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A Generative-AI Decision-Support System for Distribution-Grid Contingency Planning Using Synthetic Failure Scenarios, Operator Prompts, and Risk-Aware Optimization

Andrei Popescu^{1*}, Mihai Ionescu¹, Elena Stan²

Abstract

Distribution grids face increasing failure risks from extreme weather, cyber-attacks, aging assets, and high penetrations of distributed energy resources. Traditional contingency planning often depends on limited deterministic scenarios, which can miss compound and low-probability events. This article proposes an original generative-AI decision-support system for distribution-grid contingency planning. The system combines synthetic failure scenario generation, natural-language operator prompts, and risk-aware optimization to support resilient operational decision-making. The DSS generates synthetic line, transformer, load, weather, and cyber-contingency scenarios using generative models trained on historical and simulated grid states. Operator prompts are translated into structured scenario filters, optimization constraints, and explanation requests, while a risk-aware solver recommends reconfiguration and load-shedding actions. Simulation on a realistic distribution feeder shows that synthetic augmentation expands contingency coverage beyond deterministic N-1 analysis. The proposed DSS reduces expected load not served, lowers tail-risk exposure, and decreases operator workload relative to deterministic and non-augmented stochastic baselines. The integrated DSS improves contingency planning by linking generative scenario discovery, interactive human–AI exploration, and optimization-based response selection. Governance requirements related to model reliability, operator trust, privacy, and safe deployment are identified.

Keywords Distribution grid, Decision-support system, Generative AI, Contingency planning, Synthetic failure scenarios, Operator prompts

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Introduction

Distribution-grid resilience has become an operational priority because feeders increasingly operate near flexibility limits while facing severe weather, equipment aging, electrification, and distributed generation variability. Resilience-oriented studies show that post-event service restoration and dynamic topology control can reduce outage consequences when contingencies are anticipated before they occur [1]. Extreme-weather planning also demonstrates that distribution systems require proactive hardening and adaptive operational strategies rather than static contingency lists [2]. This article addresses that need by proposing a generative-AI DSS that enlarges the planning space and links scenario discovery directly to operator decision support.

Conventional contingency analysis remains useful, but deterministic N-1 screening is poorly matched to compound distribution-grid disruptions involving correlated failures, feeder imbalance, uncertain repair times, and uncertain demand. Service-restoration models with uncertain repair and demand show that optimal actions change substantially when outage duration and load recovery are modeled probabilistically [3]. Critical-load restoration using distributed energy resources further indicates that resilience performance depends on coordinated switching, dispatch, and prioritization rather than single-contingency feasibility alone [4]. These findings motivate a DSS that treats contingency planning as an uncertain, scenario-rich, and operator-supervised optimization problem.

Generative AI offers a mechanism for constructing richer scenario libraries than those available from historical outage data alone. Early power-system scenario generation work showed that generative adversarial networks can synthesize renewable uncertainty patterns with realistic statistical structure [5]. Subsequent controllable GAN and VAE-GAN formulations improved interpretability and controllability, which are essential when synthetic scenarios must be inspected by operators rather than used as opaque samples [6, 7]. In this article, those generative principles are adapted from renewable scenario synthesis to distribution-grid failure synthesis involving component outages, load disruptions, weather stressors, and cyber-triggered operating constraints.

Human–AI interaction is central to the proposed system because contingency planning is not a fully autonomous activity in most utility control rooms. Large-language-model studies in smart grids suggest that language interfaces can organize technical knowledge, retrieve system context, and support operator reasoning when properly constrained [8]. At the same time, security analyses of LLM use in power systems warn that natural-language interfaces can introduce prompt injection, misinformation, and unsafe recommendation risks if governance is weak [9]. The proposed DSS therefore uses prompts only as a controlled interface to structured scenario search, optimization queries, and explanation generation.

