

REVIEW

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# A Critical Review of Generative AI for Smart-Grid Operation: Synthetic Load Profiles, Contingency Simulation, Human-in-the-Loop Dispatch, and Governance Risks

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## Abstract

Generative AI, including generative adversarial networks, diffusion models, variational approaches, and large language models, is increasingly being explored for smart-grid operation. Its appeal lies in its ability to create synthetic data, expand scenario sets, and support human operators facing complex and uncertain grid conditions. This review critically examines the state of generative AI in four key smart-grid applications: synthetic load profiles, contingency simulation, human-in-the-loop dispatch, and associated governance risks. It evaluates not only technical capability but also reliability, accountability, privacy, and operational readiness. A critical review of 28 peer-reviewed articles published between 2017 and 2026 is conducted. The selected literature is synthesized across methodological contributions, application domains, evaluation practices, and governance concerns. Generative AI shows promise in creating realistic load data and expanding contingency sets, but reliability, interpretability, and governance frameworks remain underdeveloped. Human-in-the-loop dispatch integration is still nascent, and most studies remain closer to proof-of-concept than operational deployment. While generative AI can enhance grid flexibility, simulation richness, and planning capability, its current maturity is uneven. Substantial research is needed to address technical, ethical, and regulatory challenges before these systems can be responsibly embedded in smart-grid operation.

**Keywords** Generative AI, Smart-grid operation, Synthetic load profiles, Contingency simulation, Human-in-the-loop dispatch, Governance risks

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## Introduction

Generative AI has become an increasingly visible theme in smart-grid research because modern power systems require richer data, more diverse operating scenarios, and faster operator support than traditional tools can always provide. The literature shows that synthetic load-profile generation has been one of the earliest and most concrete applications, with GAN-based approaches demonstrating that statistically plausible building and customer demand traces can be created when real data are scarce or restricted [1]. However, this review argues that the technical promise of such models should not be confused with operational maturity, because realism, causal validity, and safety relevance remain difficult to establish.

The growth of renewable generation, electrification, and distributed energy resources has also increased the need for scenario generation in power-system operation. Renewable and source-load uncertainty studies show that generative models can create diverse wind, solar, load, and charging scenarios for planning and operational studies [2]. Yet a significant weakness in the field is that scenario plausibility is often evaluated statistically rather than operationally, which means generated data may look realistic while still failing to expose the most important grid vulnerabilities.

Generative AI is also beginning to affect contingency simulation and resilience planning by enabling rare-event and adversarial operating conditions to be generated rather than manually specified. Operation-adversarial scenario generation illustrates how generative or optimization-driven scenario construction can stress-test grid decisions more aggressively than conventional historical sampling [3]. The literature shows that this is valuable, but it also raises a critical concern: models that generate extreme scenarios may amplify unrealistic edge cases unless constrained by power-system physics and operator knowledge.

Human-in-the-loop dispatch represents a newer and less settled frontier. Large language models have been proposed for advanced power dispatch, and recent work has explored their capacity to translate system states into recommendations, explanations, or natural-language support for operators [4]. This review argues that the gap between language fluency and dispatch reliability is particularly consequential because misleading recommendations in critical infrastructure may be more harmful than missing recommendations.

A critical review is therefore needed because the literature is fragmented across synthetic data generation, renewable scenario modeling, human-machine interaction, and AI governance. Reviews of explainable AI and governance in smart energy systems have emphasized interpretability and institutional oversight, but they do not fully resolve the specific risks introduced by generative models that can fabricate, transform, or extrapolate grid-relevant information [5]. This article synthesizes these strands and evaluates whether generative AI is technically, socially, and institutionally ready for smart-grid operation.

## Generative Ai Scope

### Definition and key techniques

Generative AI refers to models that learn patterns from existing data and produce new samples, representations, scenarios, or text-like outputs that resemble the learned distribution. In smart-grid literature, this scope includes GANs for load and renewable scenario generation, diffusion models for controllable scenario synthesis, and LLMs for dispatch-related reasoning and explanation [6]. The literature shows that these methods differ sharply in controllability, transparency, and failure modes, which makes it inappropriate to treat “generative AI” as a single technical category.

### Relevance to smart-grid operation

Generative models are relevant to smart-grid operation because operators and planners often lack sufficient examples of rare events, privacy-sensitive customer behavior, and extreme renewable-load combinations. Scenario-generation studies using GANs and related models demonstrate that synthetic data can expand the operating envelope available for testing dispatch, planning, and resilience tools [7]. However, this review argues that relevance depends not only on data realism but also on whether generated scenarios preserve physical feasibility, temporal dependence, and actionable operational meaning.

