eGridGPT: Trustworthy AI in the Control Room

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NREL is a national laboratory of the U.S. Department of Energy
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Input from the industry members and other reviewers does not constitute an endorsement of this report or its contents. Further, the views expressed herein do not necessarily represent the views of DOE or the U.S. Government. The authors take sole responsibility for the contents of this report.

List of Acronyms

AI	artificial intelligence
CAISO	California Independent System Operator
DOE	U.S. Department of Energy
eGridGPT	Electric Grid Generative Pretrained Transformer
EMS	energy management system
ERCOT	Electric Reliability Council of Texas
GenAI	generative artificial intelligence
G-PST	Global Power System Transformation Consortium
GPT	generative pretrained transformer
Llama	Large Language Model Meta AI
LLM	large language model
ML	machine learning
NERC	North American Electric Reliability Corporation
NIST	National Institute of Standards and Technology
NREL	National Renewable Energy Laboratory
SCADA	supervisory control and data acquisition

Executive Summary

This report is the first research effort to apply large language models (LLMs), a type of generative artificial intelligence (GenAI), in the power grid control room for decision making. Serving as the operational "brain" of the grid to balance supply and demand, operator's decision making is crucial for maintaining grid reliability from one moment to the next. Just as the human brain processes inputs from the senses to make decisions, the National Renewable Energy Laboratory Electric Grid Generative Pretrained Transformer (eGridGPT) is engineered to virtually support power grid control room operators by assisting in decision-making processes and interpreting the data and models.

Thanks to the favorable economics of new technologies and their ability to deliver secure, reliable, and resilient energy, the power sector is undergoing a significant transition, characterized by three major shifts at its core. First is the increasing use of variable renewable energy, such as wind and solar, to help decarbonize the energy sector. Second is the proliferation of distributed energy resources, including rooftop solar photovoltaics and distributed energy storage, and the increasing use of electrified loads, such as electric vehicles and heat pumps. Third is the digitization of power system communications and controls.

As the power sector transitions, it presents substantial operational and external challenges to grid operators. Inverter-based resources—such as solar, wind, and batteries—introduce new operational challenges because they behave differently from synchronous generators and push the limits of managing increasingly complex networks. Externally, operators must also navigate the grid management challenges of the impacts of increasingly frequent extreme weather events and cyber-attack by hostile nations or other malevolent actors.

Grid operators are at the forefront of this shift. These challenges test the ability of grid operators to make real-time decisions safely, efficiently, and reliably while meeting decarbonization goals and evolving customer needs. The critical question that emerges is: How can researchers assist operators' decision making?

One viable approach to assist operators is the broader implementation of artificial intelligence (AI). LLMs, a type of GenAI, are computational tools that excel at language processing and general-purpose tasks. LLMs, such as OpenAI's GPT-4 or Meta's Llama 3 (Large Language Model Meta AI), represent a remarkable breakthrough in AI by helping with increasingly complex tasks.

This report describes the first research effort to apply GenAI in the power grid control room. It outlines the synergy between human decision making and eGridGPT, where eGridGPT supports operators by analyzing procedures, suggesting actions, simulating scenarios with physics-based digital twins, and recommending optimal decisions. The system operators can then make decisions on how to adjust the grid or not based on the suggestions. A human system operator is placed in the final decision loop because eGridGPT is not legally accountable or able to automatically implement suggestions. Figure 1 shows an imagined control room of the future with an AI-based assistant to help make suggestions on system operations. The report also presents the results of a preliminary case study showing the ability of eGridGPT to handle an equipment model mapping task between real-time operations and offline planning.

Figure 1. Imagined control room of the future with AI-based assistant

Figure from Benjamin Kroposki and Seong Lok Choi, NREL, and DALL-E

In addition, the report addresses the challenges and limitations of GenAI, stressing the importance of model accuracy and high-quality data, ethical AI use, trustworthiness of the suggested actions, and cybersecurity concerns. The report also emphasizes low-budget eGridGPT solutions for smaller utilities that can be implemented on-premises with limited resources. The report concludes that the integration of eGridGPT in the power grid control room is important to help industry transition to successful operations of a more complex clean, resilient, and affordable future energy system.

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1 Introduction

The primary goal of the power industry is to operate a safe and reliable electrical power grid. This "keeping the lights on around the clock" approach has been the bedrock of modern society. Power system reliability requires three major steps: First is to know how much load there will be moment by moment, second is to schedule the power generation to meet the load, and third is to identify which lines and associate equipment will be used for the power to flow from the generation to the load. All these steps are managed inside the power grid control room.

The control room, therefore, is the brain of grid operation; see Figure 2. It is similar to how the human brain processes information from the eyes and ears and makes decisions on how to act. The control room receives grid operational data from the generation, transmission, and distribution systems. It also receives look-ahead planning data, such as outage, load, interchange schedule, generation, and weather forecast. Inside the control room, system operators or dispatchers play a unique role in decision making, while information technology personnel and engineers support the operators by maintaining critical hardware infrastructure, analytical software tools, and data and ensuring they are providing essential information.