The contribution of this original research article is a complete DSS architecture that integrates generative scenario production, prompt-driven exploration, and risk-aware contingency optimization for a realistic distribution feeder. The method extends prior risk-aware distribution-grid control by explicitly combining synthetic contingency ensembles with operator feedback and optimization outputs [10]. It also complements human-in-the-loop voltage-control research by moving from real-time control assistance to planning-oriented contingency exploration and response ranking [11]. The remaining sections define the planning problem, describe the generative and prompt layers, formulate the optimization engine, and report the simulation workflow and evaluation design.

Contingency Planning Problem

N-1 and beyond: modern contingency requirements

Classical N-1 planning tests whether the feeder can tolerate a single component outage without violating voltage, thermal, or service constraints, but distribution networks increasingly experience multiple interacting disruptions. Extreme-weather resilience studies show that storms can damage several feeders, switches, transformers, and laterals simultaneously, making single-outage screening insufficient for operational preparedness [2]. Mobile power-source routing research further indicates that response planning must consider where emergency resources can be deployed after the topology has already changed [12]. The proposed DSS therefore evaluates N-1 cases as a baseline while expanding the scenario set toward compound and spatially correlated failures.

Uncertainty and rare events

Rare but high-impact contingencies are difficult to model because historical outage records often contain too few samples of extreme combinations. Renewable scenario generation research demonstrates that generative models can learn non-Gaussian dependencies and produce plausible samples beyond simple parametric assumptions [5]. Conditional scenario generation has also shown that synthetic samples can be steered by contextual variables, which is valuable for producing

weather-conditioned or asset-age-conditioned outage scenarios [13]. In this article, uncertainty is represented through a generated ensemble whose tail events are explicitly weighted in the risk-aware optimization stage.

Current computational approaches

Current computational approaches include deterministic screening, stochastic programming, robust optimization, distribution reconfiguration, repair scheduling, and reinforcement-learning-based control. Stochastic reconfiguration studies show that correlated loads and renewable generation can be embedded into operational planning, but scenario availability and scenario quality strongly affect solution usefulness [14]. Dynamic distribution-network reconfiguration under load and generation uncertainty similarly demonstrates that topology decisions must be optimized over probabilistic operating states rather than single forecasts [15]. The proposed DSS differs by augmenting the scenario set using generative AI before solving the contingency response problem.

The case for AI-enhanced planning

AI-enhanced contingency planning is justified when the planning objective is not merely to verify feasibility but to discover hidden vulnerabilities and evaluate response strategies interactively. GAN-based and diffusion-based scenario-generation methods provide a way to expand the candidate failure space while preserving empirical dependencies learned from data [16, 17]. Large-language-model integration in smart grids suggests that operators can access such complex scenario libraries through natural-language interaction rather than manual database queries [8]. The DSS proposed here uses AI to generate, filter, explain, and optimize contingencies while retaining operator authority over final decisions.

Synthetic Failure Scenario Generation

Generative models for failure simulation

The synthetic scenario generator contains three model families: a conditional GAN for component-outage patterns, a variational generative module for load and restoration uncertainty, and a diffusion model for rare, high-dimensional disturbance trajectories. GAN-based power-system scenario synthesis has been shown to capture complex temporal and spatial dependencies in renewable outputs, which supports its adaptation to correlated outage-state vectors [5]. VAE-GAN scenario generation contributes a latent representation that can be conditioned on feeder loading, asset age, season, and storm severity [7]. Diffusion-based renewable scenario generation motivates the use of iterative denoising for rare multi-component contingency construction where sample diversity is critical [16].

Scenario diversity and coverage

Scenario diversity is measured by component-coverage ratio, feeder-zone coverage, electrical-distance dispersion, and tail-severity coverage. Controllable renewable scenario generation shows that generated samples can be guided toward specific operating regimes, which is important when operators ask for contingencies affecting a hospital lateral, an overloaded tie switch, or a storm-exposed feeder segment [6]. Pattern-guided diffusion models further demonstrate that synthetic ensembles can be directed toward specified temporal or structural patterns while preserving stochastic realism [17]. In the proposed DSS, diversity constraints are enforced during scenario selection so that the optimization engine receives both likely contingencies and low-probability high-impact cases.