### Current adoption trends

Current adoption is uneven, with synthetic load and renewable scenario generation being more mature than human-in-the-loop dispatch. Studies on multi-load GANs, renewable energy scenario generation, and electric-vehicle charging diffusion models indicate a steady movement from single-source data synthesis toward spatially and temporally coupled

scenario construction [8]. By contrast, LLM applications in electric energy systems remain exploratory, and the literature cautions that their capabilities are accompanied by security and reliability concerns [9].

### Limitations of existing reviews

Existing reviews provide useful foundations for explainability, maintenance, and responsible AI in energy systems, but they often address AI broadly rather than the specific epistemic risks of generative systems. For example, reviews of explainable AI for energy maintenance and AI concerns in power systems identify transparency, robustness, and accountability challenges that are directly relevant to generative smart-grid tools [10]. Few studies have addressed how synthetic load generation, contingency simulation, dispatch support, and governance risks interact as one operational ecosystem.

**Figure 1** summarizes how generative AI applications in smart-grid operation progress from synthetic load-profile generation and contingency simulation toward operator-facing dispatch support, while showing the validation, governance, and accountability barriers that currently limit operational readiness.

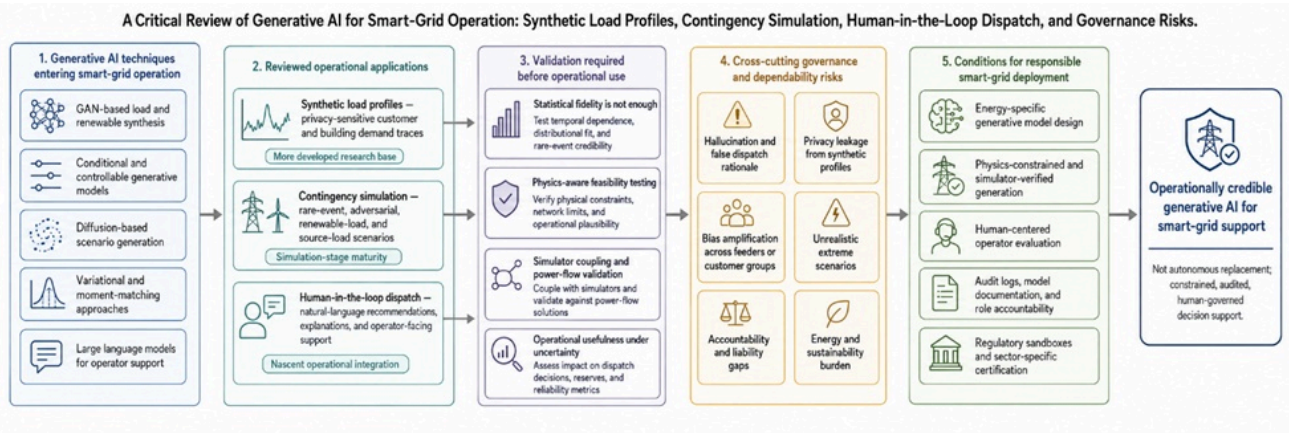


**Figure 1.** Operational-readiness pathway for generative AI in smart-grid operation: from synthetic data and scenario generation to human-in-the-loop dispatch and governance control.

## Synthetic Load Profiles

### Generative models for load data

Synthetic load-profile generation is among the clearest applications of generative AI in smart grids because load data are often high-dimensional, privacy-sensitive, and unevenly available. GAN-based building load-profile work shows that generative models can produce demand traces that reproduce important statistical patterns of real consumption [1]. Nevertheless, the literature shows that most models remain dependent on historical representativeness, meaning that generated profiles may reproduce past biases and understate structural changes caused by electrification, prosumers, or climate-driven demand shifts.

### Fidelity and evaluation metrics

Evaluation of synthetic load profiles commonly relies on distributional similarity, temporal correlation, peak behavior, and downstream usability in planning or operation studies. Data-driven synthetic load-pattern research demonstrates that generative models can capture usage habits and aggregate demand behavior, but it also reveals the difficulty of proving that synthetic data are valid for unseen operating conditions [11]. This review argues that fidelity metrics should move

beyond visual similarity and marginal distributions toward operational tests such as feeder loading, voltage impact, reserve adequacy, and dispatch sensitivity.