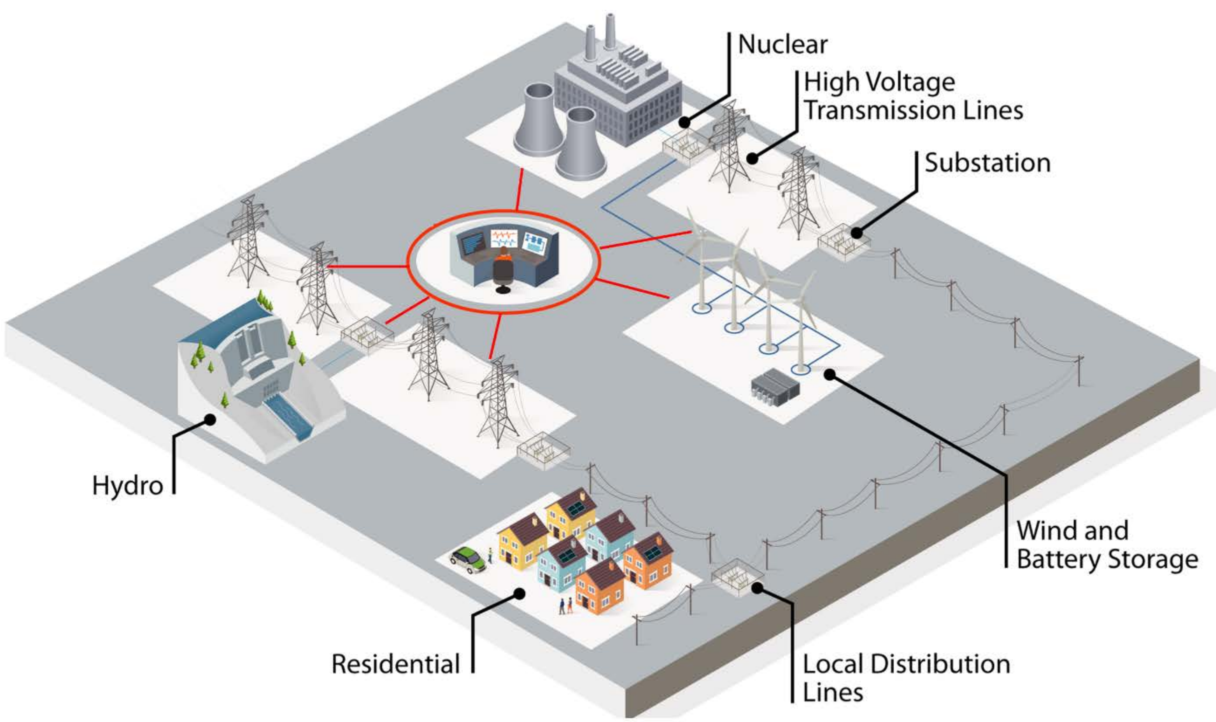

Figure 2. Power grid control room as the operational "brain" of the grid to balance supply and demand

Image from Christopher Schwing, NREL

As a decision maker, transmission operators are well prepared, having passed the North American Electric Reliability Corporation (NERC) system operator exam and undergone extensive training specific to their grid network. Additionally, they are certified by fellow operators, and they collaborate to reach consensus on operational decisions (NERC 2023b). In short, they are well trained to keep the lights on by balancing generation and load from one moment to the next and proactively looking ahead for potential grid problems.

Over the years, the power sector has seen significant changes due to the cost-effectiveness of new technologies and their capacity to provide secure, reliable, and resilient energy. These changes are driven by three primary trends. First is the increasing use of low-cost, variable renewable energy, such as wind and solar, to help decarbonize the energy sector. Second is the proliferation of distributed energy resources, including rooftop solar photovoltaics and distributed energy storage, and the increasing use of electrified loads, such as electric vehicles and heat pumps. Third is the digitization of power system communications and controls such as smart grid or wide area monitoring systems. These changes are all aimed at improving system operational efficiency and reducing the carbon footprint.

As the power sector transitions, it presents substantial operational and external challenges to grid operators. They are at the forefront of this shift, managing the transition from traditional power operations—characterized by one-way flow from large-scale generation to the distribution level, fixed power dispatch capacity, and a predictable dispatch schedule—to more dynamic and complex system. The future grid will feature more bidirectional flow from customers back to substations, variable generation output that fluctuates with weather conditions, and less visibility of behind-the-meter customer generation resources, making the resources non-dispatchable from the control room. In addition to adapting to these operational changes, grid operators in the control rooms also face nonoperational but externally critical emerging threats, such as extreme weather conditions and cyberattacks.