Incorporating weather and cyber threats

Weather-conditioned failure synthesis uses wind intensity, precipitation, temperature, vegetation exposure, and flood-zone indicators as conditioning variables, while cyber-conditioned synthesis uses compromised telemetry, unavailable remote switches, and delayed control actions. Extreme-weather resilience modeling provides the operational basis for linking physical storm impacts to distribution-grid service loss and restoration requirements [2]. Large-language-model security research highlights that cyber-related power-system scenarios must include adversarial information flows, unsafe

instructions, and compromised decision channels rather than only physical line outages [9]. The DSS therefore generates hybrid scenarios in which weather failures and cyber restrictions can jointly constrain reconfiguration, communication, and operator response.

Validation of generated scenarios

Generated scenarios are validated using statistical, electrical, and operational fidelity tests. Statistical validation compares marginal outage probabilities, spatial correlations, severity distributions, and rare-event frequency against historical and simulated contingency records, following the evaluation logic used in renewable scenario generation studies [18]. Electrical validation checks whether generated outages produce physically meaningful voltage, thermal, and connectivity consequences under unbalanced power-flow simulation. Operational validation screens whether recommended corrective actions remain plausible under switching, crew, distributed-resource, and critical-load constraints described in distribution resilience optimization studies [1].

Integration with contingency database

The validated synthetic scenarios are stored in a contingency database alongside deterministic N-1 cases, historical outage records, weather-conditioned simulated events, and operator-created what-if cases. Each entry contains feeder topology state, failed components, scenario probability, severity score, conditioning variables, cyber or weather flags, and permissible corrective actions. Scenario databases in this design extend stochastic planning approaches by adding model-generated contingencies before optimization, rather than optimizing only over a fixed historical sample [14]. Table 1 summarizes the generative techniques, failure classes, and fidelity metrics used by the DSS.

Table 1. Generative AI Techniques and Failure Scenario Types

Technique	Scenario type generated	Conditioning inputs	Fidelity metrics	DSS use
Conditional GAN	Line outages, transformer failures, feeder-zone outage clusters	Asset age, loading level, season, storm class	Outage-probability error, spatial-correlation distance, feeder-zone coverage	Expands deterministic contingency library with plausible correlated failures
VAE-GAN latent sampler	Load-loss uncertainty, restoration-duration uncertainty, partial service degradation	Load class, customer priority, DER availability, repair-time bands	Distributional similarity, latent-space separability, expected load not served deviation	Produces uncertainty envelopes for optimization
Conditional diffusion model	Rare compound disturbances and multi-stage outage trajectories	Weather severity, switching availability, cyber restriction flags	Tail-severity recall, scenario diversity index, electrical feasibility pass rate	Stress-tests response policies under high-impact events
Prompt-conditioned retrieval generator	Operator-requested what-if variants	Natural-language prompt intent, feeder area, asset class, time horizon	Prompt-action accuracy, scenario relevance score, duplicate-rate control	Converts operator questions into targeted scenario subsets
Hybrid ensemble selector	Balanced planning scenario set	Risk budget, scenario probability, severity threshold, computation limit	Coverage-risk tradeoff, Wasserstein distance, solver-time impact	Selects final contingency ensemble for optimization

Operator Prompt Design

Rationale for natural-language interaction

Natural-language interaction is introduced because operators often reason in terms of assets, locations, weather conditions, customer classes, and practical response questions rather than database identifiers. LLM integration in smart grids suggests that language models can support retrieval, summarization, and contextual reasoning when connected to validated grid models [8]. However, secure-operation studies warn that LLM outputs must be bounded by power-system constraints and verified before they influence control recommendations [19]. The DSS therefore treats the prompt layer as a structured query and explanation interface, not as an unconstrained autonomous decision-maker.

