Generative AI for Power Grid Operations

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List of Acronyms

AI	artificial intelligence
BERT	bidirectional encoder representations from transformers
CAISO	California Independent System Operator
CIP	Critical Infrastructure Protection
DOE	U.S. Department of Energy
DSO	distribution system operator
eGridGPT	Electric Grid Generative Pretrained Transformer
EIA	U.S. Energy Information Administration
EMS	energy management system
ERCOT	Electric Reliability Council of Texas
FERC	Federal Energy Regulatory Commission
GPT	generative pretrained transformer
ICCP	Inter-Control Center Communications Protocol
ML	machine learning
MRO	Midwest Reliability Organization
NERC	North American Electric Reliability Corporation
NIST	National Institute of Standards and Technology
NLP	natural language processing
NREL	National Renewable Energy Laboratory
PG&E	Pacific Gas & Electric Company
RPD	recognition-primed decision
RTAG	Real-Time Analytics for Grids
RTU	real-time unit
SCADA	supervisory control and data acquisition
SPP	Southwest Power Pool
TSO	transmission system operator
WAPA	Western Area Power Administration

Executive Summary

Historically, humans have relied on various lighting sources, from natural daylight to artificial means like torches and gas lamps, to extend their daytime hours. The advent of the electric light bulb, pioneered by Thomas Edison in 1882, marked a transformative era. Edison's invention promised to redefine working hours; however, realizing this potential required a parallel development in power generation and distribution infrastructure. As on-site residential electricity generation remained impractical, utility companies emerged to bridge the gap between power sources and consumers. The role of the utility companies in delivering this essential service is often reflected in their names (e.g., Florida Power and Light Company).

Despite the transformative potential of electric lighting, its adoption was not without resistance. Concerns about the safety of the filament melting, the reliability of how long the light could stay on, and the economic shift within the gas lighting industry raised skepticism. Thus, the electric light bulb serves as a case study in the complex interplay between technological innovation and societal acceptance.

Generative artificial intelligence (AI) has catapulted into the mainstream, demonstrating capabilities that once belonged solely to the realm of human cognition. From defeating world champions in complex games (e.g., Chess and Go) to generating human-quality text and images, generative AI has proven its potential to revolutionize countless industries. The electric power grid is no exception. Generative AI's ability to rapidly process vast amounts of data, assist in decision support, and identify patterns could significantly enhance power grid operations. For example, generative AI could improve state estimation where measurements are not available or more efficiently integrate renewable energy sources with probabilistic forecasting.

But the introduction of generative AI into critical infrastructure should be carefully addressed. Like the public's initial unease toward the electric light bulb in the 19th century, there can be concerns about generative AI's credibility, safety, and potential consequences. Issues such as data privacy, cybersecurity, and hallucination with unforeseen outcomes must be carefully addressed.

To harness the full potential of generative AI while mitigating risks, rigorous testing, validation, and human oversight will be crucial. By carefully considering the potential benefits and drawbacks, the power grid industry can embrace technological advancements while maintaining the reliable, stable, and affordable delivery of electricity.

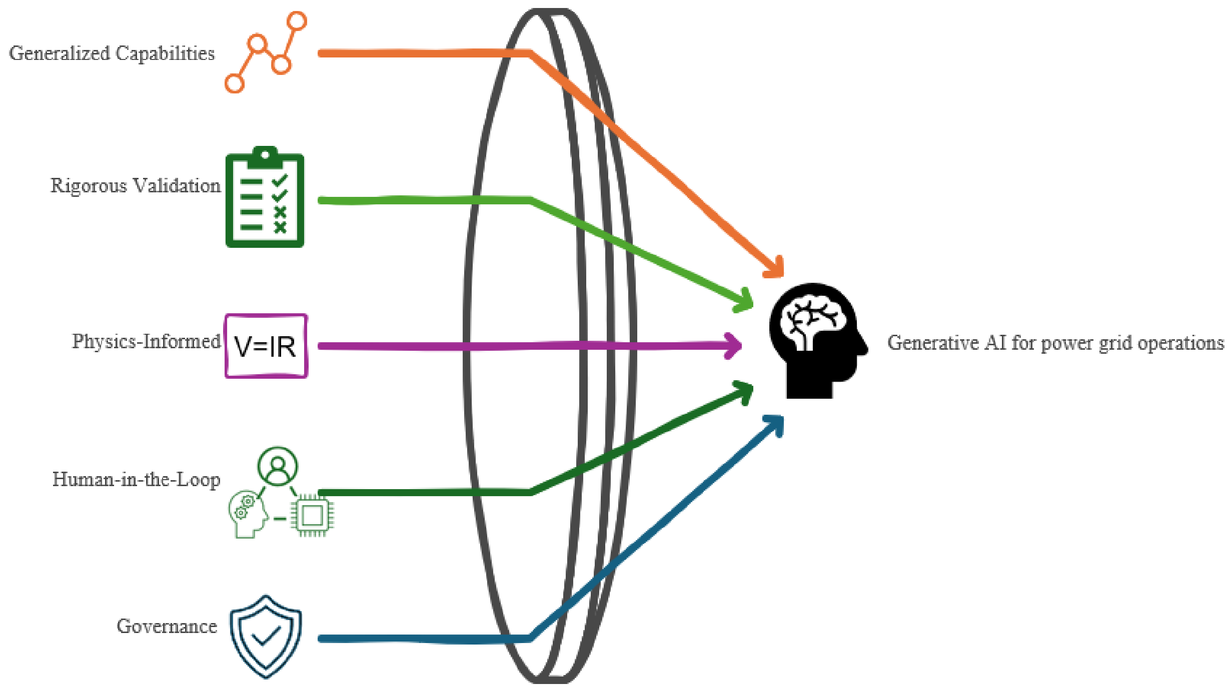

Figure 1. Generative AI for power grid operations

The key contributions of this paper are as follows. The paper:

- *Provides a comprehensive overview of generative AI's applications in power grid operations*: The paper highlights the opportunities in areas such as forecasting and state estimation, and it demonstrates the potential to enhance power grid efficiency, reliability, and resilience.
- *Expands generative AI's impact through synergies with emerging technologies:* The paper introduces the Electric Grid Generative Pretrained Transformer (eGridGPT), developed by the National Renewable Energy Laboratory, and it explores how AI orchestration, multi-agent systems, and digital twins can collaborate to optimize grid operations, addressing the complexities of a decarbonized and electrified future.
- *Offers an in-depth analysis of challenges in implementing generative AI:* The paper considers data availability and quality, model validation, certification, and ethical concerns that must be addressed to ensure responsible AI deployment.
- *Emphasizes human-AI collaboration:* The paper underscores the importance of trustworthiness and explainability in AI systems to promote seamless interactions between human operators and AI, ultimately improving decision-making.
- *Explores future research and development:* The paper identifies critical areas for further advancement to fully realize generative AI's potential in power grid operations.

This paper serves as a valuable resource for researchers, practitioners, and policymakers looking to harness generative AI for a more reliable, stable, and cost-effective power grid.

Table of Contents

List of Figures

List of Tables

1 Introduction

The power sector is undergoing a significant transformation, driven by technological advancements, the electrification of other industry sectors, changing consumer demands, and the urgent need for sustainable clean energy solutions. During this transformation, reliability, stability, and affordability remain the most important objectives of grid operation. Electricity must be available 24/7 (reliability) at the scheduled frequency and voltage (stability) with the least cost of generation (affordability).

To be reliable, stable, and affordable, minute-by-minute grid operations involve many parties—from generation power plants, to transmission and distribution line management, to substation switching operations. Coordinating, adjusting, and communicating with many parties requires a central coordinator. In the United States, reliability coordinators provide the ultimate authority of reliability and stability, and independent system operators/regional transmission organizations and balancing areas support affordable grid service via an energy market, as shown in Figure 2. The scale of this transmission control center operation is immense. In the United States alone, approximately 140 primary and backup transmission control centers process data from hundreds of thousands of substations every few seconds, highlighting the complexity and criticality of their role (DOE 2019). Although generation and distribution control centers play essential roles, the transmission control center acts as the grid's central nerve system. Unlike generation and distribution control centers, which have limited visibility into the broader grid, the transmission control center possesses a comprehensive view of the power system.

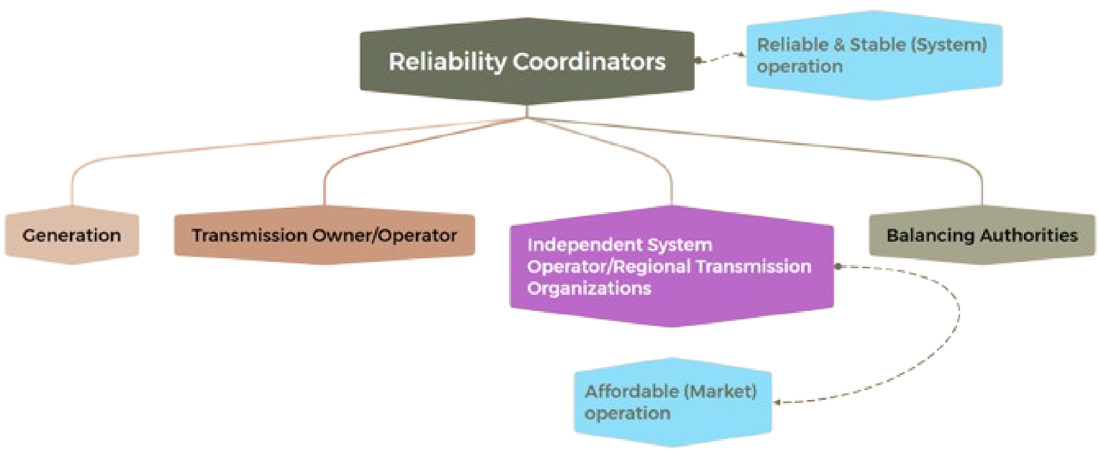

Figure 2. Reliable, stable, and affordable operation hierarchy

1.1 Where Power Grid Operation Meets AI: Control Room

Transmission control rooms (or centers)—where data are collected, analyses are provided, and decisions are made—are a logical location for discussing the benefits of artificial intelligence (AI). In this report, AI includes the cyber machines that can think or inference like humans. The integration of AI into transmission control centers presents a compelling opportunity, as shown in Figure 3. Analogous to the human brain, which processes sensory data to control bodily functions, the power grid in the United States relies on the coordinators and operators working in control rooms. The abundance of data processed within these centers, coupled with the presence of human operators who capable of making informed decisions minute by minute, creates a fertile ground for AI applications.