Decision-making tool challenges: The responsibility for decision making in grid operations still predominantly rests with system operators. This is largely because the technology for helping decision making, whether software or hardware, is not yet sufficiently advanced for deployment in control rooms. Consequently, operators must depend on their experience, memory, and available tools when making decisions. What tools do they have? Presently, the decision-making tools are mainly supervisory control and data acquisition (SCADA) systems and energy management systems (EMS). SCADA systems are used to monitor and control the grid, whereas EMS provides advanced computations and visualizations of the current and contingent states of the system. Simply monitoring and measuring data is insufficient for effective grid control. It is crucial to transform this data into actionable information, enhancing situational awareness for operators, particularly in energy emergency scenarios. Additionally, SCADA and EMS were designed for conventional generators that provide stable, dispatchable, and weather-independent output. As a result, the current tools do not adequately support operators when dealing with high levels of integration of variable renewable energy, which is variable, non-dispatchable, and dependent on weather conditions. Another challenge has been that earlier versions of SCADA and EMS did not include battery modeling within the generator elements. With the growing increase in the use of batteries and other energy storage systems to provide grid support, especially during periods when solar PV generation declines (like at sunset), vendors of SCADA/EMS have updated their software to account for the state of charging and discharging of batteries. To take advantage of this new feature, the control room must upgrade their SCADA/EMS, which can be years of lengthy and complex process.

Decision-making regulatory challenges: Even with a new tool, the operators' decisions need to comply with massive volumes of protocols and multiple governance requirements. For instance, the latest NERC standard is 1,926 pages (NERC 2023a). Combined with regional electric reliability organization standards, independent system operator technical manuals, and utility standards and procedures, grid operators need to review several thousand pages of documentation and be able to quickly retrieve this information. This increases the margin of error for making decisions, especially under time-critical events.

Motivation: Numerous challenges, from operational to regulatory, make it hard to prepare grid operators for the power system transformation during the clean energy transition. Although grid operators build knowledge over time to improve decision making, the evolving grid complexity hinders this. If there is an unpredictable load pattern due to the weather, it requires an uncertainty quantification of the imbalance risk between the generation and load. For example, on July 26, 2021, the California Independent System Operator (CAISO) issued energy emergency alerts from 6 p.m.–10 p.m. asking the public to reduce their energy demand against a heat wave (CAISO 2021) and there are increasing numbers of critical energy emergency alerts (EEA) over the last 5 years (NERC 2023c). Figure 3 shows EEA level 3 issuance, which represents actual energy deficiency, has risen from 6 in 2017 to 25 in 2023. Moreover, with the rapid growth of variable renewable energy sources, control rooms urgently need advanced decision-making solutions to manage the variability and uncertainty of the power output introduced by weather while still operating traditional synchronous generators. The crucial issue at hand is: How can researchers assist operators with these challenges?