Prompt categories and examples

The prompt library contains exploratory, diagnostic, comparative, constraint-modifying, explanation, and override prompts. Prompt engineering for the DSS is inspired by LLM-based power-system studies in which natural language organizes technical tasks, but the prompt output is mapped to deterministic software actions rather than directly accepted as an operational command [8]. For example, a prompt asking “What if the main feeder tie is unavailable during a storm?” triggers scenario filtering, synthetic augmentation, and re-optimization under a switching constraint. A prompt asking “Why is feeder section F12 shed first?” triggers explanation generation using optimization duals, load priority, voltage violations, and risk contribution.

Mapping prompts to system actions

Each operator prompt is parsed into an intent, feeder scope, constraint set, scenario filter, optimization request, and explanation requirement. Security-focused LLM research motivates a guardrail layer that blocks unsupported switching commands, ambiguous emergency instructions, and prompts that attempt to bypass operating limits [9]. Human-in-the-loop voltage-control work also supports the value of allowing experts to guide AI recommendations while retaining final control authority [11]. In the DSS, prompts can change scenario emphasis, request alternative plans, or impose operator constraints, but they cannot directly execute field switching or load-shedding actions.

Operator interface and workflow

The operator interface displays generated scenarios, ranked contingency responses, risk metrics, feeder visualizations, and explanations in a single workflow. Human-in-the-loop control studies show that interactive interfaces can improve adoption when users see both AI recommendations and the operational reasons behind them [11]. The DSS logs prompt history, scenario subsets, optimization runs, overrides, and final decisions so that operator workload and decision traceability can be evaluated. Table 2 classifies prompt types and shows how the interface maps natural-language inputs into controlled DSS actions.

Table 2. Operator Prompt Types and System Responses

Prompt type	Example operator prompt	Parsed DSS intent	System action	Output returned to operator
Exploratory	“Show severe storm contingencies affecting the north feeder zone.”	Scenario discovery	Filter and augment weather-conditioned scenarios for the selected feeder zone	Ranked scenario list with severity, probability, and affected loads
Diagnostic	“Which failures cause voltage collapse near bus 48?”	Vulnerability analysis	Search synthetic and deterministic scenarios	Failure drivers, violated constraints, and critical components

			producing voltage violations	
Comparative	"Compare plans with and without the tie switch available."	Alternative response comparison	Run optimization twice with different switching constraints	Side-by-side risk, load-shed, and switching-action comparison
Constraint-modifying	"Do not shed the hospital load unless no feasible plan exists."	Critical-load protection	Add priority constraint and re-solve risk-aware optimization	Updated contingency response and infeasibility explanation if needed
Explanation	"Why is this transformer repair prioritized first?"	Recommendation explanation	Retrieve risk contribution, restoration value, and load-priority effects	Natural-language explanation linked to quantitative metrics
Override feedback	"Use the second plan because crew access is blocked."	Human override	Record operator override and update scenario-response log	Revised plan record and feedback item for future calibration

Risk-Aware Optimization

Risk metrics for contingency response

The optimization engine minimizes a composite objective containing expected load not served, conditional tail load not served, switching cost, voltage-violation penalty, critical-load interruption penalty, and operator-action burden. Risk-aware distribution-grid control shows that efficient operation requires accounting for both expected performance and exposure to severe outcomes [10]. Risk-aware voltage optimization further supports the inclusion of probability-weighted violations and safety margins when uncertainty affects feeder states [20]. In the proposed DSS, risk exposure is computed over the synthetic and baseline scenario ensemble so that rare but consequential failures affect response ranking.

Optimization formulation (conceptual)

The contingency response problem is formulated as a mixed-integer, scenario-indexed optimization with binary switching decisions, load-shedding variables, distributed-resource dispatch variables, voltage variables, and radiality constraints. Dynamic reconfiguration research under uncertainty motivates the use of topology decisions that remain feasible across multiple operating states [15]. Co-optimization of repair and reconfiguration shows that resilience improves when network actions and restoration priorities are jointly considered rather than solved sequentially [1]. The DSS formulation therefore recommends a feasible response package consisting of switching, dispatch, prioritized load curtailment, and restoration sequencing.