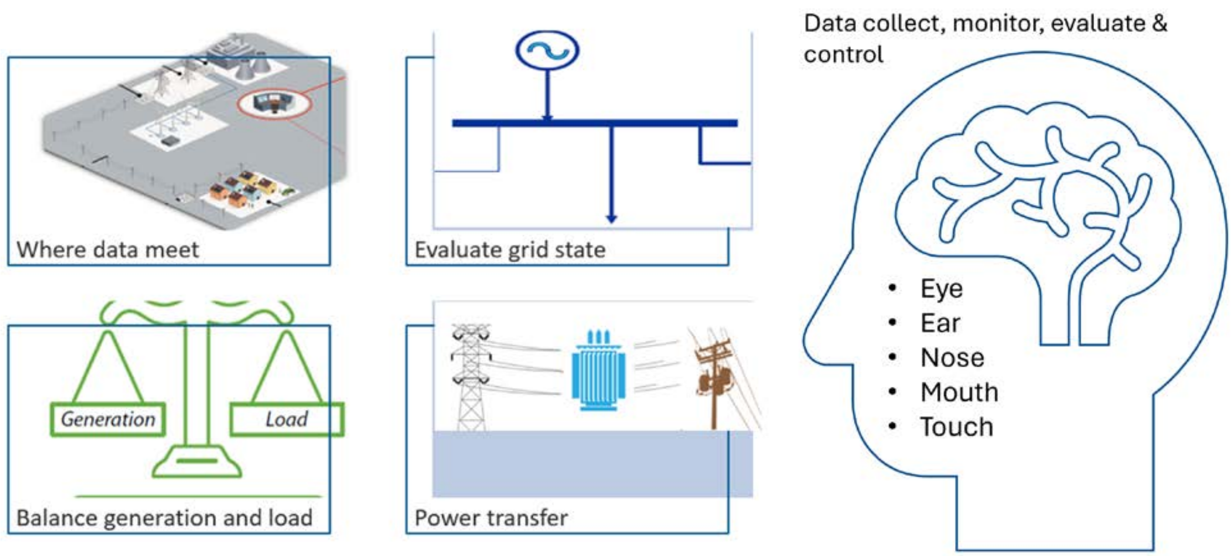

Figure 3. The power grid control center is analogous to the human senses and the brain.

Many utilities have conducted their own AI/machine learning (ML) projects to tackle problems such as predictive asset maintenance or energy forecasting (Carter et al. 2023). These efforts require significant AI/ML expertise, labeling of data, high computing assets, and human/financial resources, so many utilities shy away from adopting AI/ML in general.

Recent advancements in deep learning, particularly in the development of transformer architectures, a type of neural network, have revolutionized natural language processing (NLP), computer vision, and other computing fields. Transformers leverage a self-attention mechanism that allows them to capture long-range dependencies in data, making them particularly well-suited for processing sequential data like time series or text. This ability to understand complex dependencies or relationships within data makes transformers a promising tool for tasks such as load forecasting, renewable generation prediction, and grid stability analysis. Generative AI is a catch-all phrase for a collection of AI techniques that can use transformers to generate data or make predictions.

In other words, there are new avenues for utilities to easily and rapidly deploy AI solutions that are dependent on massive datasets (Niu, Zhong, and Lu 2021). Model developers first train these neural networks using self-supervision, a type of unsupervised learning. After this step, these AI models can be shared with customers, who customize and deploy them with minimal effort. Attention allows generative AI models to focus on the most relevant information, for instance, enabling the analysis of time-series data. Transformers, with their self-attention and cross-attention mechanisms, have further enhanced the ability to capture complex relationships between different data types (Vaswani et al. 2017). Generative AI, built upon these transformer models, represents a new frontier for power grid operations. Thanks to generative AI's unsupervised learning, utilities are now less reliant on the actual knowledge of AI experts and more focused on the generative AI outputs.

This report is intended to bridge the knowledge gap between power grid operations and generative AI development. It answers the questions "What is generative AI?" and "How can power grid operations benefit from it?"

1.2 What Is Generative AI?

Generative AI refers broadly to generative models. Generative models are a type of AI model that can be prompted by a user to create synthetic data. One of the most popular and commonly used models, a generative pretrained transformer (GPT), is a specific type of generative AI model based on the transformer architecture. It is "pretrained" on a massive dataset of text and code using self-supervision, allowing it to learn patterns, dependencies, and relationships within the data. This pretraining enables GPT to generate human-quality text, translate languages, write different kinds of creative content, and answer questions in an informative way. GPT models are characterized by their ability to understand and generate human-like text, making them well-suited for applications such as NLP, chatbot development, and software code generation.

Unlike conventional AI/ML, which primarily focuses on pattern recognition, classification, and prediction, generative AI can create new synthetic data and simulate a wide range of scenarios (Chen et al. 2024). Generative AI models predict answers with varying probabilities so that they can generate diverse content. They also represent a new frontier in the optimization of power systems, offering capabilities that go beyond traditional AI/ML approaches (Majumder et al. 2024; Zaboli et al. 2024). By leveraging generative AI, utilities can enhance their decision-making processes, improve grid resilience, detect anomalies and achieve more efficient and sustainable energy management (Benes, Porterfield, and Yang 2024). As the power sector continues to embrace digital transformation, generative AI is poised to play a pivotal role in transitioning to clean energy.

This report focuses on the application of a particular style of self-supervised pretraining for generative AI for power grid operations. This approach is called input masking pretraining. In generative AI—particularly in fields like computer vision, shown in Figure 4—input masking involves deliberately obscuring or hiding portions of the input data and training the AI model to predict the missing pieces. For instance, in NLP, this method is crucial for training models like bidirectional encoder representations from transformers (BERT), where certain words in a sentence are masked, and the model is trained to predict the masked words based on the context provided by the visible words (Pichai and Hassabis 2024). Another example in computer vision is masked autoencoders, which learns to generate the whole input from partial or missing data (He et al. 2024). These examples of text, data, or image masking resemble one of the most important concepts in power systems, called state estimation.

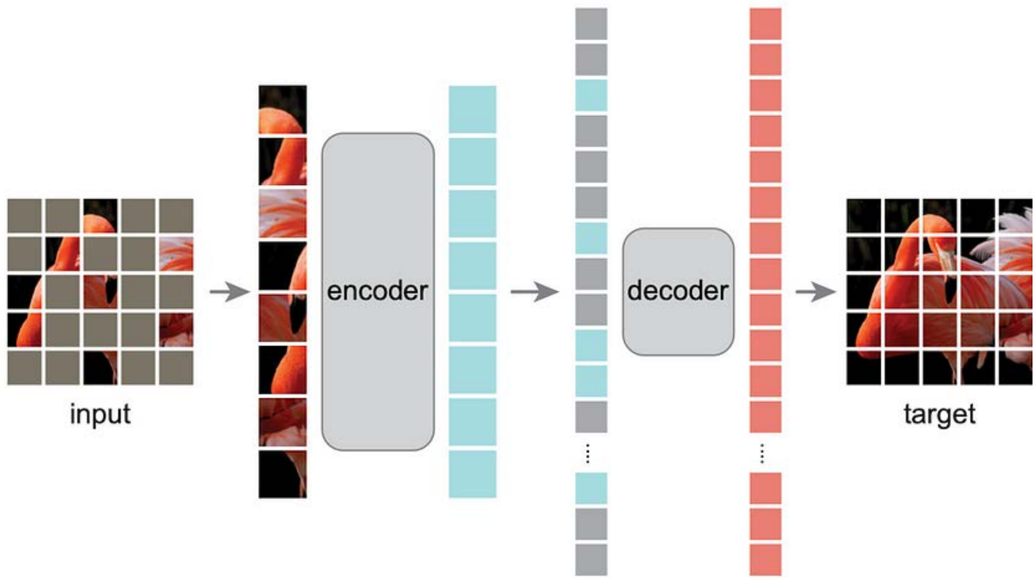

Figure 4. Vision transformer trained with input masking

Source: He et al. 2021

1.3 Application of Generative AI to Power Grid Operation

State estimation is determining the value of all the parameters in a power system at an instant in time that is needed to predict future behavior—for example, determining the voltages and currents of all nodes in a power system at a specific time and set of conditions. State estimation is often used in dealing with partial, noisy, or missing supervisory control and data acquisition (SCADA) data. After processing incomplete SCADA data, state estimation reconstructs the accurate current grid snapshot for the downstream applications, such as contingency analysis and optimal power flow, shown in Figure 5.

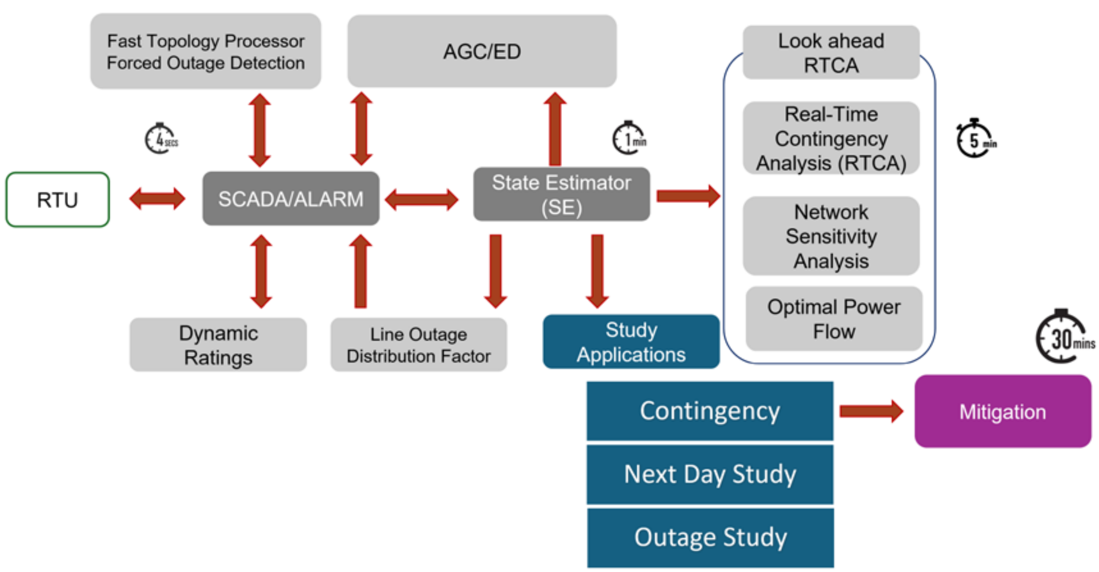

Figure 5. Control room application flow

Source: Zhang 2021a

The accuracy of the grid status powered by state estimation is a key for operators to run the grid reliably, securely, and hence affordably. SCADA data inform operators about which lines are energized, which generators are online, how much current is flowing, and the voltage at electrical nodes based on data collected from field devices known as remote terminal units (RTUs) and its grid network topology model, shown in Figure 6. A network topology model shows the location, connection, settings, and characteristics of various grid assets. RTU measurements indicates both their value and status. Both the model and measurements are then matched and presented to a system operator to determine the correct grid situation.

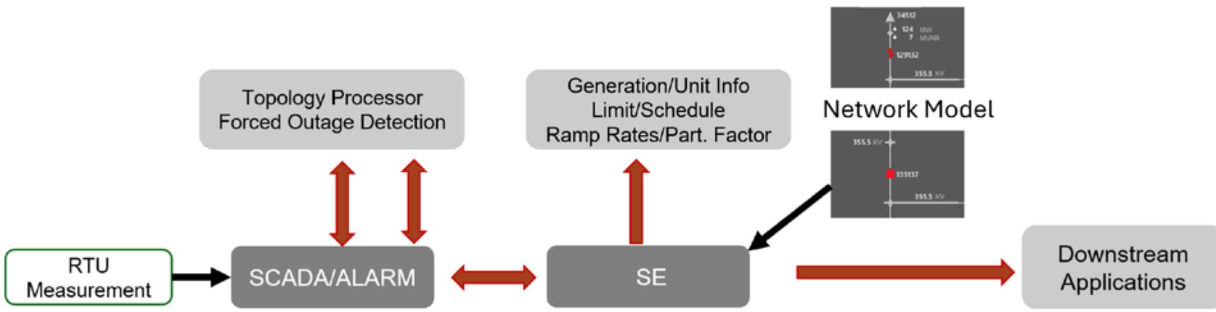

Figure 6. State estimation flow

But there are many reasons why the model and measurements might not match. For example, Figure 7 shows Line 1 with 58 MW and 18 MV(AR), but the circuit breakers (CB1 and CB2) connecting to Line 1 are open; therefore, Line 1 should indicate that no electricity is flowing. How does this mismatch between the model and measurement occur?