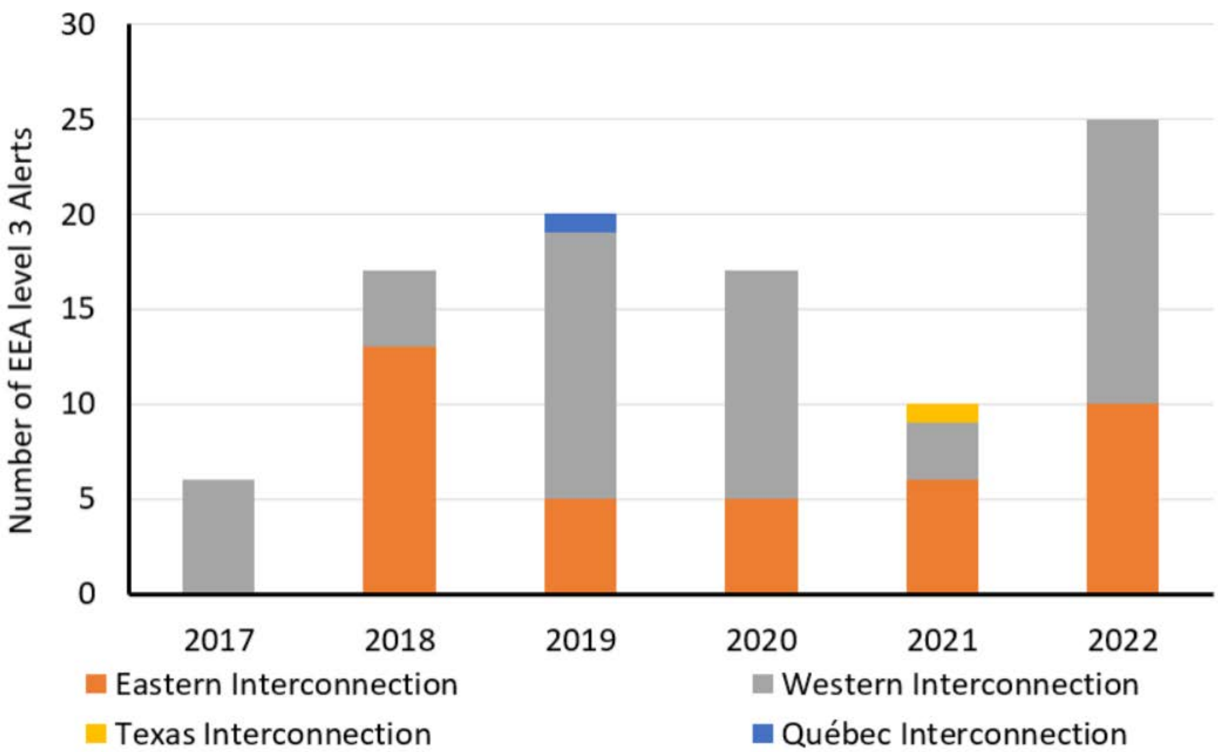

Figure 3. NERC Energy Emergency Alerts Level 3

Generative AI: To address these challenges, we reviewed the use of generative artificial intelligence (GenAI). GenAI, most notably through large language models (LLMs), has revolutionized the field of natural language processing and machine learning (ML) in general, especially with the introduction of transformer models (Vaswani et al. 2017). The generative pretrained transformer (GPT) (Brown et al. 2020) family of models has demonstrated remarkable achievements across various domains, including passing medical exams, scoring high on standardized tests, composing music, and creating art (OpenAI 2023). Exploring how next-generation GenAI can increase community preparedness for climate-related risks, enable clean energy deployment, and enhance grid reliability and resilience is a considerable yet critical endeavor (The White House 2023).

Decision-making platform: With GenAI and classical analytical systems used in the power industry today, we envision the development of a trustworthy Electric Grid Generative Pretrained Transformer (eGridGPT). eGridGPT builds on the ability of ML and LLMs. Understanding natural language and preserving the context is key to enhancing situational awareness and tailoring the response to the needs of grid operators. eGridGPT is aimed as an ever-evolving ecosystem for control room operators that can adapt the available tools to their needs and grid operation requirements. It is the underlying platform being developed at the National Renewable Energy Laboratory (NREL) that integrates LLMs, digital twins, and advanced visualizations to provide holistic decision support for grid operators and improve their situational awareness; see Figure 4. There are two reasons for introducing eGridGPT: (1) the trustworthiness of GenAI response and (2) the advanced display capability by adopting the multimodality of GenAI from the operators' queries and prompts. As defined by the National Institute of Standards and Technology (NIST), "trustworthy AI is valid and reliable, safe, fair, and bias is managed, secure and resilient, accountable and transparent, explainable and interpretable, and privacy-enhanced" (NIST 2022). In this report, we discuss how eGridGPT addresses several characteristics of AI trustworthy, such as validation and explainable.

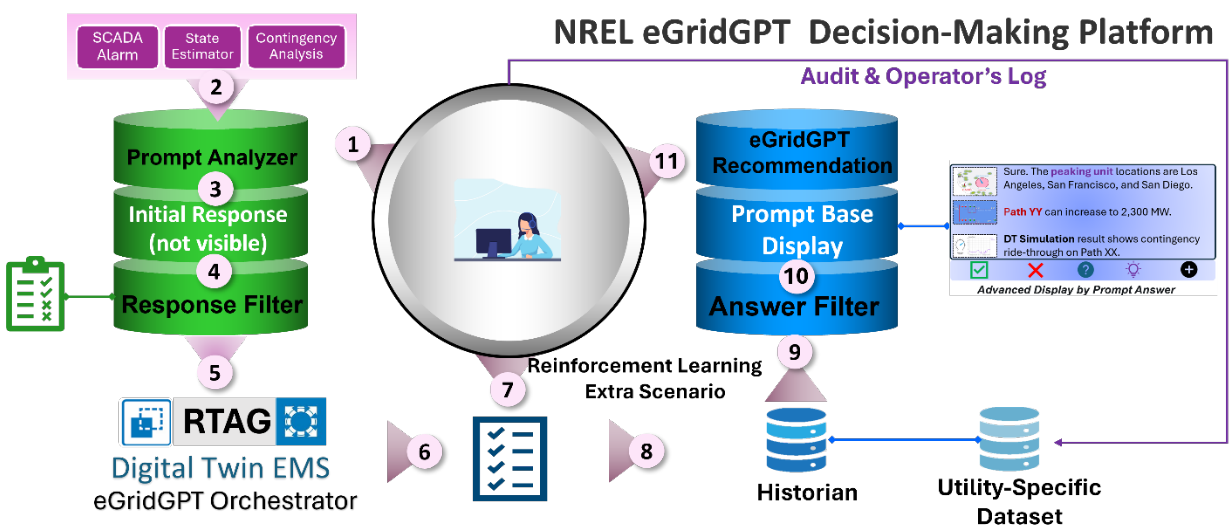

Figure 4. eGridGPT architecture, an AI-based decision support system for grid control rooms

eGridGPT integrates large language models, digital twin simulations, and advanced visualizations to provide holistic recommendations to grid operators.

In this report: eGridGPT, a GenAI-based virtual operator assistant, can enable to (1) understand and respond to operator queries/prompts, (2) empower the analysis of grid conditions by augmenting digital twins and analytical tools based on the request, (3) orchestrate recommendations from the tools and relevant actions into an understandable display format, and (4) build operators' trust with a human-in-the-loop framework where LLM recommendations are vetted by operators. The essence of eGridGPT lies in its ability to act as an interface between a screen in front of the operator and the orchestrator for the comprehensive processing of large volumes of data, scenarios, and digital twin simulations.