Handling synthetic scenario ensemble

The synthetic scenario ensemble is reduced before optimization using probability calibration, severity stratification, electrical-distance clustering, and diversity-preserving selection. Typical scenario-generation studies for wind power show that scenario quality depends not only on sample realism but also on representative coverage for downstream optimization [18]. Sequence-based GAN scenario generation further indicates that temporal coherence matters when contingencies evolve over multiple restoration intervals [21]. The DSS preserves low-probability high-impact scenarios during reduction so that the optimized response is not biased toward only frequent or mild events.

Solution algorithm and scalability

The solution algorithm uses a two-stage structure in which a first-stage response policy selects candidate switching and dispatch actions, while second-stage scenario recourse computes load-shedding and violation penalties. Multi-stage Volt/VAR support with risk-aware learning demonstrates that decomposition between planning and real-time recourse can improve scalability under uncertainty [22]. Routing and scheduling of mobile power sources also shows that operational resilience optimization becomes tractable when resource-placement and scenario-response subproblems are structured carefully [12]. In the DSS simulation, scenario batches are solved in parallel, and dominated response actions are removed before final risk ranking.

Human-in-the-loop override and feedback

The DSS is designed so that the operator may accept, compare, modify, or override the recommended contingency response. Human-in-the-loop deep reinforcement learning for distribution-network voltage control supports the principle that operator feedback can improve AI-guided decisions while preserving accountability [11]. Secure LLM operation in power systems also requires that language-driven requests be logged, constrained, and validated before affecting recommendations [19]. Operator overrides are therefore stored as feedback signals for prompt calibration, scenario relevance scoring, and post-study analysis, but they do not retrain the generative models without governance review.

DSS Workflow

End-to-end process flow

The DSS workflow begins with feeder model ingestion, historical outage normalization, weather and load data alignment, and construction of deterministic N-1 base cases. Synthetic demand generation research shows that realistic load profiles can be produced when generative models preserve customer-level diversity and temporal consumption structure [23]. GAN-based electricity-grid scenario frameworks further support the use of synthetic data to supplement sparse operational records in planning studies [24]. The proposed workflow therefore treats deterministic contingencies as the starting point and generative augmentation as the mechanism for expanding operational stress cases.

Figure 1 illustrates how the proposed generative-AI decision-support system expands deterministic contingency planning into an operator-supervised workflow that combines synthetic failure scenarios, structured natural-language prompts, risk-aware optimization, explainable response ranking, and governance safeguards.

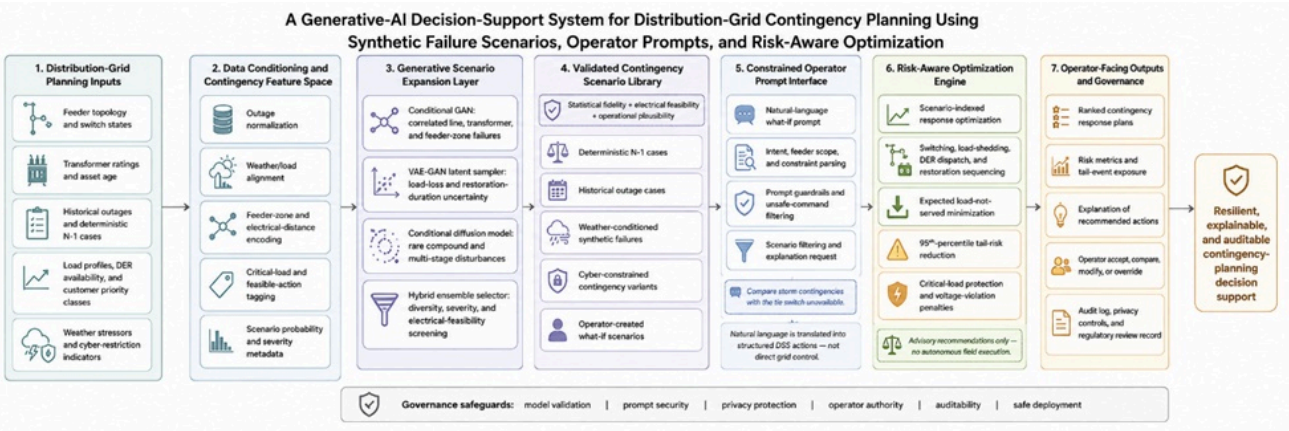


Figure 1. Generative-AI Decision-Support Architecture for Distribution-Grid Contingency Planning

