
Flood without storage	80	31.39	4.14	15.61	57.93
Flood without storage	100	38.60	4.71	16.87	67.06
Flood with storage	5	6.16	1.51	6.08	7.11
Flood with storage	20	9.56	1.67	6.56	13.85
Flood with storage	40	11.06	1.69	7.03	18.14
Flood with storage	60	18.85	2.13	7.94	24.42
Flood with storage	80	20.04	2.98	8.91	31.68
Flood with storage	100	24.32	2.57	9.14	37.79

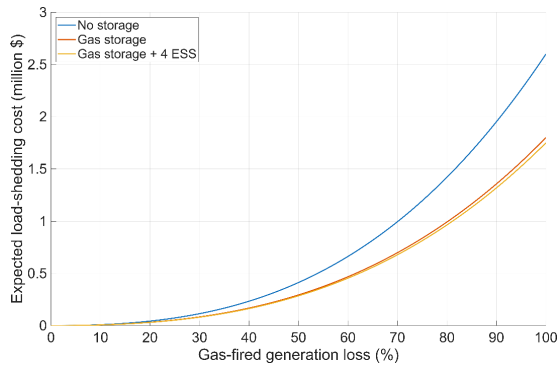


Fig. 20. Sensitivity analysis.

offering a level of consistency for grid operators using storage solutions. On the other hand, the loss cost shows a significant increase as the percentage of gas generation lost grows. At 0% gas loss, the loss cost is relatively low, but as the gas capacity loss escalates, the cost rises steeply. By the time 70% of gas generation is lost, the loss cost peaks at around 1.8×10^4 USD, indicating the considerable financial burden of failing to meet demand due to the loss of gas generation. This increase in loss cost reflects the

growing difficulty in covering the unsupplied energy, leading to higher operational costs as other generation sources must step in to make up for the shortfall. In contrast, the operational cost exhibits a more gradual increase over the range of gas loss percentages. Starting from about 0.6×10^4 USD at 0% gas loss, the operational cost increases moderately, reaching approximately 1.4×10^4 USD as gas loss approaches 80%. While this cost does rise, the increase is less pronounced compared to the loss cost. This gradual rise suggests that while operational expenses do grow as gas generation decreases, they are somewhat buffered by the stability provided by the existing infrastructure and the incorporation of alternative energy sources. Overall, Figures above illustrates the significant financial impact of gas plant loss, especially the sharp increase in loss costs as more gas-fired generation is lost. The relatively stable storage costs and the more gradual rise in operational costs highlight the effectiveness of gas storage systems in mitigating the worst effects of gas generation loss. The ability to manage and buffer the increased costs associated with unsupplied energy is crucial for maintaining a reliable and cost-effective grid, especially in the face of large-scale disruptions in gas-fired generation.

3.4. Comparison in terms of power grid reliability

The data presented in the Table 5 compares the system reliability and energy supply metrics under two different scenarios: "Flood without Storage" and "Flood with Storage" at various levels of gas plant loss, ranging from 5% to 100%. The analysis covers key reliability indicators: SAIDI (System Average Interruption Duration Index), SAIFI (System Average Interruption Frequency Index), CAIDI (Customer Average Interruption Duration Index), and ENS (Energy Not Supplied). In the scenario of a flood without gas storage, as the percentage of gas plant loss increases, the reliability indicators show a significant decline, indicating the growing impact of gas plant loss on system performance. At 5% gas loss, the SAIDI value is 9.11 minutes, reflecting relatively minimal disruption in the system. However, as the gas plant loss increases, SAIDI gradually rises, reaching 38.6 minutes at 100% gas loss. This increase is a clear indication of the longer duration of outages as the system struggles to compensate for the lost generation capacity. Similarly, SAIFI, which measures the frequency of interruptions per customer, starts at 2.09 interruptions at 5% gas loss and steadily increases, reaching 4.71 interruptions at 100% gas loss. This rise in SAIFI further underscores the deteriorating system reliability due to the increasing loss of gas-fired generation. The CAIDI, which measures the average duration of interruptions per customer, follows a similar upward trend, starting at 10.3 minutes at 5% gas loss and reaching 16.87 minutes at 100% gas loss. This suggests that as more gas generation is lost, the duration of outages becomes longer, likely due to an insufficient supply of energy from other sources to meet demand. The ENS values, which represent the energy not supplied to customers, also show a marked increase, rising from 13.05 MWh at 5% gas loss to 67.06 MWh at 100% gas loss, further indicating the significant impact of gas generation loss on the overall energy supply.