2 Overview of eGridGPT

We developed eGridGPT to aid bulk energy system operators by providing a decision-making platform with advanced real-time grid analytics, rigorous simulations, and visualization tools (Figure 4). eGridGPT enables system operators to analyze events, find similarities to historical events, and assess mitigation options. Our vision is that eGridGPT will serve as the larger decision-making tool that will integrate and coordinate a host of additional tools to verify and validate its outputs.

Below are the steps in the eGridGPT workflow as shown in Figure 4. **At step 1**, the system operator initiates a query while, concurrently, real-time data from SCADA, state estimation and contingency analysis is being streamed from **step 2**. **Step 3** involves the AI system analyzing the operator's query alongside the real-time data to understand the context of the question. Since the AI's training is not real time, it uses various techniques to generate responses or suggestions appropriate for the situation, though these are not yet visible.

In step 4, the AI's recommendations are tested through simulation. This process, called reinforcement learning, requires simulation to verify the accuracy of the AI's suggestions. One major challenge with generative AI is ensuring accuracy where the absence of simulation can lead to a lack of "ground truth." This lack of verification through power flow models can result in inaccurate recommendations, highlighting the need for **a fifth step** involving simulation using a digital twin.

During the sixth step, recommendations generated by the AI are refined through digital twin simulations, with only the most viable options being forwarded. The operator then assesses these options, determining their effectiveness. **Step 7** allows operators to introduce alternative scenarios, such as a failure in communication equipment leading to a disruption in data communication. Simulations including these hypothetical situations are then conducted.

The outcomes of these simulations are documented in **step 8** and subsequently evaluated in **step 9** to identify any potential adverse effects on power operations. This involves an additional filtering process to exclude recommendations that could cause significant disruptions, like a major power outage due to the intentional disconnection of critical transmission lines.

By step 10, only the recommendations that are considered safe are presented to the operator. Finally, **in step 11**, the operator reviews these vetted suggestions to make the final decision.

The role of eGridGPT is to coordinate and refine the execution of the approach to process a given request and to guide system operators through challenging grid conditions. With additional insights, grid operators can make informed decisions to manage the grid and ensure reliable operations with high integration levels of renewable generation.

Above all, the resulting system must be trustworthy. A key focus in developing eGridGPT is ensuring it embodies the principles of trustworthy AI development. As previously noted, NIST characterizes trustworthy AI as being "valid and reliable, safe, secure and resilient, accountable and transparent, explainable and interpretable, privacy-enhanced, and fair with managed harmful bias." The following section of the report will detail how eGridGPT has implemented these principles in its decision-making framework.

2.1 Trustworthiness of eGridGPT

eGridGPT incorporates several safeguards to be trustworthy and is being designed to ensure:

- **Validity and reliability**: The three-step training process (Section 2.2, Figure 5) and benchmarking against NERC system operator exams can ensure that eGridGPT outputs are accurate and consistent. Digital twin verification (Section 2.3) provides further validation.
- **Safety, security, and privacy**: Restricting eGridGPT to open-source models that can run locally without public network access enables compliance with NERC's Critical Infrastructure Protection (CIP) standards. Additionally, following the best practices in NIST Cybersecurity framework will further mitigate any risks (NIST 2024). Utility-specific fine-tuning is performed on-premises with data access restricted to authorized personnel. Further measures to protect sensitive data used in training will also be explored and implemented.
- **Fairness and bias management**: We are curating the training datasets to consciously detect and remove sources of bias throughout the process. Human oversight will also allow monitoring for unintended biases.
- **Accountability and transparency**: Human-in-the-loop decision making will ensure that grid operators vet the system's recommendations. Audit logs enable tracing actions back to the source. The outcomes will be marked with a timestamp and source (e.g., eGridGPT vs. operator).
- **Explainability and interpretability**: The physics-informed approach (Section 2.4) and explainability (Section 2.5) will allow operators to understand the rationale behind eGridGPT outputs. Inconsistencies with physical laws can be identified.

2.2 Training eGridGPT Inferences

eGridGPT AI model is trained in three steps; see Figure 5:

1. Train state-of-the-art LLM models on general power engineering knowledge, transmission bus system, or publicly available grid data,
2. Train using control room operational procedures from NERC, electric reliability organizations, independent system operators, state public utility commissions, the Institute of Electrical and Electronics Engineers, and other U.S. grid standards, and,
3. Train using supervised fine-tuning on system operator/utility operational and management procedures, power system data, field settings, and infrastructure information.