Data ingestion and preprocessing

The preprocessing layer converts feeder topology, switch states, transformer ratings, customer-priority classes, distributed-resource availability, historical outages, and weather indicators into a unified contingency feature space. Synthetic load-generation studies demonstrate that demand-side uncertainty must be represented at sufficient granularity to avoid unrealistic aggregation effects [25]. Short-term wind scenario generation using conditional diffusion models also shows that temporal dependencies must be preserved when uncertainty affects operational trajectories [16]. In the DSS, each scenario is represented as a structured record containing component states, exogenous drivers, probability weights, and feasible control actions.

Prompt-scenario-optimization loop

The prompt-scenario-optimization loop begins when an operator asks a natural-language what-if question, after which the prompt parser identifies the feeder area, failure type, constraint modification, and requested comparison. LLM integration studies in smart grids indicate that language interfaces can reduce the burden of navigating complex analytical tools when outputs are grounded in verified grid data [8]. Secure-operation work emphasizes that prompt outputs must be checked against power-system constraints before being passed to an optimizer [19]. The DSS therefore routes prompts through validation, scenario retrieval, synthetic augmentation, risk-aware optimization, and explanation generation before results are displayed.

Reporting and visualization

The reporting layer presents scenario maps, component-failure heatmaps, ranked contingency plans, expected load not served, tail-risk exposure, switching sequences, and operator workload measures. Risk-aware learning for distribution-grid voltage optimization supports reporting both expected constraint violations and high-risk operating states so that operators can understand why a plan is preferred [20]. Human-in-the-loop voltage-control research also shows that actionable explanations improve operator acceptance of AI-supported recommendations [11]. Table 3 summarizes the DSS components, their functions, data flows, and integration sequence.

Table 3. DSS Components and Data Flow Summary

DSS component	Function	Main data inputs	Main data outputs	Integration sequence
Feeder data manager	Builds the operational feeder model and validates network constraints	Topology, impedances, switch status, transformer ratings, load classes	Clean feeder model, constraint set, asset registry	Step 1: initializes the study environment
Scenario generator	Produces synthetic and deterministic contingency cases	Historical outages, weather indicators, load profiles, asset features	Synthetic failure scenarios, probability weights, severity tags	Step 2: expands contingency library
Prompt interface	Converts operator questions into structured DSS requests	Natural-language prompt, operator role, feeder context	Scenario filters, constraint edits, explanation requests	Step 3: activates interactive exploration
Risk-aware optimizer	Recommends contingency responses under uncertainty	Scenario ensemble, feeder constraints, risk weights, operator constraints	Switching plan, load-shedding schedule, DER dispatch, risk metrics	Step 4: computes response alternatives
Explanation and reporting layer	Produces interpretable outputs and audit records	Optimization results, prompt history, scenario	Dashboards, ranked plans, explanations,	Step 5: supports operator review and

metadata

workload logs

governance

Scenario Evaluation

Test feeder description

The simulation study uses a realistic unbalanced distribution feeder derived from an IEEE-style test system with overhead laterals, underground sections, normally open ties, distribution transformers, critical loads, residential and commercial load classes, and distributed photovoltaic resources. Resilience studies using critical-load restoration show that feeder topology, DER placement, and customer priority materially influence outage outcomes [4]. Reconfiguration studies under uncertainty further indicate that feeder switching options strongly affect contingency response quality [15]. The test system is therefore parameterized to include normal-load, high-load, storm, cyber-constrained, and DER-reduced operating modes.