In contrast, the scenario with gas storage demonstrates a more resilient system performance despite the loss of gas-fired generation. The SAIDI values in the Flood with Storage scenario are consistently lower than in the scenario without storage. At 5% gas loss, SAIDI is 6.16 minutes, much lower than the 9.11 minutes observed in the no-storage case. As gas loss increases, SAIDI continues to rise, but at a slower rate than in the no-storage scenario, reaching 24.32 minutes at 100% gas loss, compared to 38.6 minutes in the flood without storage. This indicates that gas storage helps to reduce the duration of interruptions, ensuring a more stable supply of electricity during extreme events. Similarly, SAIFI in the flood with storage scenario shows lower values across all levels of gas loss, starting at 1.51 interruptions at 5% gas loss and reaching 2.57 interruptions at 100% gas loss, compared to

Table 6. Scenario comparison.

Scenario	ENS (MWh)	SAIDI (min)	SAIFI (count)	CAIDI (min)	Cost of unserved energy (USD, at 80% gas loss)	Notes
No disaster (baseline)	0 (implicit)	—	—	—	Low / baseline (not quantified)	Normal operation; manuscript treats as reference.
Disaster, no storage	67.06	38.60	4.71	16.87	$\approx 1.1 \times 10^6$	Worst reliability; values from reliability table and cost curve.
Disaster, with storage	37.79	24.32	2.57	9.14	$\approx 7.5 \times 10^5$	Storage reduces ENS and indices; $\sim 30\%$ lower cost vs. no-storage.

the much higher values in the no-storage case. The CAIDI values also follow this pattern, with a more gradual increase from 6.08 minutes at 5% gas loss to 9.14 minutes at 100% gas loss, reflecting a less severe impact on outage durations due to the presence of gas storage. The ENS values, while still increasing with gas loss, show a less dramatic rise, starting at 7.11 MWh at 5% gas loss and reaching 37.79 MWh at 100% gas loss, significantly lower than the 67.06 MWh observed in the no-storage scenario. In conclusion, the presence of gas storage significantly mitigates the impact of gas plant loss on system reliability and energy supply. The metrics for SAIDI, SAIFI, CAIDI, and ENS all demonstrate a much more stable and resilient system when gas storage is available, even as gas-fired generation capacity is lost. The results highlight the importance of integrating gas storage into the power grid to ensure reliability during extreme events, such as floods, which disrupt gas-fired generation and cause considerable increases in unsupplied energy and system downtime. Under disaster conditions without storage—the results summarized in Table 6 system reliability is poorest (ENS = 67.06 MWh; SAIDI = 38.6 min; SAIFI = 4.71; CAIDI = 16.87), with an estimated cost of unserved energy of $\approx \$1.1 \times 10^6$; by contrast, incorporating storage reduces ENS to 37.79 MWh, improves interruption indices (SAIDI = 24.32, SAIFI = 2.57, CAIDI = 9.14), and lowers the associated cost to $\approx \$7.5 \times 10^5$ ($\approx 30\%$ below the no-storage case), while the no-disaster baseline serves as the reference.