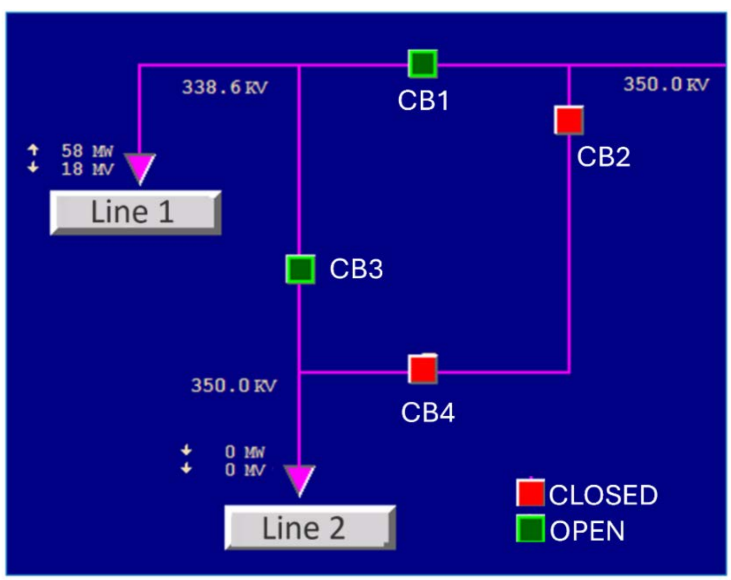

Figure 7. Model and measurement mismatch

From the network model side, the model might be not up to date (CB1 should be closed), or the model might not reflect the true characteristics of the asset, such as a generation unit. For example, utility-scale photovoltaic inverter models are treated like a black box, so they can cause unexpected behavior when there is a disturbance (NERC 2021). From the measurement side, there are several issues. First, measurements are not available at all locations because installing measurement devices might be cost-prohibitive. For example, because distribution systems typically do not have extensive measurements, the distribution control room might find it difficult to run a state estimation model. Second, measurements can be missing due to communication issues between the RTUs and SCADA data or because of an equipment malfunction at a substation. Third, the measurement might be suspicious because the data could be too high or low compared to normal values or because there is a modeling issue.

These partial, missing, or suspicious measurements require adjusting the analog value, reconciling the status, or filtering the noise of the measurement conducted by state estimation. After knowing the current state, the application runs the power flow to check whether the generation could supply the demand via lines without overloading them. With state estimation and power flow, contingency analysis is conducted to avoid uncontrolled cascading outages (NERC 2023a); thus, state estimation is the basis of reliable, stable, and affordable operation.

State estimation has been successfully operating for several decades with the help of mathematical calculations and without the need for AI/ML. In particular, transmission control rooms run state estimation quickly, typically within 60 seconds, thanks to increased computing power, solving around 99.9% of cases due to factors such as redundant measurements and rapid model updates by real-time operation engineers (Zhang et al. 2021a). But state estimation operates sequentially rather than in parallel. Using parallel state estimation powered by graphics processing units would offer operators greater scalability and the ability to conduct multiple scenario-based analyses simultaneously. Although various AI/ML approaches have been proposed to address state estimation issues (Kundacina et al. 2022), this paper explores how generative AI can enhance state estimation through input masking with model image processing.

1.4 This Paper

This paper explores the transformative potential of generative AI to improve the operation of the power grids. We explore the varying challenges and opportunities where generative AI has the potential to bring transformative improvements. This paper:

- *Provides a comprehensive overview of generative AI's applications in power grid operations*: The paper highlights the opportunities in areas such as forecasting and state estimation, and it demonstrates the potential to enhance efficiency, reliability, and resilience.
- *Expands generative AI's impact through synergies with emerging technologies:* The paper introduces the Electric Grid Generative Pretrained Transformer (eGridGPT), developed by the National Renewable Energy Laboratory (NREL), and it explores how AI orchestration, multi-agent systems, and digital twins can collaborate to optimize grid operations, addressing the complexities of a decarbonized and electrified future.
- *Offers an analysis of challenges in implementing generative AI:* The paper considers data availability and quality, model validation, certification, and ethical concerns that must be addressed to ensure responsible AI deployment.
- *Emphasizes human-AI collaboration:* The paper underscores the importance of trustworthiness, transparency, and explainability in generative AI to promote seamless interactions between human operators and AI, ultimately improving decision-making.

- *Explores future research and development:* The paper identifies critical areas for further advancement to fully realize generative AI's potential in power grid operations.

This paper serves as a valuable resource for researchers, practitioners, and policymakers seeking to understand and leverage the power of generative AI to create a more sustainable, reliable, and resilient power grid.

2 Generative AI and Power Grid Operation

The primary goal of the power industry is to keep the lights on and power loads at the scheduled frequency and voltage around the clock with the cheapest cost of generation and transmission. Maintaining reliable grid operations minute by minute requires balancing generation and load at all timescales. The idea of "generation following load" has been working for many decades because the typical load curves are similar from year to year or from season to season, as shown in Figure 8 (PJM 2024), and generation has been dispatchable to meet the demand. Operators ensure that the generation is enough to cover the loads plus provide additional reserves for load forecasting error or contingencies.

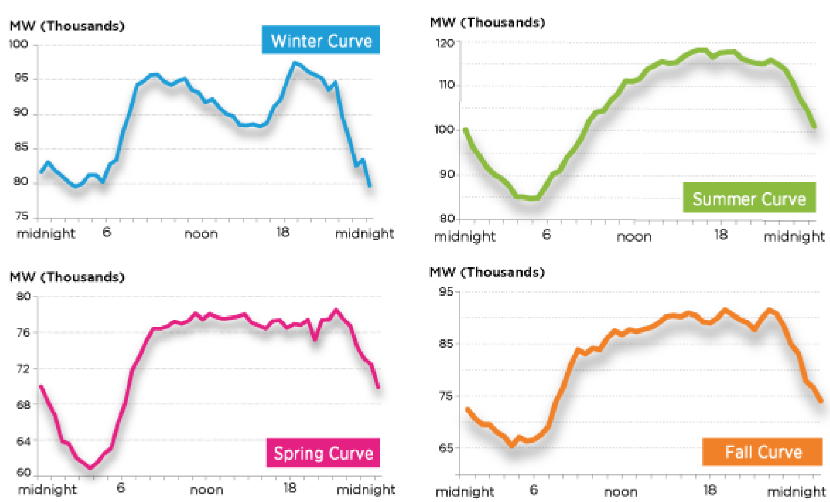

Figure 8. PJM's typical load curve

Source: PJM

Recently, variable renewable energy sources such as wind and solar have seen a significant increase in penetration levels. Initially driven by the need to address climate change, these energy sources are now more cost-effective than traditional coal or natural gas power plants (NREL 2024), as shown in Figure 9.

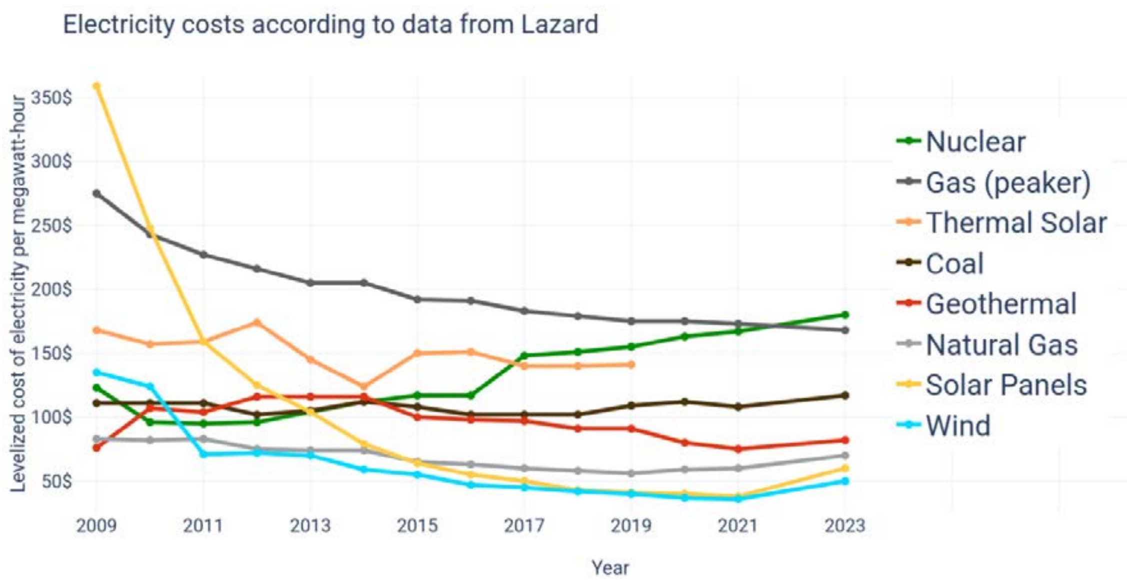

Figure 9. Solar is cheaper than coal

Source: Lazard 2023

With high penetration levels of renewable energy, power system operations are changing from "generation following load" to "load adapting to generation." In other words, it is not the load to be figured out first, but how much the generation would be under a certain weather scenario. For example, in the evening when the sun sets and solar power is no longer available, there is a rapid increase in electricity demand from other energy sources such as batteries or natural gas. This requires the grid to quickly ramp up production from non-solar sources to meet the net load, as shown Figure 10 (EIA 2023).

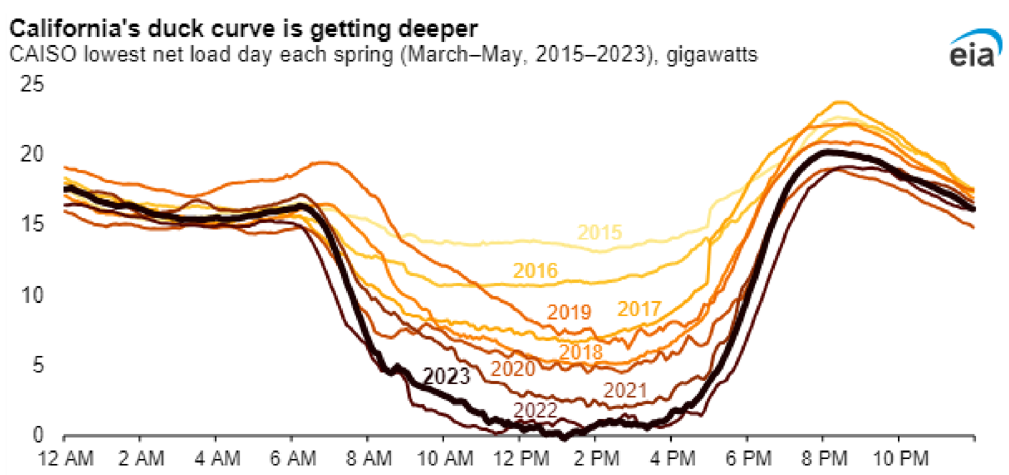

Figure 10. California's duck curves are getting deeper.

Source: EIA

As climate change leads to more unpredictable weather patterns, which directly affect solar and wind energy, traditional deterministic forecasting methods have become less adequate. Unlike deterministic forecasts that provide a single predicted value, probabilistic forecasts account for the uncertainty inherent in predicting complex systems such as weather and variable energy generation. Because humans are not naturally inclined to handle uncertainty, generative AI plays a crucial role in addressing this challenge.