Privacy implications

Privacy is a central motivation for synthetic load generation, yet it is also a major unresolved risk. Differentially private GAN approaches show that privacy guarantees can be embedded into load-profile synthesis, but they also highlight the trade-off between privacy protection and statistical utility [12]. A significant risk is that synthetic profiles may still leak behavioral patterns, household routines, or commercially sensitive demand characteristics if privacy is treated as an afterthought rather than a design constraint.

Use Cases in grid planning and operation

Synthetic load profiles can support distribution planning, flexibility assessment, tariff studies, and stress-testing of operational algorithms when real customer data are limited or restricted. MultiLoad-GAN illustrates the value of modeling spatial-temporal correlations among load groups, which is important because feeder-level operation depends on correlated rather than independent demand behavior [8]. Table 1 summarizes the main generative approaches for synthetic load-profile generation, but the critical point is that usefulness depends on whether synthetic profiles improve operational decisions rather than merely resemble historical curves.

Table 1. Generative Techniques for Synthetic Load-Profile Creation: Capabilities, Metrics, and Operational Considerations

| Technique family                           | Representative smart-grid use                        | Typical fidelity metrics                                              | Strengths identified in the literature                               | Key challenges for operation                                         |
|--------------------------------------------|------------------------------------------------------|-----------------------------------------------------------------------|----------------------------------------------------------------------|----------------------------------------------------------------------|
| GAN-based load synthesis                   | Building and customer load-profile generation        | Distributional similarity, peak-demand matching, temporal correlation | Produces realistic-looking profiles and can augment limited datasets | May reproduce historical bias and lacks guaranteed physical validity |
| Conditional or controllable GANs           | Load-group generation under contextual attributes    | Conditional distribution fit, diversity, spatial-temporal dependence  | Supports scenario customization for planning studies                 | Conditioning variables may be incomplete or poorly validated         |
| Differentially private GANs                | Privacy-preserving customer demand synthesis         | Privacy budget, utility loss, re-identification resistance            | Provides explicit privacy framing for sensitive load data            | Stronger privacy can reduce fidelity and downstream usefulness       |
| Generative moment matching networks        | Cooling, heating, and power load scenario generation | Moment matching, scenario diversity, aggregate-load consistency       | Can capture multi-energy load relationships                          | May miss rare operational extremes if trained on ordinary conditions |
| Diffusion-based load or charging synthesis | Electric-vehicle charging and extreme load scenarios | Tail accuracy, controllability, temporal realism                      | Better controllability and stable generation in some settings        | Computational burden and limited field validation remain concerns    |

Contingency Simulation

Role of generative AI in rare-event simulation

Contingency simulation is a natural application for generative AI because rare but consequential grid events are underrepresented in historical data. Renewable scenario-generation work using GANs demonstrates that synthetic scenarios can broaden the range of uncertainty considered in power-system studies [2]. However, this review argues that rare-event generation is only valuable when the resulting cases are physically meaningful, operationally interpretable, and connected to credible initiating conditions.

## Scenario generation methods

Scenario generation methods have expanded from GANs toward more controllable and cross-modal architectures. Conditional improved Wasserstein GANs for wind-power scenarios show that generative models can produce multiple plausible trajectories across wind farms, capturing uncertainty that deterministic forecasts cannot fully represent [13]. Still, many scenario-generation studies emphasize statistical diversity over causal mechanisms, which limits confidence that generated contingencies correspond to real weather, equipment, or market-driven disturbances.

## Adversarial and stress-testing scenarios

Adversarial scenario generation is especially important because smart-grid controls must be robust not only to average uncertainty but also to worst-case or strategically difficult conditions. Operation-adversarial scenario generation shows that scenarios can be constructed to expose vulnerabilities in operational decisions, shifting the purpose of generation from imitation to stress testing [3]. The critical challenge is that adversarial realism must be carefully governed, because unrealistic stress cases can misdirect investment, distort reliability assessment, or produce excessive conservatism.

## Integration with grid simulators

Integration with grid simulators remains a decisive barrier between generative scenario research and operational adoption. Cross-modal generative adversarial networks and joint wind-solar-load scenario models show progress toward producing richer input sets for simulation environments [14]. Yet this review argues that generative models must be coupled with power-flow, stability, protection, and operator-response models before their outputs can be considered credible contingency evidence.