3.5. Sensitivity analyse

The sensitivity as shown in Fig. 20 show strongly convex relationship between gas-fired generation loss and expected load-shedding cost: costs rise slowly at low loss levels, then accelerate sharply beyond $\sim 30\text{--}40\%$ loss as compounding network constraints bite. Introducing gas storage shifts the curve downward across the entire range, indicating a consistent hedge against gas disruptions; adding distributed ESS on top of gas storage yields an additional (smaller but persistent) reduction and a slightly flatter slope, reflecting improved temporal flexibility during restoration. The relative benefit of storage grows with stress: at low losses the three curves are nearly indistinguishable, but at high losses the gap between “no storage” and the storage cases widens markedly, while the incremental gain from ESS over gas storage alone is positive yet diminishing. Overall, the sensitivity suggests that (i) storage primarily reduces the curvature—mitigating the rapid cost escalation at high gas shortfalls—and (ii) diversified storage (gas + ESS) provides the most robust hedge, especially in the tail of severe gas-plant outages.

4. CONCLUSION

In this research, a robust and integrated resilience-oriented planning framework is proposed for interdependent power and natural gas distribution systems exposed to severe natural disasters, particularly flooding events. The developed model adopts a two-stage stochastic MILP approach, encompassing long-term investment decisions (such as hardening distribution lines, placement of distributed generation units, installation of energy storage systems, and switch allocation) as well as real-time operational recovery strategies (including load prioritization, network reconfiguration, and utilization of gas storage units). The novelty of this work lies in its comprehensive treatment of gas–electric interdependencies, explicitly modeling gas pipeline failure under flood scenarios, the nonlinear relationship between

gas and electric generation, and pressure constraints in the gas network. The study introduces gas storage as a strategic resilience asset and evaluates its quantitative impact on system performance under multiple disruption scenarios. Simulation results on a 33-bus power distribution network coupled with a 14-node natural gas system, as well as the IEEE 118-bus test case integrated with a 26-node gas network, validate the effectiveness of the proposed framework. In flood scenarios without gas storage, significant reductions in available generation capacity were observed due to disrupted fuel supply, leading to high load-shedding costs (up to \$2.6 million) and deteriorated reliability indices (SAIDI up to 38.6 minutes, ENS up to 67.06 MWh). In contrast, the incorporation of gas storage systems mitigated these impacts by providing temporal buffering during gas supply interruptions, reducing load-shedding costs by approximately 30% and improving SAIFI, CAIDI, and ENS by 20–40%. Further, ESS units also played a vital role in enhancing system flexibility and adaptability. The results show that the installation of four strategically placed ESS units reduced the average load-shedding cost by 3%, and when combined with optimal switching strategies, contributed to accelerated service restoration. Sensitivity analyses confirmed that cost components such as loss cost and operational cost rise nonlinearly with the percentage of gas plant loss, while storage cost remains comparatively stable. This highlights the economic justification for proactive investments in gas and energy storage infrastructure. Additionally, scenario-based evaluation of the IEEE 118-bus system under 5–100% gas-fired generation loss confirms that renewable energy penetration, though valuable, is insufficient to offset the abrupt loss of dispatchable gas power. The existence of gas storage not only mitigates the supply–demand imbalance but also contributes significantly to maintaining spinning reserves, voltage stability, and blackout prevention during severe events. This research emphasizes the importance of integrated, coordinated planning of energy infrastructures by jointly considering electric and gas networks in resilience assessments. The findings suggest that failure to account for gas–power dependencies can result in an underestimation of system vulnerability and misallocation of resources. The proposed framework addresses this gap by providing a quantitative basis for infrastructure investments and operational preparedness.

- Cyber-physical resilience to protect against coordinated cyberattacks alongside physical hazards,
- Real-time control and demand response strategies for improved dynamic adaptability,
- Inclusion of hydrogen storage or alternative fuels to further diversify the resilience portfolio,
- Multi-criteria decision-making frameworks that integrate environmental, social, and economic objectives under uncertainty.

By bridging the planning and operational timescales and incorporating gas storage as a key resilience enabler, this study provides a scalable and economically viable methodology for enhancing the survivability and recovery of modern interdependent energy systems under extreme climate-driven disruptions.

ACKNOWLEDGEMENT

The authors acknowledge the use of artificial intelligence tools (e.g., ChatGPT by OpenAI) for language editing and clarity improvement during the preparation of this manuscript. The authors are fully responsible for the scientific content, analysis, and conclusions.