Forecasting and uncertainty are not the only challenges system operators face. There are lots of other operational challenges that are mainly introduced by high variable renewable energy mixes and electrification (see Table 1). Generative AI can play a role in these operational challenges as well.

Table 1. Grid Operational Challenges and Their Impacts on the Control Room

Characteristics	Tradition	New Trend	Control Room Impact
Power flow direction	One-directional	Multi-directional	Requires TSO-DSO coordination [a]
Balance generation and load	Deterministic	Probabilistic with uncertainty	Underserved load risk
Network visibility	Full measurement	No visibility of behind-the-meter devices	Uncertainty quantification
Unit dispatch	Full control	Weather-dependent, unpredictable, and non-dispatchable renewable energy sources	Optimization with scenarios
Decision-making	Predefined decision-making	Dynamic decision-making in emergencies with uncertainty	More operator intervention

[a] TSO: transmission system operator; DSO: distribution system operator

With these grid operating challenges, this report explores how generative AI can play a key role in power grid operations by helping human operators perform more efficiently through human-AI collaboration. Human-AI collaboration can improve an operator's situational awareness and enhance their decision-making. Several use cases of generative AI are listed in Table 2, followed by detailed explanations.

Table 2. Samples of Generative AI Use Cases in Power Grid Operation

Modality	Topic
Natural language processing	• Decision-making
Time series	• Energy forecasting
Computer vision	• Power system identification and modeling • State estimation with sparse measurement coverage
Inference	• Correlating real-time actionable choices against SCADA alarms

2.1 Decision-Making

Human decision-making is a complex process shaped by the present circumstances, anticipated future outcomes, and available choices. Decisions are typically made based on past experiences, operational procedures, and the pursuit of specific goals. For generative AI to replicate this process, this paper outlines how humans make decisions, highlighting the steps where it can be integrated to enhance decision-making.

In the exploration of the decision-making processes, the works of Rasmussen (1976) and Klein (2021) provide profound insights into how humans navigate the complexities of choices in various contexts. These authors investigate the cognitive mechanisms that underpin decision-making, highlighting the interplay among situational awareness, an evaluation of future possibilities, and the constraints within which decisions are made. Rasmussen provides the cognitive aspects of human-machine interaction and decision-making in a power plant (Rasmussen 1976). Klein's concept of the recognition-primed decision (RPD) model presents a compelling framework for understanding how experienced individuals who have deep knowledge make decisions in real-world settings, such as firefighters (Klein 2021).

In the utility control room, decision-making has historically been the sole responsibility of system operators. In the past, the complexity of decisions was less entangled with uncertainty, and there were fewer reliable computational resources available for support. As a result, operators have typically relied on their experience, trusted tools, and established procedures to guide their decision-making, following the steps outlined in Figure 11.

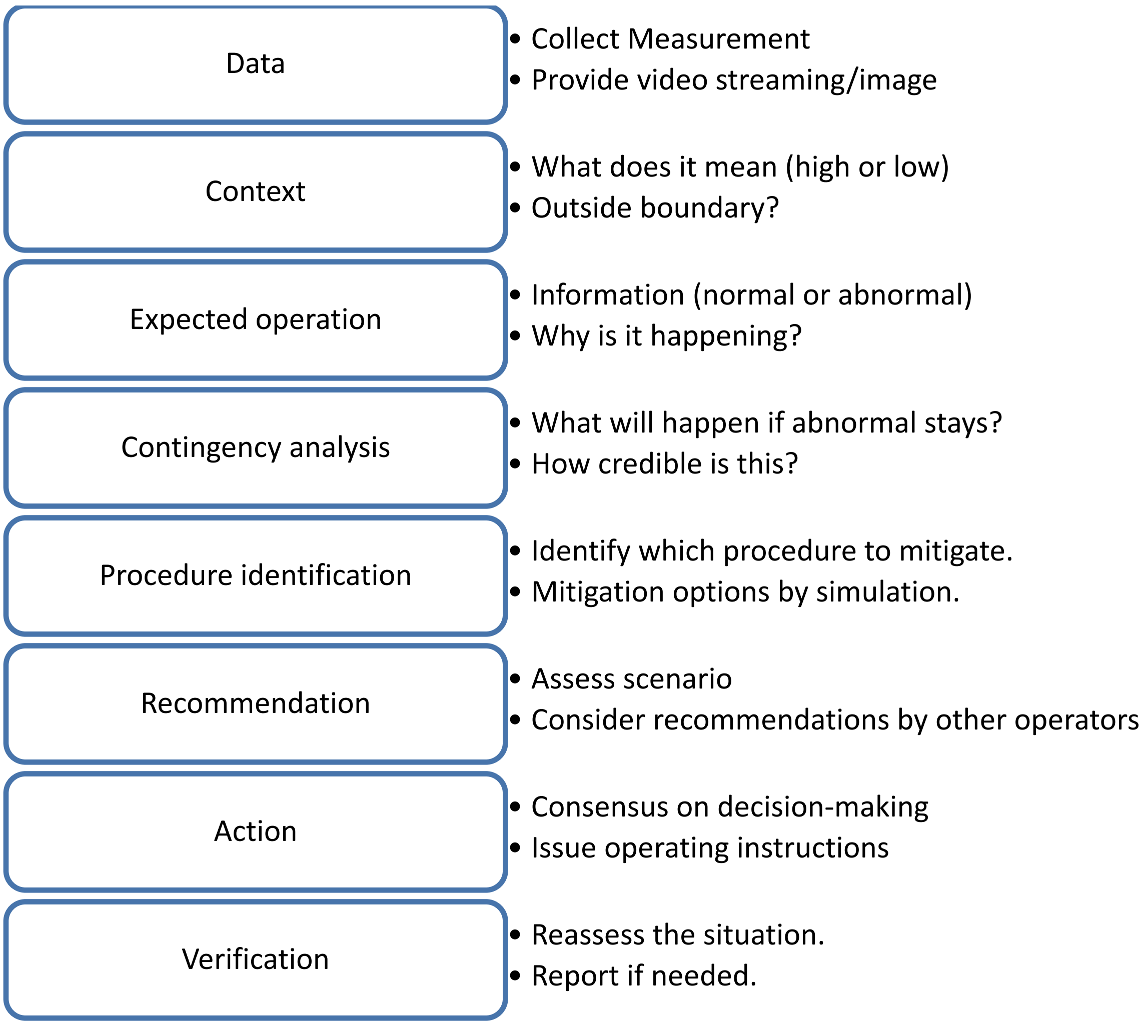

Figure 11. An operator's decision-making steps in a power system control room

Recently, barriers to AI adoption have diminished due to decreasing hardware costs and advancements in software, allowing smaller versions of generative AI models to run on devices like the Google Pixel 9 Pro (Pichai and Hassabis 2024). AI expertise is also becoming less critical because generative AI can now classify data, generate image prompts, and even develop new algorithms through interactions with other AI agents.

2.2 Energy Forecasting

Energy forecasting has been developed for decades, starting with load forecasting and recently renewable energy forecasting. Energy forecasting techniques started with statistical time-series models, followed by shallow ML models and deep learning models (Sun et al. 2023). Although breakthroughs have been made by introducing AI/ML techniques, a few challenges exist that cannot be addressed by traditional AI/ML but could be tackled by generative AI. First, generative AI could help enhance the modeling of tail events, e.g., extreme weather events in which most ML models underperform. Specifically, generative AI can learn from patterns in the rare events and generate scenarios to enhance the energy forecasting models. Second, generative AI, once trained, can have a much faster inference/processing speed, which will benefit the uncertainty quantification by creating large amounts of ensemble forecasts in energy forecasting.

Third, generative AI transformer architecture can learn from the entire time series, which is hardly possible for models such as recurrent neural networks. This will enable generative AI to capture long-term variations in climate, which will be helpful in understanding climate change and its impact on energy forecasting.

2.3 Power System Identification and Modeling

Generative AI can also be applied to power system infrastructure recognition and modeling. A promising use of large multi-modal models with image processing capabilities is the estimation of behind-the-meter photovoltaic systems. This can be achieved by combining various input images that include meteorological data and detailed information about the distribution system. (e.g., satellite imagery showing building rooftops, which might help detect the presence of rooftop solar). This large multi-modal model is first pretrained on large amounts of images that can be semantically unrelated to the model's downstream use cases (Hamann et al. 2024), and then later fine-tuned on a small amount of high-quality data. The training process involves input masking during pretraining, where certain portions of the input image(s) are randomly hidden or altered with noise. The model is then trained to reconstruct or predict the missing parts. This report envisions such a process being useful for solving a wide range of tasks in the estimation of the noisy state of distribution systems.

2.4 State Estimation with Sparse Measurement Coverage

Researchers have studied state estimation issues that come from either measurements or modeling problems. Recently, graph neural networks are gaining popularity, but control room operation relies on operational models (node breakers), which have many unusual situations that graph neural network (bus-branch) cannot handle. An example challenge is if the measurements are flowing and the node status is open, but there is a mismatch, as shown in Figure 7. A graph neural network cannot effectively deal with this type of issue.

Instead, this paper suggests a novel approach that moves away from traditional mathematical algorithms by recognizing that state estimation is similar to the "denoising autoencoding" technique used in training generative AI models, particularly in image-based models. The core concept of denoising-based training is to deliberately obscure, corrupt, or mask sections of the input data (Table 3).

Table 3. State Estimation Inputs and Outputs

State Estimation Input	Station Estimation Output
• Bus voltage magnitudes and angle measurements • Injections (gen-load) • Branch (line) flow • Switching • Transformer and phase shifter tap position	• Voltage angle and magnitudes • Branch MW and MVar flow • Loss sensitivities • Injection (gen-load) • Load tap change position • Limit violation

With the input measurement and network topology, the generative AI model will be trained to accurately predict these hidden or unobserved parts, as shown Figure 12. The model learns to infer the missing values based on the correlations and patterns present in the observed data.

During the training process, a comparative technique validates its output, and the training loss is back-propagated through both the encoder and decoder.

The crucial advantages of this training approach are its simplicity and generality—its performance scales well with more high-quality real and simulated data and computing. It can also be used with many different data types beyond images, such as text, time series, and graphs. To summarize, generative AI infers the state of a system from limited measurements by leveraging historical data and probabilistic models, providing valuable insights where human analysis might be insufficient.