# Human-in-The-Loop Dispatch

## Concept of AI-assisted dispatch

Human-in-the-loop dispatch refers to systems in which AI supports, rather than replaces, operator judgment in real-time or near-real-time grid decisions. Work on human-in-the-loop deep reinforcement learning for volt/var control shows that operator involvement can shape automated control while preserving human oversight [15]. The literature shows promise here, but it also reveals a tension between automation speed and human comprehension, especially when generated recommendations must be reviewed under time pressure.

## Generative AI for operator recommendation

Generative AI can support dispatch by translating system states into natural-language summaries, suggesting corrective actions, or generating explanations for alternative operating strategies. A large language model for advanced power dispatch demonstrates how LLMs may be adapted to dispatch-related reasoning, but it also illustrates that linguistic coherence is not equivalent to secure or optimal control [4]. This review argues that operator recommendation systems must be evaluated against grid outcomes, failure recovery, and human decision quality rather than only response fluency.

## Explainability and operator trust

Explainability is central to operator trust because dispatch decisions must be justified, auditable, and consistent with grid codes and safety constraints. Reviews of AI explainability and governance in smart energy systems show that transparent reasoning and institutional accountability are prerequisites for responsible deployment [5]. A significant risk is that generative systems may provide persuasive explanations for incorrect recommendations, making trust calibration harder than in conventional decision-support tools.

## Pilot deployments and evaluations

Pilot deployments and evaluations remain limited, particularly for LLM-enabled dispatch support in realistic control-room settings. Studies exploring LLMs in the electric energy sector identify promising capabilities but also emphasize limitations in domain grounding, mathematical reliability, and operational safety [16]. **Table 2** compares representative generative AI tools for human-in-the-loop dispatch and highlights that evaluation must include operator behavior, explainability quality, and failure handling, not only technical accuracy.

**Table 2.** Generative AI Tools for Human-in-the-Loop Dispatch: Interaction, Explainability, and Operational Evaluation

| Tool category                            | Dispatch-support function                                        | Interaction mode                          | Explainability approach                                     | Evaluation status                         | Critical concern                                          |
|------------------------------------------|------------------------------------------------------------------|-------------------------------------------|-------------------------------------------------------------|-------------------------------------------|-----------------------------------------------------------|
| LLM-based dispatch assistant             | Summarizes system state and proposes actions                     | Natural-language dialogue                 | Textual rationale and stepwise explanation                  | Mostly exploratory and benchmark-oriented | May hallucinate constraints or justify unsafe actions     |
| Human-in-the-loop reinforcement learning | Supports volt/var or corrective control decisions                | Operator-guided control updates           | Policy feedback and human correction                        | Demonstrated in research environments     | Human oversight may be too slow for fast contingencies    |
| Scenario-aware recommendation engine     | Uses generated scenarios to rank dispatch options                | Decision dashboard or ranked alternatives | Scenario comparison and risk indicators                     | Often simulation-based                    | Scenario quality strongly affects recommendation validity |
| Explainable generative interface         | Converts complex model outputs into operator-readable narratives | Natural-language or visual explanation    | Feature attribution, rule summaries, uncertainty statements | Conceptual to early-stage                 | Explanations may be persuasive without being faithful     |
| Security-aware LLM monitor               | Flags suspicious recommendations or unsafe prompts               | Advisory warning layer                    | Risk labels and constraint checks                           | Emerging research direction               | Requires robust domain grounding and adversarial testing  |

## Governance Risks

### Hallucination and factual reliability

Hallucination is one of the most serious governance risks for generative AI in smart-grid operation because generated outputs may appear coherent while violating physical constraints, operational procedures, or factual system states. Security-focused work on large language models in power systems shows that LLMs can introduce new threat surfaces when they are used for grid reasoning, recommendation, or operator-facing support [9]. This review argues that

hallucination in critical infrastructure is not merely an information-quality problem; it is a dependability problem that can affect safety margins and operator confidence.

### Data privacy and leakage

Data privacy risks are especially acute in synthetic load-profile generation because electricity-use patterns can reveal occupancy, business activity, appliance use, and socioeconomic characteristics. Differentially private load-profile synthesis shows that privacy protection can be formalized, but the literature also demonstrates that privacy-utility trade-offs remain difficult to manage in operationally useful datasets [12]. Federated generative learning for renewable-energy scenarios further suggests that distributed learning can reduce direct data sharing, although it does not eliminate risks of model inversion, leakage, or weak governance over derived synthetic outputs [17].