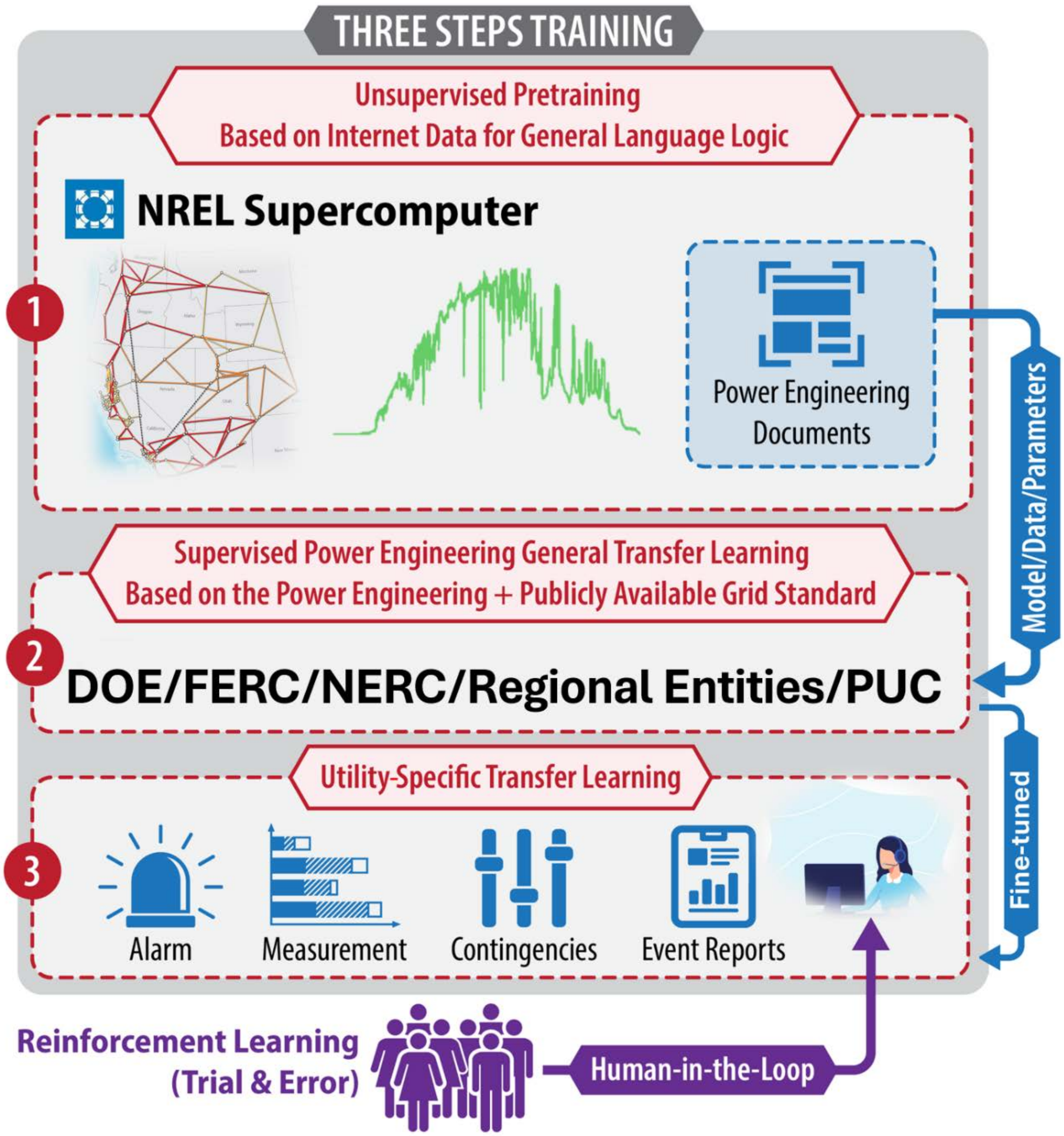

Figure 5. Three-step training process for eGridGPT assets: (1) Train on general power engineering knowledge. (2) Train on control room operational procedures and standards. (3) Fine-tune using utility-specific data

Illustration from Besiki Kazaishvili, NREL

During the third step, information specific to each implementation is used by a system operator to create a unique instance of eGridGPT. Utility-specific knowledge obtained from operational logs, tagging notes, historical and operational analysis reports, training documents, and others will be implemented via further fine-tuning or retrieval-augmented generation (Lewis et al. 2020). The base LLMs for eGridGPT include only open-source models (e.g., Llama 3, Mistral) (Rudolph, Tan, and Tan 2023), which can be run locally without public network access, to comply with NERC CIP standards. After the training, eGridGPT is benchmarked with the NERC system operator exams (NERC 2023b), which operators must also take, to ensure its effectiveness.

2.3 Attesting eGridGPT by Digital Twin

One of the primary challenges with GenAI is its accuracy. Instances often arise during complex scenarios—referred to as "hallucinations"—where the absence of simulations can result in a lack of "ground truth" producing a faulty recommendation. With large quantities of high-quality training data, GenAI can achieve satisfactory levels of accuracy. In the power industry, data are not typically publicly shared for the purposes of research; thus, the datasets used to train eGridGPT will be a mixture of carefully curated sources, including both publicly and privately shared data and synthetic data generated by physics-based digital twin simulations. Without the ability to verify these scenarios through power flow models, the recommendations could lack adequate creditability. To improve the accuracy of the eGridGPT response, digital twins can be used. Digital twins can evaluate the accuracy and applicability of the eGridGPT response after simulations with the latest model and data.