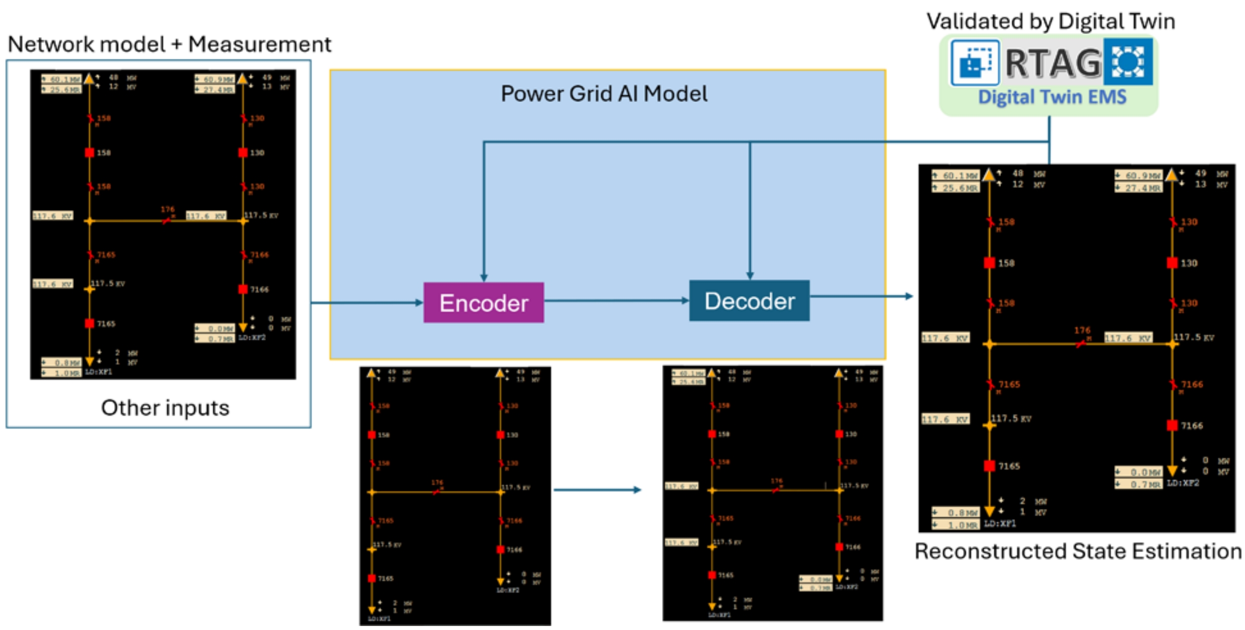

Figure 12. Generative AI pretraining of state estimation

2.5 Correlating Real-Time Actionable Choices Against SCADA Alarms

This paper proposes that generative AI can play another crucial role in diagnosing and responding to issues within complex information, such as in SCADA alarms. SCADA alarms are generated if the actual value exceeds the threshold set by the device limit via RTU, phasor measurement unit, or Inter-Control Center Communications Protocol (ICCP). The operator's role is to correlate the alarm to an actionable insight. To do this, operators rely on their experiences from prior system operations.

Under energy emergency operations, however, as witnessed in the Electric Reliability Council of Texas (ERCOT) 2021 winter storm Uri, transmission operators can be flooded with more than 100,000 alarms per day (compared to the average of 1,000 alarms a day),[1] which is very challenging for the operators (ERCOT 2021).

[1] The number of alarms is an estimate based on ERCOT's network components.

Alarm fatigue can lead to cognitive overload, heightening the chances of human errors in the control room. This overload is especially probable during crisis situations when a surge of nonactionable alarms can overwhelm operators, making it harder for them to identify and respond to critical alarms. Utilities have asked energy management system (EMS) vendors to solve the alarm flood issue for more than a decade, but not much progress has been made. By correlating real-time actionable choices against SCADA alarms, generative AI can identify and localize events faster and more accurately than human operators, as shown in Figure 13. This capability is essential for minimizing the processing time from the alarm to the control action and for ensuring the reliability of critical infrastructure.

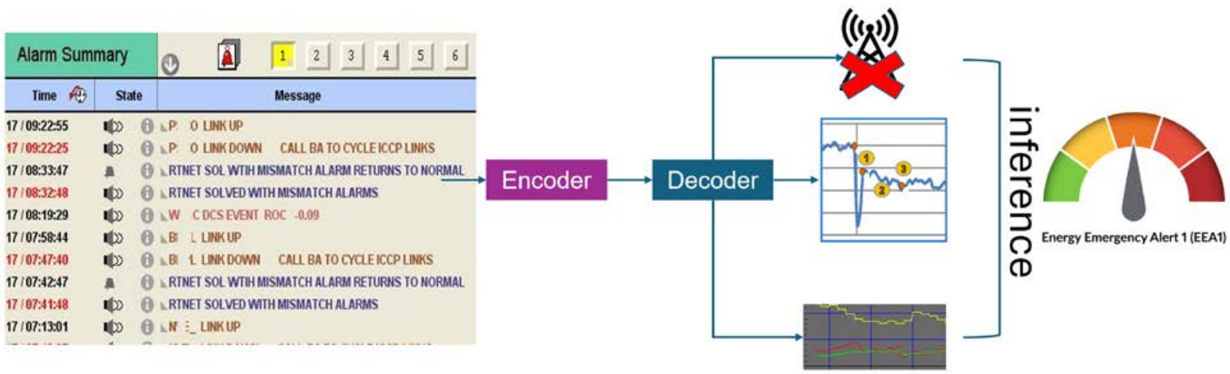

Figure 13. Alarm processing inference

3 AI Enhances Grid Operations With eGridGPT, Orchestration, Multi-Agent, Digital Twin, and Dynamic Display

The full potential of generative AI in power grid operations can be truly unlocked when it is seamlessly integrated into and made interoperable with other cutting-edge technologies. Figure 14 shows control room applications, including an EMS, a market management system, an outage management system, and a distributed energy resource management system. In addition, a wide variety of analysis tools, from stability analysis to weather analysis, help with energy forecasting and understanding the impact of outage schedules in real-time grid operations.

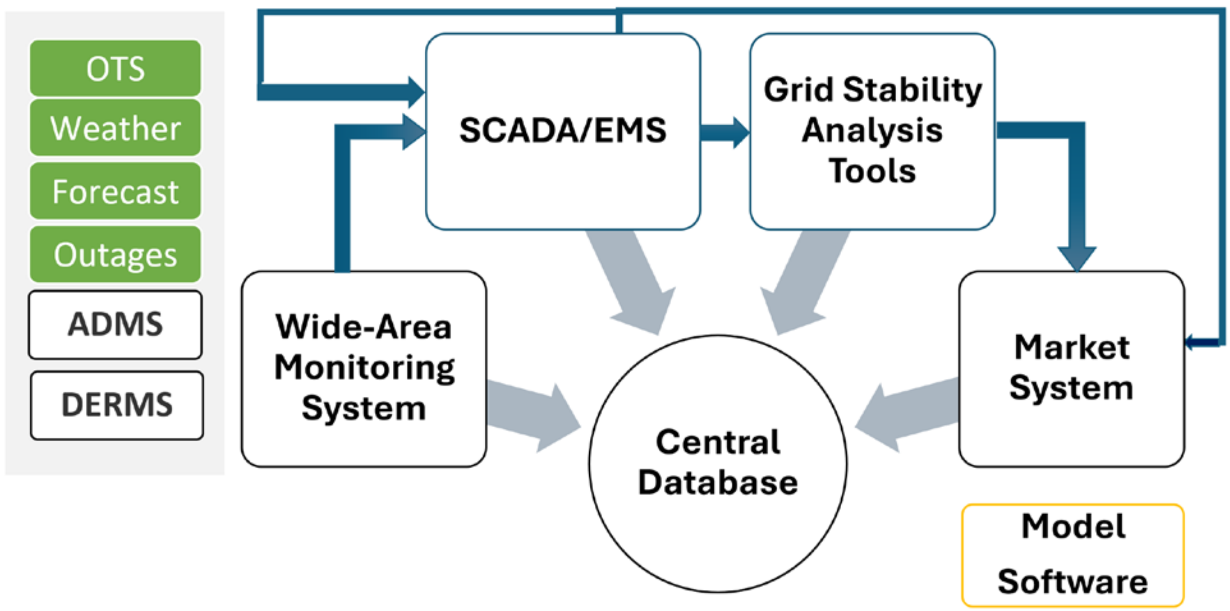

Figure 14. Transmission control room applications

Power system operators must perform numerous manual processes to integrate various applications, tools, and data. Automation efforts are often hindered by inconsistent data formats across applications, varying timescales, differing data intervals, and the lack of unified displays. Even when automation is implemented, operators must be informed by a single source of truth for the data. These limitations within control room applications can be resolved by implementing AI orchestration, digital twins, and dynamic displays, allowing for the full potential of generative AI to be realized in power grid operations. To unlock the full potential of generative AI, NREL introduced the eGridGPT platform (Choi et al 2024).

3.1 eGridGPT: Generative AI Initiative for Power Grid Operations

One initiative led by NREL is eGridGPT, a platform that focuses on applying generative AI to enhance power grid operation. The primary goal of eGridGPT is to create AI-assisted decision-making platforms that aid operators in managing the grid amid increasing complexity and uncertainty from shifting loads and generation sources. To achieve these objectives, eGridGPT leverages various AI techniques, including deep learning, reinforcement learning, and NLP, as shown in Figure 15. The framework also highlights the importance of human-AI collaboration, digital twins, and the development of explainable AI systems to foster trust and ensure operator acceptance.

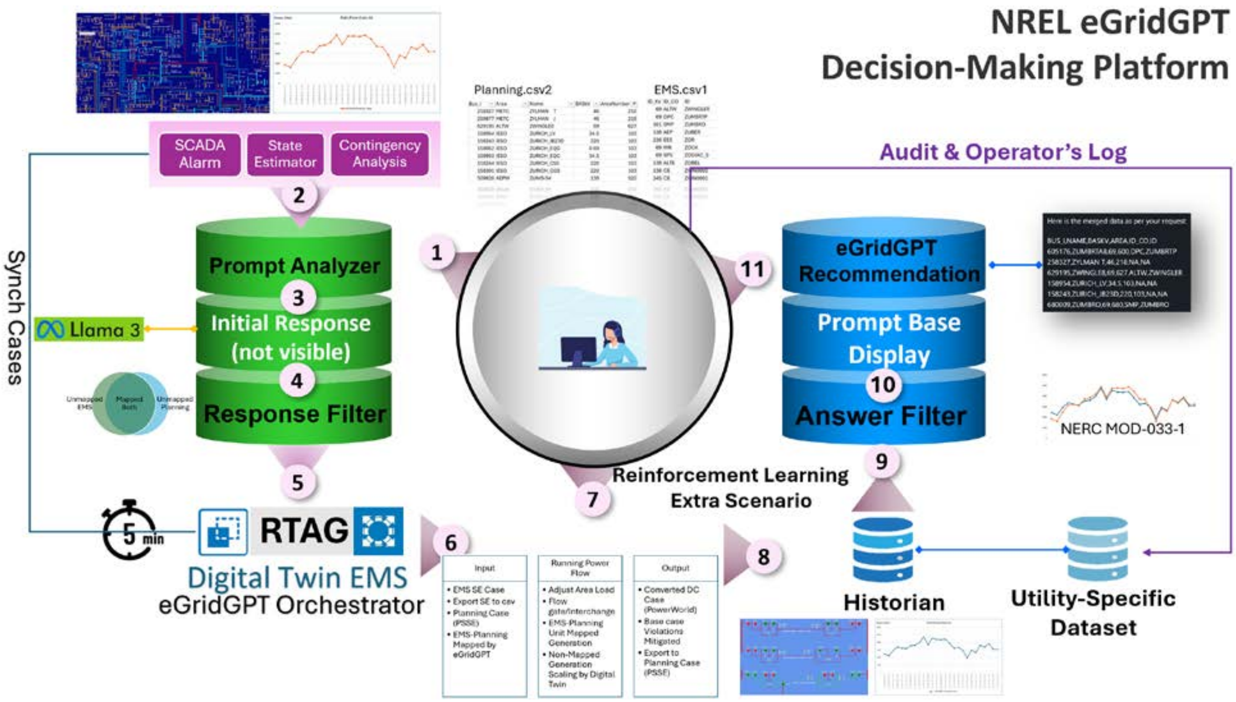

Figure 15. The NREL eGridGPT platform

3.2 AI Orchestration

Orchestration addresses the question of which action to take next. For example, when an application returns a specific result, the orchestration helps understand if it can pass the information on to another application or if certain scenarios need to be rerun for further processing. AI orchestration, within the context of power grids, refers to the automated arrangement, coordination, and management of diverse AI models, algorithms, applications, tools, and data sources to achieve unified and optimized grid operation. It involves integrating AI capabilities with existing grid management systems, tools, and data to enhance decision-making, improve efficiency, and ensure reliable and resilient grid performance.