### Bias and fairness

Bias and fairness concerns arise when generative models reproduce uneven data coverage, regional inequalities, or historically embedded assumptions about demand and flexibility. Extreme-weather labelled wind-solar-load scenario generation shows that generative models can represent stressful operating conditions, but the literature also implies that modelling choices determine which communities, assets, and weather regimes receive attention [18]. A significant risk is that synthetic or generated scenarios may normalize historical under-service or under-protection if fairness is not explicitly incorporated into evaluation.

### Regulatory and liability gaps

Regulatory and liability gaps remain substantial because smart-grid generative AI sits between software, critical infrastructure, market operation, and public accountability. Governance research on generative AI emphasizes that responsibility is difficult to assign when outputs are probabilistic, adaptive, and partly shaped by training data that may be opaque [19]. **Table 3** maps governance risks to smart-grid applications and shows that technical mitigation alone is insufficient without auditability, institutional accountability, and sector-specific rules.

**Table 3.** Governance Risks in Smart-Grid Applications: Manifestations, Mitigation, and Residual Challenges

| Governance risk      | Smart-grid application most affected     | Example of risk manifestation                                              | Potential mitigation strategy                                           | Remaining limitation                                     |
|----------------------|------------------------------------------|----------------------------------------------------------------------------|-------------------------------------------------------------------------|----------------------------------------------------------|
| Hallucination        | Human-in-the-loop dispatch               | LLM recommends an infeasible corrective action or misstates a constraint   | Physics-based validation, constraint checking, operator approval        | Validation layers may not catch context-dependent errors |
| Privacy leakage      | Synthetic load-profile generation        | Synthetic profiles reveal household routines or commercial demand patterns | Differential privacy, federated learning, access controls               | Utility may decline as privacy guarantees strengthen     |
| Bias amplification   | Load and contingency scenario generation | Underrepresented feeders or vulnerable customers are poorly modeled        | Fairness-aware sampling, subgroup evaluation, transparent documentation | Fairness metrics for grid operation remain immature      |
| Unrealistic extremes | Contingency simulation                   | Generated rare events are mathematically extreme but                       | Coupling with grid simulators and domain                                | Physical plausibility is difficult to prove              |

|                                  |                                          | physically implausible                                   | constraints                                                       | across all cases                                              |
|----------------------------------|------------------------------------------|----------------------------------------------------------|-------------------------------------------------------------------|---------------------------------------------------------------|
| Accountability failure           | Operator recommendation systems          | Harmful advice is produced but responsibility is unclear | Audit logs, role definitions, model cards, regulatory review      | Liability frameworks lag behind generative AI deployment      |
| Energy and sustainability burden | Large-scale generative model development | Model training increases computational and energy demand | Efficient architectures, lifecycle assessment, targeted model use | Benefits and environmental costs are rarely assessed together |

# Critical Assessment

## Strengths and opportunities

The strongest contribution of generative AI to smart-grid operation is its ability to expand the range of data and scenarios available for planning, testing, and decision support. Controllable renewable-energy scenario generation shows that generative models can create diverse outputs while preserving user-specified operational characteristics [7]. This review argues that such controllability is valuable because future grids will need tools that can deliberately explore uncertainty rather than passively replay historical data.

## Technical immaturity

Despite rapid progress, the technical maturity of generative AI remains uneven across smart-grid applications. Diffusion-based source-load scenario generation and pattern-guided renewable-energy models show improved controllability and diversity, but these methods are still largely evaluated in research settings rather than embedded operational environments [6]. The literature shows that high-quality generation is not enough; models must also be robust, calibrated, computationally tractable, and compatible with real-time grid constraints.

## Integration barriers

Integration barriers include data interoperability, simulator coupling, operator workflow design, cybersecurity, and institutional approval. Electric-vehicle charging scenario generation through diffusion models illustrates how specialized generative models can support emerging grid challenges, yet integrating such outputs into dispatch or planning platforms requires assumptions about mobility behavior, charging infrastructure, and distribution-network constraints [20]. Few studies have addressed the full pipeline from generative model training to validated operational decision-making.

## Trustworthiness and dependability

Trustworthiness and dependability are the central unresolved criteria for using generative AI in critical grid functions. Reviews of explainable AI for energy systems maintenance show that interpretability is necessary but not sufficient, because users must also understand uncertainty, limits of applicability, and failure modes [21]. This review argues that dependable generative AI must combine explanation, verification, security testing, and institutional oversight rather than relying on model performance metrics alone.