2.4 Physics-Informed eGridGPT

When making decisions, operators are required to document and justify their chosen actions. NERC CIP standards mandate the disclosure of details like measurement data, study findings, or network models, alongside a description of how consensus was reached among operators. This requirement for transparency, interpretability, and accountability should extend to GenAI-based decisions as well. Therefore, the predictions made by GenAI tools for power systems should be consistent with the fundamental laws of physics. Physics-informed eGridGPT, such as those that accurately simulate the flow of electricity through the grid, can lead to more efficient, explainable, and reliable solutions. This can be achieved in a few different ways, such as by adopting physics-based digital twin simulations.

2.5 Explainable eGridGPT

As GenAI becomes more capable, it also becomes more complex, limiting the ability of users to understand how it arrives at a particular decision. This gap in understanding hinders trust. For these systems to be practically helpful, they should be able to make decisions that are physically grounded and human interpretable, and they should be able to provide explanations detailing the intermediate decisions that were made along the way. eGridGPT interactive, dynamic display transforms how operators trust monitoring systems. It responds to the operator's prompts, adapting continuously to the most current data and emphasizing critical information based on the alarm's severity and the situation's urgency powered by digital twin. This feature streamlines the workflow for operators, enhancing their decision-making process by clearly presenting explainable recommendations.

3 Preliminary Result for Equipment Model Mapping Between Real-time Operation and Offline Planning

This section describes the preliminary results for the equipment model mapping between the simulated real-time operations (node-breaker) and the offline planning (bus-branch). The offline planning cases are developed by regional entities with data provided by the transmission system operators. A major issue in developing the offline planning cases is that the names and bus numbers in the real-time operation model usually do not match the planning names and bus numbers, as shown in Table 1. The worst case is when the name does not match within the utility department. Finally, offline planning cases that assume maximum power output from all generators and assume all transmission lines are energized face significant challenges in developing accurate scenarios for upcoming extreme weather events, such as hurricanes or ice storms, based solely on the planning model; therefore, the offline planning cases must adjust their network topology with the EMS operational measurement and switch statuses.

Table 1. Sample of Mismatched Equipment Names and Bus Numbers Between EMS Operational Models and Planning Models Illustrating the Model Mapping Challenge

EMS Operational Model

ID_CO	ID
AL	Z LER
CS	Z 2
CS	Z
DF	Z RTP
SM	Z RO
AE	Z
EE	Z
W	Z
PG	Z
SP	Z C_S
AL	Z
CS	Z
CE	Z 002
CE	Z 001

Planning Model

Bus_I	NAME	BASKV	AREA
258327	Z	46	218
629195	Z	69	627
158954	Z V	34.5	103
158243	Z 23D	220	103
158952	Z QG	0.69	103
158953	Z QC	34.5	103
158244	Z SS	220	103
158391	Z GS	220	103
509826	Z	138	520

Integrating the offline planning with the real-time operating conditions and system responses after the equipment model mapping becomes crucial to managing the reliability and resilience of the power network. This integration, through the conversion of models between the real-time operations and the offline planning, enables a more realistic analysis of power systems. It ensures the accuracy of the initial operating conditions for downstream applications.

This mapping conversion from the real-time operations to the offline planning process usually takes multiple weeks by regional entity staff. NREL has developed a technique to generate large numbers of simulations of operational data using planning models that can provide valuable datasets for AI training. With pretrained datasets, eGridGPT is able to fine-tune mappings of the EMS operational models and the planning models, as shown Figure 6 and Table 2.

Figure 6 shows the prompt instruction on how to map between the EMS operational models and the planning models by identifying similar name identification fields in the planning fields and name fields in the EMS, as shown in Table 2. Once the similar model's name is identified, it will check to ensure that the area/ID_CO name is the same between the EMS operational models and the planning models.

> I will provide you with data in CSV syntax, CSV1 and CSV2 respectively. CSV1 has the columns 'ID_CO', 'ID'. CSV2 has the columns 'Bus_I', 'NAME', 'BASKV', 'AREA'. Merge these files based on similarity between the entries in the 'ID' column in CSV1 and 'NAME' column in CSV2. The merged outcome should have the columns in the order: 'BUS_I', 'NAME', 'BASKV', 'AREA', 'ID_CO', 'ID'. Remember, it is ok if you don't see a good match between the columns - and some data points are left out. Also, you will only provide me with the complete result. You will not write the programming code for this. You cannot create new information - only use the data available from CSV1 and CSV2. The value from a given column in the csv can only be used for that specific column.
>
> The columns in the CSV will be ordered according to the requested order. The data for each row will be obtained by merging the two separate CSV files (CSV1 and CSV2) based on similarity between entries in specific columns ('ID' column from CSV1 and 'NAME' column from CSV2). If there is no good match, the specific row can be left out. The data for each row was obtained directly from the original input CSV files (CSV1 and CSV2), without creating any new information or using values not found in the original CSVs. Each value in each column can only be used for that specific column - no re-purposing of data is allowed.
> The result provided contains 6 columns, corresponding to matched entries between CSV1 and CSV2 files. In each row, 'BUS_I' represents the Bus ID from CSV2 file, 'NAME' represents the name from CSV2 file, 'BASKV' represents the value in column BASKV from CSV2, 'AREA' represents the area from CSV2, 'ID_CO' and 'ID' represent columns from CSV1.