Generative AI models can simulate various coordination strategies and identify the most effective approaches for balancing generation and load, managing grid congestion, and maintaining frequency and voltage stability; however, generative AI models are trained on historical data and do not have access to the latest network information. For AI to effectively assist in these critical tasks and deliver actionable insights, it is essential to leverage the most current, real-time data from across the utility's operations. This is where AI orchestration plays a vital role—by enabling real-time data analysis and seamless information flow between AI agents and other control room systems, such as EMS or transient analysis.

In many ways, AI orchestration can be considered as the higher-level management layer that sits above individual AI applications. It facilitates seamless data exchange, lining up applications in a proper sequence and communicating between different AI models, enabling them to work together effectively. For instance, an AI orchestrator can integrate forecasting models, state estimation algorithms, and optimization tools to provide a comprehensive and real-time view of the grid and recommend optimal control actions. If an operator is asking for a transient analysis, the AI orchestrator can write a Python program to retrieve the necessary files and call the transient tool with the operator's input parameters. After the results are returned showing cascading outages, the AI orchestrator can write another Python code to run other power flow analyses to redispatch generation or possibly to implement a switching operation, as shown in Figure 16.

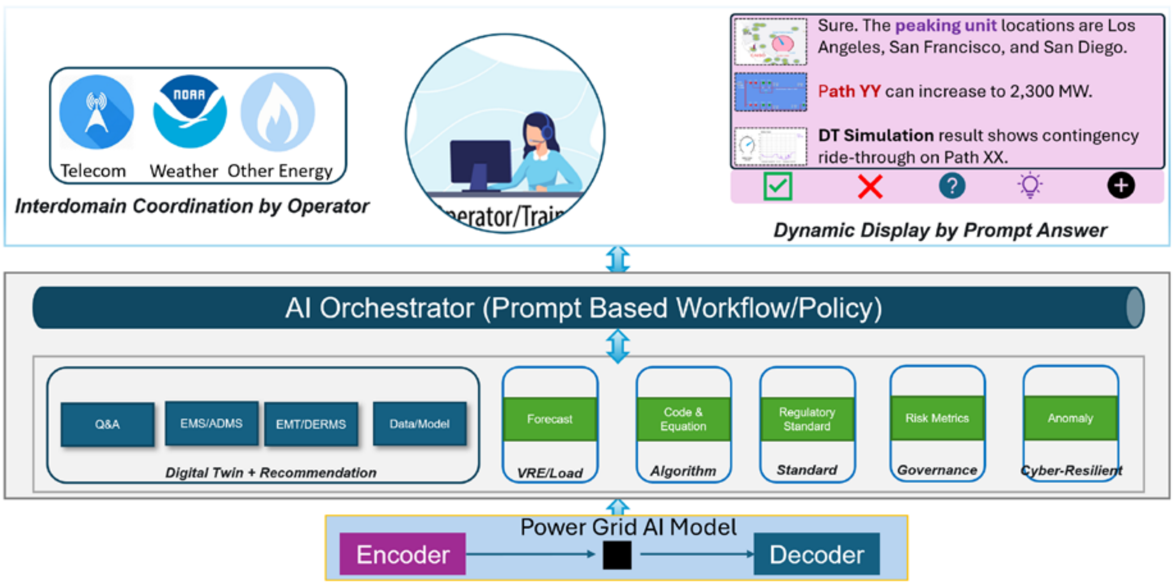

Figure 16. eGridGPT orchestrator

Source: Benes, Porterfield, and Yang 2024

AI orchestration can ensure that AI-driven insights and recommendations are explainable by following the metaphorical train of thought through the messages between the individual agents while ensuring that the outcomes are always based on the most current and accurate assessment of the situation at hand. By breaking down data silos and creating a more cohesive, responsive, and self-optimizing grid, AI orchestration can be key to realizing the full potential of artificial intelligence in driving efficiencies, enhancing resilience, and supporting the transition to a more sustainable energy future.

Most importantly, validating these orchestrations is equally crucial. Yet, replicating these processes becomes challenging without monitoring and management platforms in place. One such platform, Real-Time Analytics for Grids (RTAG), is a suite of software tools developed by NREL that provides advanced analytics and visualization capabilities for power grid operators.

3.3 RTAG

RTAG is an NREL-developed national-level future grid simulator based on the GE Energy Management System (EMS) software tool. RTAG has implemented a full-topology, production-grade, and reliability coordinator-operated EMS model (see Table 4).

Table 4. RTAG Western Interconnection and SPP EMS Model Statistics

	Western Interconnection (2019)	SPP Eastern Interconnection (2024)
Balancing authority	42	63
Substations	8,387	15,564
Generation units	3,526	3,304
Remedial Action Scheme	265	N/A
Buses	15,973	22,275
Branches	19,268	22,572
Lines	11,006	34,931

Additionally, NREL's partnership with the Western Electricity Coordinating Council, the Southwest Power Pool (SPP), and the Western Area Power Administration means that RTAG can simulate years of historical real-time data (peaking at 156 GW) in the Western Interconnection and days of the SPP's Eastern Interconnection, shown in Figure 17. With Western Interconnection-level historical data, RTAG accurately and realistically simulates the current control room operations under the Western Interconnection heavy summer, heavy winter, and high renewable conditions and various systems.

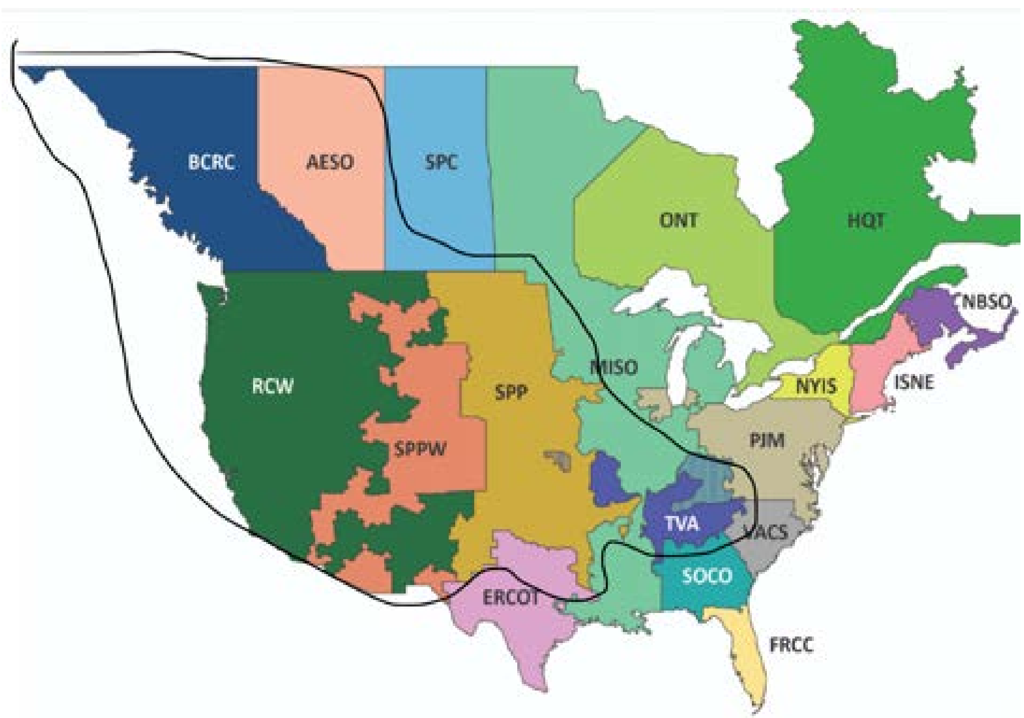

Figure 17. RTAG EMS operational model coverage

Source: NERC

3.4 AI Multi-Agent

Multi-agent systems leverage generative AI to model the behaviors and interactions of various agents within the power grid, such as generation operators, consumers, and marketers. Generative AI models create realistic scenarios that capture the complex dynamics and interdependencies among these agents. By understanding how individual agents behave and interact, multi-agent systems can optimize grid operations, enhance resource allocation, and improve overall system efficiency.

The following case study (Figure 18) on demand response optimization exemplifies the potential of AI orchestration through the large language model and multi-agent collaboration, particularly within the context of the Federal Energy Regulatory Commission Order No. 2222 (FERC 2020). This order, titled "Facilitating Participation in Electricity Markets by Distributed Energy Resources," aims to remove barriers for distributed energy resources, such as rooftop solar and battery storage, to participate in wholesale electricity markets. The proposed framework leverages the unique capabilities of large language models—such as handling ambiguity, context awareness, and adaptability—to enable collaborative problem-solving and efficient demand response planning.

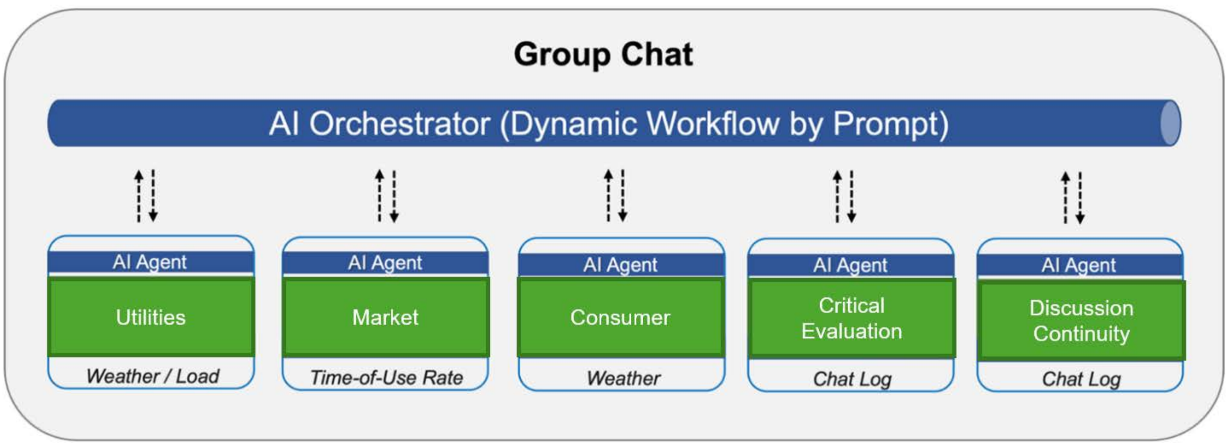

Figure 18. Proposed multi-agent framework for the demand response problem

The multi-agent system—which consists of utilities, market, consumer, critical evaluation, and discussion continuity agents—successfully negotiates a demand response plan that meets energy consumption thresholds while considering consumer comfort and cost savings. The agents' responsibilities are as follows:

- *Utilities agent*: analyzes energy consumption data and proposes a demand response plan that ensures consumer load remains below a specified threshold during peak hours
- *Market agent*: revises the plan to maximize consumer savings while calculating the potential cost reductions through participation
- *Consumer agent*: evaluates the plan based on consumer comfort preferences and weather forecasts, rejecting modifications that would cause significant discomfort
- *Critical evaluation agent*: assesses the proposed plan for potential flaws or limitations
- *Discussion continuity agent*: summarizes the conversation and highlights areas for further negotiation to improve solution quality in subsequent discussion cycles.