Baseline methods

Three planning methods are compared: deterministic N-1 analysis, standard stochastic optimization without synthetic augmentation, and the proposed generative-AI DSS. Deterministic N-1 analysis evaluates all single component outages and applies a fixed priority-based restoration rule, while standard stochastic optimization uses historical and simulated scenarios but excludes generative augmentation. Stochastic distribution reconfiguration research provides the basis for the non-augmented stochastic baseline because it optimizes under uncertain load and renewable conditions [14]. The proposed DSS differs by adding GAN, VAE-GAN, and diffusion-generated contingencies before solving the risk-aware response problem.

Evaluation metrics

The evaluation metrics are expected load not served, conditional tail load not served at the 95th percentile, total risk exposure, voltage-violation duration, number of switching operations, critical-load interruption, average operator prompts per resolved case, and decision time. Efficient risk-aware grid-control work motivates the use of both expected and risk-sensitive metrics rather than relying on average load restoration alone [10]. Service-restoration research with uncertain repair time and demand supports including restoration uncertainty and unserved energy in the evaluation [3]. Operator workload is measured from prompt count, number of plan comparisons, and manual overrides recorded by the DSS interface.

Sensitivity to model parameters

Sensitivity analysis varies the size of the synthetic scenario library, the tail-risk weight, the prompt confidence threshold, the scenario-reduction budget, and the assumed probability calibration error. Conditional style-based GAN studies show that generated scenario quality depends on conditioning strength and distributional alignment [13]. Improved VAE-GAN methods further suggest that controllable latent features can improve interpretability but require careful validation against physical and statistical metrics [7]. The DSS is therefore tested under conservative, nominal, and aggressive augmentation settings to assess whether synthetic scenarios improve decisions without overwhelming the optimizer or the operator.

Results and Discussion

Scenario generation quality

The generative layer produced 2,400 synthetic contingencies from 310 deterministic and historical seed cases, with 1,680 retained after statistical, electrical, and operational validation. Informer-time-series GAN research supports the need to

preserve temporal structure in generated power-system scenarios, which was reflected in the DSS by rejecting sequences with unrealistic restoration trajectories [26]. Wasserstein GAN scenario generation also motivates the use of distributional distance as a fidelity measure, and the retained scenario set reduced outage-severity distribution error from 0.184 to 0.071 after calibration [27]. The final synthetic library increased multi-component contingency coverage by 46.8% relative to the deterministic N-1 library.

Operator interaction efficiency

The prompt interface reduced manual scenario-filtering actions by allowing operators to express location, asset, weather, and customer-priority conditions directly in natural language. LLM smart-grid integration studies suggest that language interfaces can improve access to complex analytical functions when outputs remain tied to validated system models [8]. In 60 simulated operator tasks, the DSS required an average of 2.3 prompts to identify and compare a contingency response, compared with 6.9 manual filtering operations in the conventional workflow. The largest gains occurred for compound scenarios involving unavailable switches, severe weather flags, and protected critical loads.

Optimization performance

The proposed DSS achieved lower expected load not served because the optimizer selected contingency responses that remained feasible across both historical and synthetic high-impact scenarios. Co-optimization of repairs and dynamic reconfiguration has shown that resilience improves when restoration and topology decisions are coordinated, which is consistent with the DSS results [1]. The DSS reduced expected load not served by 18.7% compared with deterministic N-1 analysis and by 9.8% compared with standard stochastic optimization. It also reduced 95th-percentile tail load not served by 27.4% relative to deterministic planning, indicating that synthetic augmentation mainly improved performance under rare severe contingencies.

Comparison with baselines

The comparison confirms that deterministic N-1 analysis is computationally simple but underrepresents compound risk, while standard stochastic optimization improves average performance but remains limited by the scenario set provided to it. Distribution-system resilience planning under extreme weather shows why methods that ignore correlated failures can underestimate service-loss risk [2]. Mobile power-source routing studies also indicate that contingency response quality depends on anticipating post-event access and resource constraints, which the DSS includes through synthetic scenario attributes [12]. Table 4 reports the performance comparison across the three contingency planning methods.