# Research Gaps

## Gap in real-time control integration

A major research gap concerns the integration of generative AI with real-time control, where latency, safety constraints, and operator attention are decisive. Human-in-the-loop deep reinforcement learning for volt/var control demonstrates that

human supervision can be embedded into control learning, but generative outputs have not yet been systematically tested under realistic control-room timing and communication constraints [15]. Few studies have addressed how generated scenarios or recommendations should be updated, rejected, or overridden during fast-moving contingencies.

## Gap in evaluation standards

Evaluation standards remain fragmented, with different studies relying on distributional similarity, visual realism, diversity, privacy scores, or downstream task performance. Extreme load scenario generation using classifier-guided diffusion and extreme value theory shows the importance of tail-focused evaluation, because average-case metrics may hide failures in precisely the conditions that matter most for reliability [22]. This review argues that the field needs standardized benchmarks that combine statistical fidelity, physical feasibility, operational usefulness, privacy protection, and robustness under distribution shift.

## Gap in governance and ethics

Governance and ethics remain underdeveloped relative to technical model innovation. Systematic mapping of generative AI ethical concerns identifies risks such as misinformation, bias, privacy loss, lack of transparency, and accountability failures, all of which become more consequential when transferred into energy infrastructure [23]. The literature shows that smart-grid generative AI research often treats governance as a discussion section rather than as a design requirement embedded across data collection, model development, deployment, and audit.

## Gap in cross-domain generalization

Cross-domain generalization is another unresolved challenge because models trained on one region, customer class, climate regime, or market structure may fail elsewhere. Wasserstein GAN-based wind-power scenario generation and related renewable studies demonstrate strong performance in specific datasets, but they do not fully establish transferability across power systems with different weather patterns, grid codes, and renewable portfolios [24]. A significant risk is that generative AI tools may be overfit to local histories while being marketed as general-purpose grid intelligence.

# Future Directions

## Development of energy-specific generative models

Future research should prioritize energy-specific generative models that encode grid topology, power-flow constraints, equipment limits, and market rules rather than relying on generic architectures. Large-language-model research for energy systems suggests that domain adaptation can improve relevance, but it also shows that general models require grounding in power-system knowledge before they can support safety-critical reasoning [25]. This review argues that energy-specific models should be smaller, verifiable, and task-aligned where possible, rather than simply larger and more fluent.

## Robustness and safety testing

Robustness and safety testing should become a core requirement for generative AI in smart-grid operation. Controllable renewable scenario generation and adversarial scenario construction show that generative models can be used not only as planning aids but also as tools for probing model and system weaknesses [26]. Future work should combine adversarial testing, uncertainty quantification, simulator validation, and red-teaming to determine whether generated outputs remain safe under extreme, noisy, or malicious conditions.

## Human-AI collaboration frameworks

Human-AI collaboration frameworks must move beyond interface design toward measurable effects on operator cognition, situational awareness, workload, and accountability. Research on LLM capabilities in the electric energy sector indicates that these systems can assist with explanation and synthesis, but it also warns that limitations in reasoning and grounding remain significant [16]. This review argues that future dispatch-support systems should be evaluated with operators in realistic scenarios, including cases where the AI is uncertain, wrong, or adversarially manipulated.

## Regulatory sandboxes and guidelines

Regulatory sandboxes and sector-specific guidelines are needed to test generative AI under controlled conditions before deployment in critical grid operation. The growing energy footprint of artificial intelligence also indicates that governance should consider not only safety and accountability but also the resource cost of training and operating large models [27]. Future governance should link technical certification, environmental assessment, privacy review, incident reporting, and operator responsibility into a coherent framework for smart-grid generative AI.

## Conclusion

Generative AI offers important opportunities for smart-grid operation, particularly in synthetic load-profile generation, contingency simulation, and operator support. Its ability to create new data, expand scenario diversity, and produce human-readable recommendations makes it attractive for increasingly complex, uncertain, and decentralized power systems.

At the same time, this review finds that technical progress is ahead of operational validation. Many studies demonstrate promising generation quality, but fewer prove that generated outputs improve real grid decisions, remain valid under distribution shift, or support safe human action during high-pressure events.

The most important cross-cutting risks are hallucination, privacy leakage, bias amplification, weak accountability, and inadequate evaluation standards. These risks are not peripheral concerns; they directly shape whether generative AI can be trusted in critical infrastructure.

Future progress will require energy-specific model design, physics-aware validation, human-centered evaluation, robust governance, and regulatory experimentation. Generative AI should be treated not as a replacement for grid expertise but as a powerful and risky tool that must be constrained, audited, and aligned with public-interest reliability.

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