3.5 Digital Twin

A digital twin for power grids is a digital representation of the power network model and real-time measurements that has the ability to simulate a variety of scenarios (Haag and Anderl 2018). Digital twins serve as digital replicas of physical grid assets, enabling proactive and risk-free simulations and analyses. Because recreating the national power grid from scratch is not cost-effective, digital mirroring of the power grid for simulations is logical, and simulation software has been implemented in control rooms since the 1970s. A simulator called a dispatcher (or operator) training simulator has been used in control rooms by studying potential scenarios, such as a transmission line outage, after retrieving the real-time snapshot of events, as shown in Figure 19.

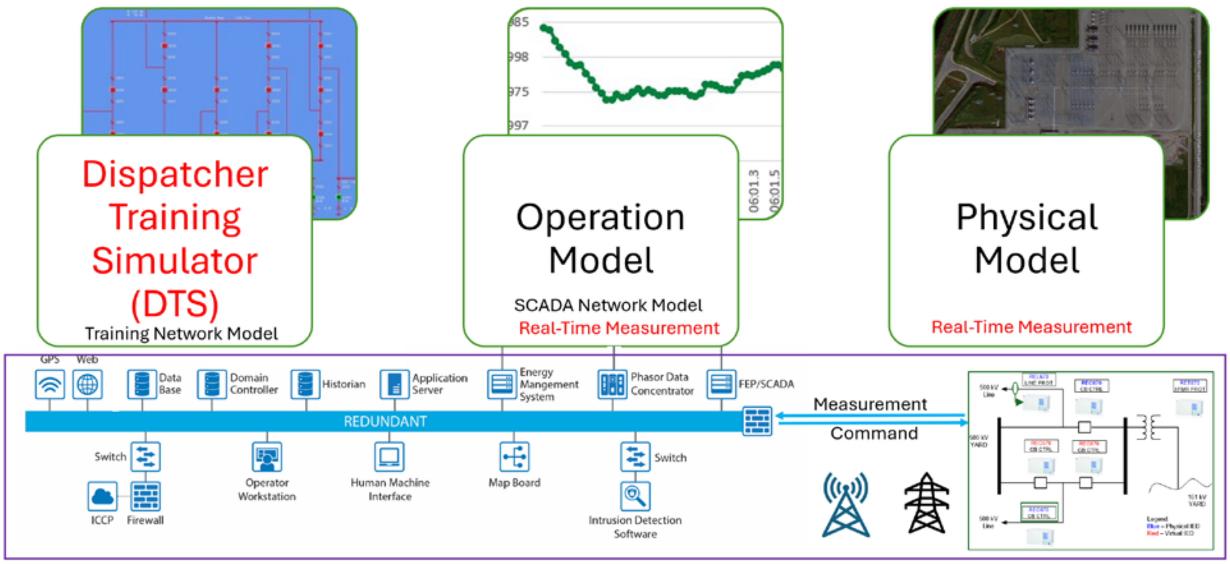

Figure 19. Digital twin in the power grid control room

The ability to simulate with full automation and seamlessly transfer data and the network topology from the live operational system is invaluable for testing new technologies, identifying vulnerabilities, and evaluating the impact of potential disruptions from extreme weather events before they happen. This full automation enables digital twins to run parallel simulations effectively. Figure 20 shows how NREL implemented a digital twin to validate contingency ride-through (Zhang 2021b).

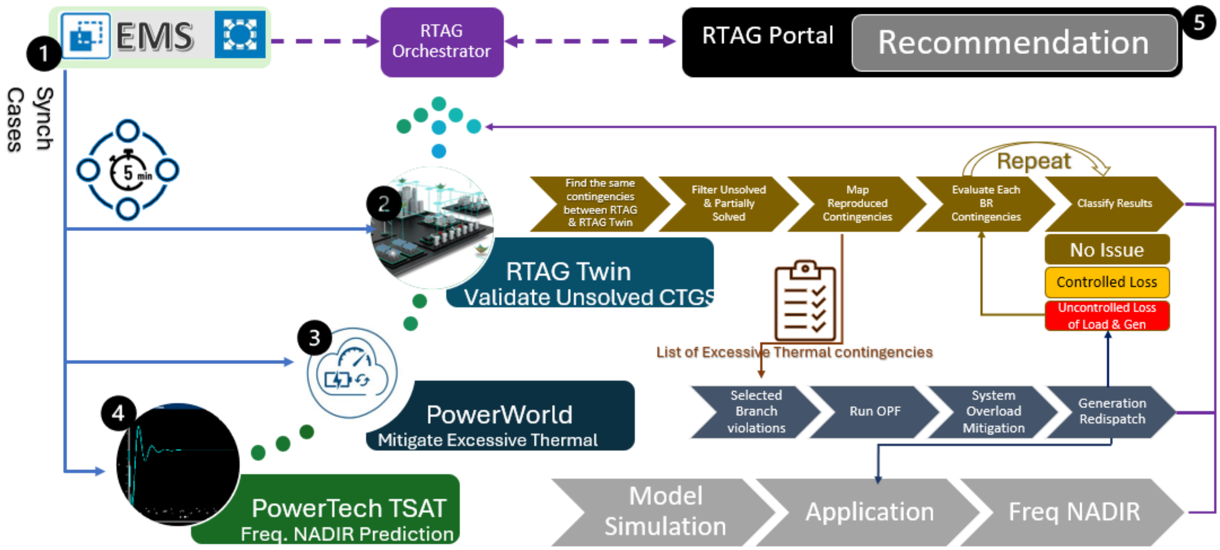

Figure 20. The NREL RTAG digital twin

A digital twin can be used for three purposes: (1) to evaluate the accuracy, applicability, and validity of the generative AI response during or after the training; (2) to improve power grid control room operations by providing accurate mitigation options after validating the AI response; and (3) to provide synthetic training data when future operational data are not available. By generating synthetic grid states, digital twins can be used to train generative AI models under a variety of scenarios without the risk of affecting real-world operations, as shown in Figure 21. This approach enables the development of robust models that can handle rare and extreme events, ensuring that generative AI is well-prepared to manage a wide range of situations. By creating realistic simulations of these events, digital twins allow grid operators to understand how different contingencies impact system stability and performance. This capability supports the development of effective mitigation strategies and enhances the grid's resilience to unexpected disruptions of grid conditions.

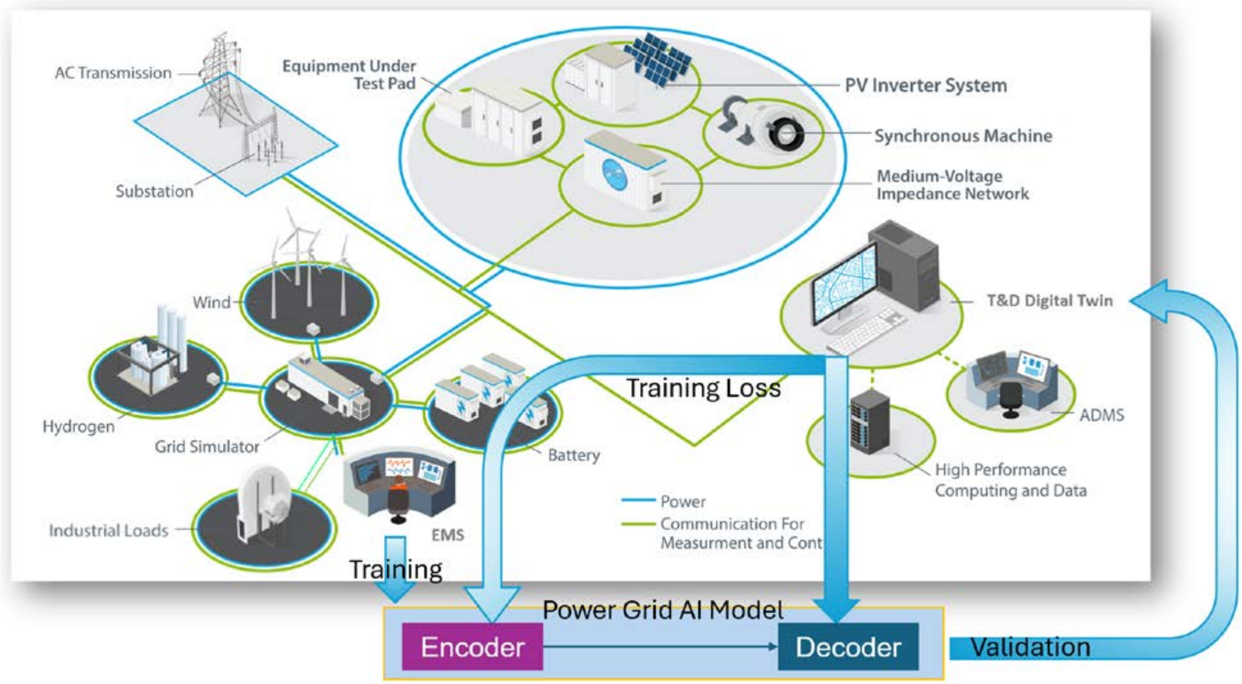

Figure 21. Digital twin pretraining

Illustration by Barry Mather, NREL

3.6 Dynamic Display Based on Answers from Prompt

The primary aim of the dynamic display is to streamline the grid operator's interface by reducing the multitude of tools, data, and displays they need to access. For example, operators manage eight local monitors on average (four from SCADA used for checking applications and four from internal company applications), in addition to large-scale displays and map boards, as shown in Figure 22.

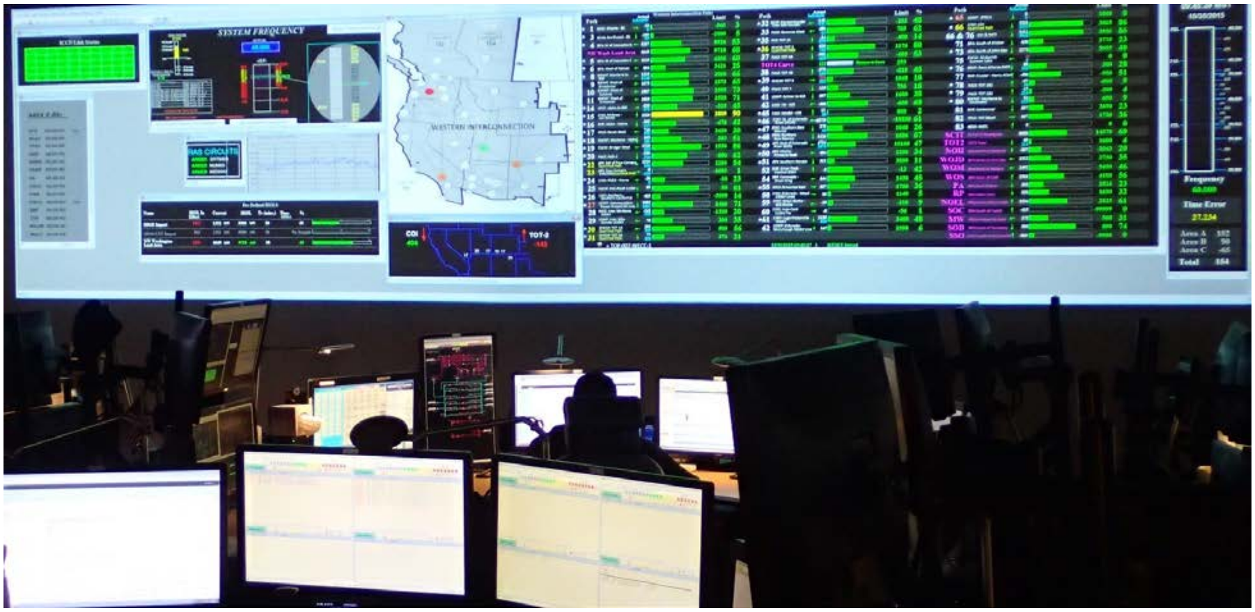

Figure 22. PeakRC operator's desk setting

Source: Zhang 2021a

This large number of displays has been shown to be too much for an operator to handle (Miller 1956). Instead, this report proposes a prompt-based dynamic dashboard in which operators can interact with minimal information that is focused on critical parameters and events. The display proactively identifies pertinent data based on text or alarms in real time, contrasting with a static dashboard where the operator must recall the location of the data and manually select the appropriate display. The display can consist of multiple options tailored to the mitigation strategies that are relevant to the current situation, as shown in Figure 23. Because the real-time data update every 4–10 seconds, this dynamic display will constantly adjust to reflect the current operational conditions.