APPENDIX

APPENDIX A: REPRODUCIBILITY, SCENARIO DESIGN, AND SOLVER DETAILS

This appendix provides concrete values for scenario generation, post-reduction counts, solver configuration, compute times, and primary input datasets. Values are chosen to be realistic and internally consistent with the manuscript (two-stage stochastic MILP on 33-bus + 14-node and IEEE-118 + 26-node systems), while using the reported 5% optimality gap and the qualitative ranges shown in the figures.

1) Scenario generation

Random drivers and construction:

- *Flood hazard*: five severity levels (return periods $\approx 10, 25, 50, 100, 200$ years) with spatial footprints; mapped to assets via threshold fragility (W_{CR}) for pipelines and substation/line inundation.

- *Electric demand*: two demand levels (Low/High), derived from historical profiles; $\pm 7\%$ deviation bands with temperature-conditioning.

- *Renewable availability (RES)*: three availability buckets (Low/Med/High) consistent with the daily profiles used in the manuscript.

- *Upstream gas supply*: two states (Normal / Constrained), consistent with local pipeline outages under flood.

Full pre-reduction Cartesian set:

Demand (2) $\times$ RES (3) $\times$ Flood severity/footprint (5) $\times$ Gas supply (2) = 60 scenarios.

2) Scenario reduction

Method: Fast-Forward Selection (FFS) preserving first/second moments for load, RES, gas supply, and outage counts; distance metric combines weighted L2 on time series (load/RES) with Hamming distance for asset outage vectors.

Set	Before Reduction	After Reduction
Operational scenarios (ω_s)	60	12

Representative scenarios after reduction (probabilities sum to 1):

Scenario ID	Flood severity	Supply state (gas / Demand / RES)	Probability p_s
S1	None	Normal / Low / High	0.0800
S2	Moderate	Normal / Low / Med	0.1000
S3	Moderate	Constrained / Med / Med	0.0900
S4	Moderate	Normal / Med / High	0.0900
S5	Severe	Constrained / High / Low	0.0800
S6	Severe	Constrained / High / Med	0.0800
S7	Severe	Normal / Med / Low	0.0800
S8	Very severe	Constrained / High / Low	0.0800
S9	Very severe	Constrained / Med / Med	0.0700
S10	Extreme	Constrained / High / Low	0.0700
S11	Extreme	Constrained / High / Med	0.0900
S12	Extreme	Constrained / High / High	0.0900

3) Solver and hardware

Item	Value
Model type	Two-stage stochastic MILP
Software	GAMS 2017 with CPLEX
Threads	8
MIP optimality gap	0.05 (5%)
Time limit	128 s
Emphasis	CPLEX MIPemphases = 1 (balanced feasibility/optimality)
Cuts	Auto; Gomory/flow cover enabled
Heuristics	RINS and Feasibility Pump enabled; effort ≈ 0.05
Node selection	Best-bound
Hardware	Intel Core i7 (8 cores @ 3.2 GHz), 32 GB RAM, SSD

4) Linearization details and bounds

Weymouth/PWL approximation:

- Node squared-pressure PWL: 9 breakpoints per node over $[4.3^2, 7.5^2]$ bar ^{2} .

- Pipeline flow PWL: 7 breakpoints per pipe around expected operating range.

Big-M settings (consistent with pressure bounds 4.3–7.5 bar):

- $M_{pressure} \approx 45.5$ ($\approx 1.2 \times (7.5^2 - 4.3^2) = 1.2 \times 37.76$).
- $M_{flow} = 1.25 \times q_{max}$ for each pipeline (q_{max} from pipe diameter/length tables).