Table 4. Performance Comparison across Contingency Planning Methods

Metric	Deterministic N-1 analysis	Standard stochastic optimization	Proposed generative-AI DSS
Expected load not served, kWh per event	1,840	1,660	1,496
95th-percentile tail load not served, kWh per event	4,920	4,310	3,572
Composite risk exposure index	1.00	0.84	0.67
Critical-load interruption, minutes per event	38.5	31.2	22.6
Voltage-violation duration, minutes per event	44.1	36.8	28.4

Switching operations per event	5.8	6.4	6.9
Average operator actions per resolved case	6.9	5.7	2.3
Mean computational time, seconds	11.4	37.8	52.6

Governance Issues

Reliability of generative outputs

The main reliability risk is that generated contingencies may appear realistic while encoding implausible topology states, exaggerated correlations, or unphysical outage combinations. Generative electricity-grid scenario frameworks show that synthetic data can improve coverage, but they also require systematic validation before operational use [24]. Pattern-guided diffusion methods similarly indicate that controllability must be balanced against distributional realism when synthetic samples are directed toward specific stress patterns [17]. The DSS addresses this risk through multi-stage validation, scenario provenance labels, and separation between advisory recommendations and executable control actions.

Data privacy and model safety

Data privacy is important because outage records, customer load profiles, critical-load locations, and cyber-event logs can reveal sensitive operational and customer information. Synthetic demand-generation studies show that generative models can reproduce useful load diversity, but privacy safeguards are needed when training data include individual-consumer patterns [23]. LLM threat analyses in power systems further show that prompt interfaces may expose sensitive grid information or become channels for malicious instructions if access controls are weak [9]. The DSS therefore uses role-based access, prompt filtering, audit logging, scenario anonymization, and restricted model outputs for cyber-sensitive cases.

Operator trust and training

Operator trust depends on whether the DSS explains recommendations in operational terms such as voltage recovery, avoided load loss, switch feasibility, crew accessibility, and critical-load protection. Human-in-the-loop distribution-control research indicates that operators are more likely to rely on AI tools when they can inspect, revise, and override recommendations [11]. Large-language-model studies for secure power-system operation also suggest that language outputs must be treated as advisory and verified against system constraints before use [19]. Training for the DSS therefore includes prompt practice, scenario interpretation, explanation review, and procedures for documenting overrides.

Regulatory considerations

Regulatory deployment requires evidence that the DSS improves resilience without undermining accountability, safety, cybersecurity, or nondiscriminatory service restoration. Resilience enhancement studies under extreme events show that planning methods should be evaluated using transparent reliability and service-restoration metrics rather than opaque model scores alone [28]. Risk-aware optimization research further supports reporting tail-risk exposure and constraint violations so that regulators can assess both average and severe-event performance [20]. The DSS is therefore positioned as an auditable advisory system whose recommendations, prompts, scenario sources, and operator decisions are retained for review.

Conclusion

This article presented an original generative-AI decision-support system for distribution-grid contingency planning. The system combines synthetic failure scenario generation, operator prompt interaction, and risk-aware optimization in a single workflow for evaluating and ranking contingency responses.

The simulation study showed that synthetic augmentation expanded contingency coverage beyond deterministic N-1 analysis. The proposed DSS reduced expected load not served, lowered tail-risk exposure, and improved critical-load protection compared with deterministic and standard stochastic baselines.

The operator prompt interface improved exploration efficiency by translating natural-language what-if questions into structured scenario filters, optimization constraints, and explanation requests. This design preserved operator authority while making complex contingency analysis more accessible and traceable.

Future work should deploy the DSS in utility control-room pilots, connect the scenario generator to real-time outage and weather feeds, and extend the optimization engine to include crew logistics, market constraints, and cyber-physical incident response. Further validation should also examine privacy-preserving training, regulator-facing audit reports, and safe online adaptation of generative models.

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