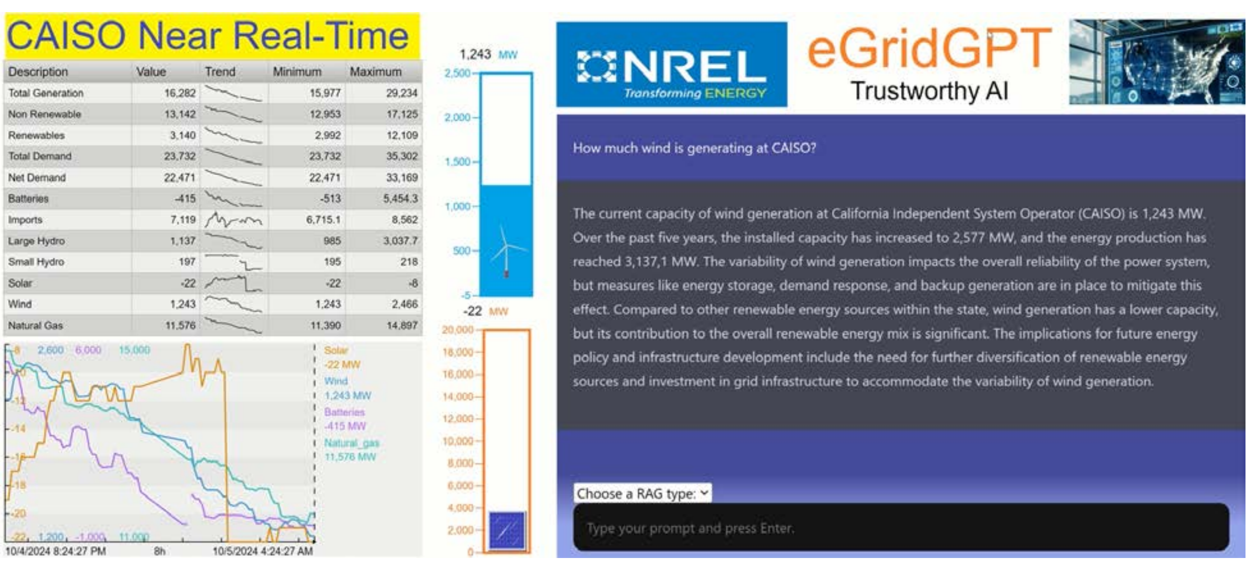

Figure 23. eGridGPT dynamic dashboard based on the prompt

4 Challenges and Limitations

The application of generative AI in the power industry must be approached carefully. AI functions in a data-driven cyberspace, which is vastly different from the physical world of the power grid, which is governed by the laws of physics. Moreover, current large multi-modal models are constrained to processing short, single-timescale data and single spatial scales, whereas the power grid inherently operates across multiple timescales and spatial scales. To successfully integrate generative AI into the power sector, the requirements listed in Table 5 are crucial (Benes, Porterfield, and Yang 2024).

Table 5. Generative AI Requirements for Power Grid Operations

Source: Summarized from Benes, Porterfield, and Yang 2024

Title	Description
Generalized capabilities	AI must have the ability to consider all relevant stakeholders in the energy ecosystem across various applications, including operations, planning, customer service, regulation, marketing, and supply chain management. This comprehensive capability allows AI to effectively support the diverse functions within the power grid.
Rigorously validated systems	The models and datasets used for AI training need to undergo rigorous validation for accuracy through comprehensive testing in simulated environments that closely mimic real-world conditions. This validation is essential to guarantee AI's reliability and safety when deployed in power grid operations.
Physics-informed and explainable	AI outputs must align with the fundamental laws of physics to deliver realistic, explainable, and practical solutions. Physics-informed AI models, like those that precisely simulate electricity flow through the grid, can result in more efficient and reliable energy distribution.
Humans-in-the-loop	Human oversight should play a crucial role in AI-driven processes to guarantee ethical, practical, and innovative results. Human-in-the-loop approaches incorporate human expertise and accountability into the decision-making process, enabling operators to review and fine-tune AI-generated recommendations.
Governance	AI systems within the power grid must adhere to strict cybersecurity policies and standards due to the infrastructure's critical importance. Compliance with frameworks such as the North American Electric Reliability Corporation (NERC) Critical Infrastructure Protection (CIP) plan is essential to mitigate cyber threats and ensure the integrity of grid operations.

4.1 Importance of Power Grid Models and Data

Reliable power grid operations count on accurate models and data, as mentioned in Section 1.3, which are crucial for operations, planning, forecasting, and control. Data become meaningful only when they are contextualized within a model. For example, a power flow value of 100 MW becomes meaningful only when it is placed within the context of a model, mapping the electricity flows from generation to customer loads through power lines. This leads to an important aspect of generative AI, which is that models and data must be available for generative AI to be trained. This means that it will be potentially difficult to develop large and general-purpose AI foundational models for power grids.

4.2 Sharing Models and Datasets with Researchers

The most pressing issue for generative AI to be useful is that the power grid models and data are limited to the industry itself, not to researchers. Utilities have established practices for model and data exchanges with each other, driven by the interconnected nature of the power grid. The interconnection enables the utilities to support one another during energy emergencies caused by generation deficiencies or extreme weather events. The power industry's hesitance to share models and data with researchers is primarily driven by a lack of control on the security implications for a country's critical infrastructure. If models and data are compromised, adversarial attacks can attain protective network details about the vulnerability of grid assets to physical attacks or impact the ability to shield operational data from potential market manipulation. As demonstrated by NREL's RTAG, secure data sharing practices, including anonymization and differential privacy, can enable collaboration with researchers while safeguarding critical infrastructure information.

4.3 Validating Models and Cleansing Datasets

Even if models and data are available to researchers, they must be validated and cleansed before they can be used for generative AI training. This is a significant challenge, especially for the power industry, as network topology models and data are developed with the end goal of recordkeeping, compliance, and analysis by humans, not for AI training. For example, a protective relay scheme (or model) is developed not only to detect abnormal conditions, such as overcurrent, but also to facilitate communications with adjacent protective relays to isolate abnormal events within a network, but these data might not be validated for use in model training. Even if the data are ready for generative AI training, the quality of the data can significantly vary due to sensor inaccuracies, communication issues, and inconsistencies in data formats.

Providing these models and historical data for generative AI training requires an additional layer of validation and cleansing to ensure that the models accurately reflect the grid behavior under various operating conditions. Data validation and cleansing techniques, such as outlier detection and noise filtering, are essential for preparing high-quality datasets for generative AI learning.

4.4 Trustworthy AI

Incorporating principles of trustworthy AI is vital throughout the development process (NIST 2022). This includes implementing safety and security measures to protect against cyber threats, ensuring that the models adhere to regulatory standards, and employing explainability techniques to make the AI's decision-making process transparent to operators. Along with Digital Twins, human-in-the-loop frameworks should be used to validate and refine the AI models, allowing human experts to oversee and guide the AI's learning process and improve the trustworthiness of AI.

4.5 Certifications and Standardizations of AI

In the power industry, NERC certifies system operators for their daily responsibilities (NERC 2023b). As generative AI begins to play a larger role in supporting engineers and operators, it is essential for the industry to establish standards and certifications for generative AI (including NERC and other compliance requirements) to ensure its trustworthiness. This could involve setting performance benchmarks for generative AI models—not only to pass the NERC system operator exam but also for specific applications such as state estimation or contingency analysis. Developing testing protocols will be key to ensuring that AI systems meet these standards.

Additionally, the certification process for AI systems might include independent audits to verify their compliance with relevant standards and regulations, such as the NERC CIP requirements. Such measures would provide greater assurance regarding the reliability and security of AI-driven systems. By adopting these strategies, stakeholders can evaluate and ensure that AI systems are safe, trustworthy, and reliable. Achieving this requires collaboration among AI developers, regulators, and users, backed by strong policies and frameworks that guide the responsible development and deployment of AI technologies.

4.6 Human-AI Collaboration

Building trust between human operators and AI systems is essential for effective collaboration. Operators need to understand how AI systems reach their recommendations and feel confident in their reliability. Ensuring transparency in AI decision-making processes, through techniques like explainable AI, helps build this trust. Explainable AI involves developing AI models that can provide human-understandable explanations of their reasoning and predictions. For example, instead of simply providing a recommendation to adjust a generator's output, an explainable AI system could explain the factors that led to that recommendation, such as predicted load changes or potential grid constraints. Operators are likely to consider generative AI recommendations when they can see the rationale behind them.

4.7 Ethical, Social, and Policy Considerations

New technologies should not introduce new risks. For example, generative AI models in the power industry must be designed to avoid biases that could lead to unfair treatment of certain groups or individuals. Techniques such as fairness-aware learning algorithms, bias-detection tools, and diverse training data are employed to create more equitable models. Regular audits and updates to the models are necessary to maintain fairness over time and ensure that generative AI systems are designed and operated in accordance with ethical guidelines and legal regulations. This includes considering privacy, nondiscrimination, and human rights and implementing auditing procedures where independent third parties review the AI system's algorithms, data, and decision-making processes to ensure compliance with ethical and legal standards. Collaborative regulatory frameworks are essential to balance innovation with public interest protection.

5 Conclusion

Utilities began providing lighting more than a century ago, and this venture has proven so successful that electricity is the core of our energy industry. Now, the industry is facing two major shifts: renewable energy and electrification. Electricity is transitioning from fossil-fueled power to clean energy sources. Similarly, the electrification of nontraditional demand—such as transportation, heating, and industrial processes—is on the horizon. As more industries adopt renewable energy and electrification, the role of generative AI is becoming increasingly significant due to managing the variability in renewable generation and the complexity in customer behavior while maintaining reliability, stability, and affordability.

Leveraging generative AI in power grid operations involves several strategic steps to ensure reliability, security, safety, and economic affordability. First, it is crucial to gather and curate high-quality, domain-specific data from various sources, including historical grid operations, weather patterns, renewable energy outputs, and equipment performance metrics. These data should be preprocessed to remove biases and ensure that they accurately represent real-world scenarios. Collaboration with industry stakeholders—such as utility companies, regulatory bodies, and research institutions—is essential to access diverse datasets and gain insights into specific operational challenges and requirements. Additionally, digital twin technology can be employed to simulate real-world scenarios, supply physics-informed pretraining datasets, and validate the AI's predictions and recommendations. Finally, dynamic displays prompted by an operator's input should be explored to streamline grid operations. This combination of advanced AI techniques, rigorous data management, and continuous human oversight will help build generative AI models that are not only powerful and efficient but also reliable, stable, and affordable for the power industry.

Incorporating generative AI into power grid infrastructure must be a strategic imperative rather than merely a technological upgrade. This integration promises enhanced security, reliability, resilience, and sustainability for power grids. As AI continues to evolve, its role in guiding the United States toward a more sustainable and equitable energy future will become increasingly critical. How the power industry leverages generative AI will determine its success.

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