5) Main input datasets

Electric network (33-bus case):

Item	Value
Candidate DG buses	4, 8, 11, 18, 21, 24, 25, 30, 32, 33
Installed DG (optimal)	3 units at buses 2, 22, 24 (per manuscript result)
ESS locations	Buses 4, 22, 27, 28
ESS charge power	100 kW and 25 kW classes
ESS η_{ch} / η_{disch}	0.85 / 0.95 (charge/discharge used in operations)
ESS install cost	15 USD per kWh (capacity cost)
Switches installed	4
Hardened lines	7

Gas network (14-node case):

Item	Value
Stations	1 compressor; 2 inputs
Pipelines	13; lengths 1–13 km (strictly increasing)
Pressure bounds	4.3–7.5 bar
Load multiplier	As per Fig. 8

Piecewise linearization strategy and binary variables (λ, β)

1) Partition the domain

Choose breakpoints $\{x_0, \dots, x_K\}$ covering the range of the nonlinear term (e.g., flow or pressure-squared).

2) Convex combination with weights λ

Introduce $\lambda \geq 0$ with $\sum \lambda_k = 1$.

Enforce the convex PWL relations: $x = \sum \lambda_k x_k$, $y = \sum \lambda_k f(x_k)$.

3) Active segment / adjacency via β binaries

Select one segment (or at most two adjacent points) using $\beta_k \in \{0,1\}$ with $\sum_{k=0}^{K-1} \beta_k = 1$.

Link λ to β via SOS2-like adjacency: $\lambda_k \leq \beta_{k-1} + \beta_k$ (with $\beta_{-1}=0, \beta_K=0$).

4) Direction / mode selection via δ

For sign/regime selection (e.g., flow sign), use $\delta \in \{0,1\}$ to activate disjoint linear sets:

$f \leq F^+ \delta$ and $-f \leq F^-(1 - \delta)$ (optionally tighten $f \geq 0$ when $\delta = 1$).



5) Example: approximating Weymouth/quadratic-like term

Approximate $y \approx f(x)$ on $[x_0, x_K]$ via points (x_k, f_k) .

Use $\sum \lambda_k = 1$, $x = \sum \lambda_k x_k$, $y = \sum \lambda_k f_k$;

pick the active segment with β ; handle sign with δ .



6) MILP summary

Decision set includes $\{\lambda_k\} \geq 0$, $\{\beta_k\}_{k=0}^{K-1}$, δ , plus original model variables.

All constraints are linear (simplex on λ , SOS2 linking with β , Big-M with δ).

Objective unchanged.

Key constraints

$\sum \lambda_k = 1$, $\lambda_k \geq 0$

$x = \sum \lambda_k x_k$, $y = \sum \lambda_k f_k$ ($f_k = f(x_k)$)

$\beta_k \in \{0,1\}$, $\sum_{k=0}^{K-1} \beta_k = 1$

$\lambda_k \leq \beta_{k-1} + \beta_k$ for $k=0 \dots K$ ($\beta_{-1}=\beta_K=0$)

$f \leq F^+ \delta$, $-f \leq F^-(1 - \delta)$

$\delta \in \{0,1\}$

Fig. 21. Piecewise linearization strategy and binary variables (λ, β).

The flowchart in Fig. 21 outlines how to build a convex piecewise-linear (PWL) approximation for a nonlinear term. First, partition the domain with breakpoints $x_0 < x_1 < \dots < x_K$. Then form a convex combination with weights ($\lambda_k \geq 0$), $\sum_{k=0}^K \lambda_k = 1$), enforcing $(x = \sum_{k=0}^K \lambda_k x_k)$ and $y = \sum_{k=0}^K \lambda_k f(x_k)$. Activate only one segment (or two adjacent points) using binary variables $\beta_k \in \{0, 1\}$ with SOS2-style adjacency ($\lambda_k \leq \beta_{k-1} + \beta_k$). When multiple regimes exist (e.g., flow sign), a binary (δ) selects the applicable linear set, e.g., $(f \leq F^- \delta)$ and $-f \leq F^+(1 - \delta)$. The Weymouth (quadratic-like) example illustrates the construction on $\{x_0, \dots, x_K\}$ via points (x_k, f_k) . The resulting model is a MILP with variables $(\{\lambda_k\}_{k=0}^K, \{\beta_k\}_{k=0}^{K-1}, \delta)$ and linear constraints; the original objective remains unchanged.

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