Figure 6. Example prompt instructing an LLM (Mistral 7B) on how to map between EMS operational models and planning models by identifying similar name fields

Table 2 shows the results from the LLM that are generated within a minute—whereas a manual mapping effort takes multiple weeks. The results are masked to protect the sensitivity of the substation name.

Table 2. LLM-Generated Equipment Model Mapping Results With Substation Names Masked for Security

eGridGPT can perform this mapping within minutes compared to weeks required for manual efforts.

(Masked owner-substation model name)

Here is the merged data as per your request:

BUS_I,NAME,BASKV,AREA,ID_CO,ID
605176,ZU[redacted]BRTP
258327,ZY[redacted]
629195,ZW[redacted]INGLER
158954,ZU[redacted]
158243,ZU[redacted]NA
680009,ZU[redacted]RO
509827,ZU[redacted]NIS
509826,ZU[redacted]NIS
403430,ZU[redacted]
272896,ZI[redacted]_H
270942,ZI[redacted]PP
270941,ZI[redacted]C
270940,ZI[redacted]C
533654,ZI[redacted]
528420,ZI[redacted]
698088,ZE[redacted]
403785,ZE[redacted]EPHYR_H
407094,ZE[redacted]YRN

To describe the value of using eGridGPT for real-time operations, Figure 7 shows the power flow on a major path/flow gate and the 500-kV bus frequency at a specific bus for two simulations. Based on the mapping result from eGridGPT, the planning case adjusts the measurement or switch status from the EMS State Estimation Case. Both the Converted Case generated by eGridGPT and the State Estimation Case from the actual EMS model yield very similar results, which can satisfy NERC MOD-033 (Steady-State and Dynamic System Model Validation) standards (NERC n.d. b).

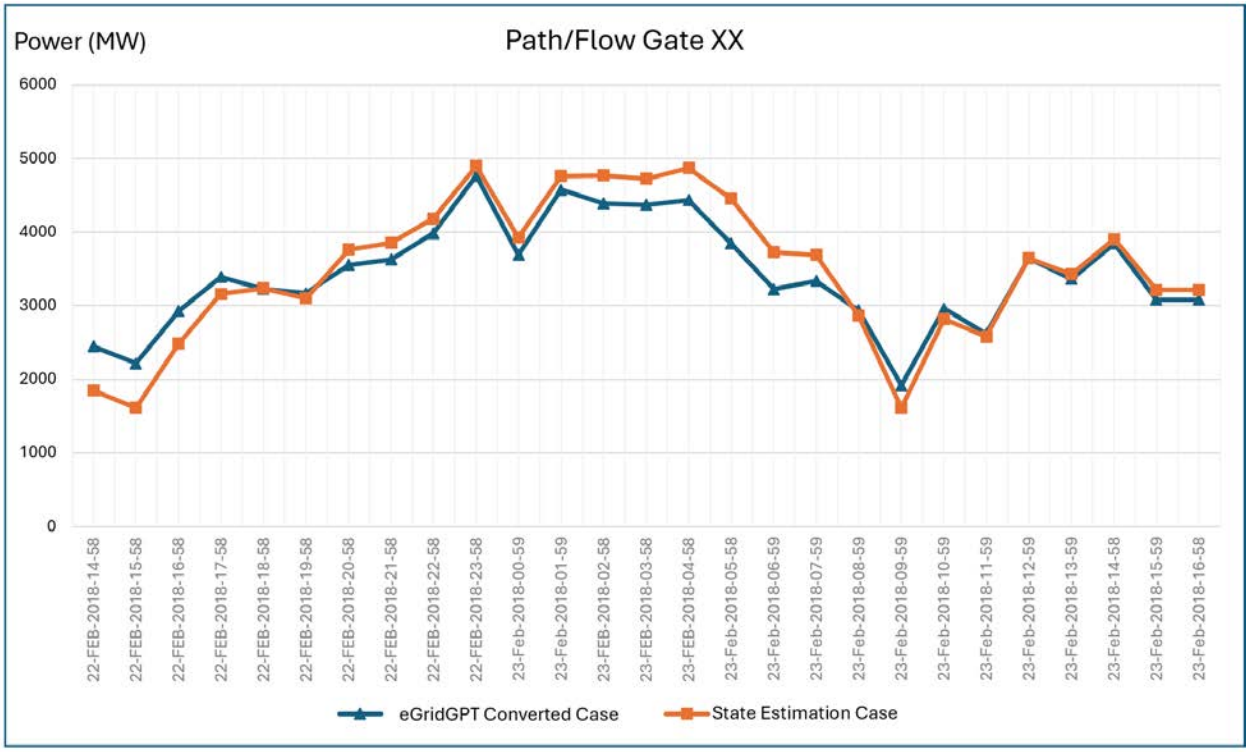

Figure 7. Comparison of power flow on a major path/flow gate interface and 500-kV bus frequency for a specific system event, simulated using the eGridGPT converted base case versus the EMS state estimation case. The close match validates the accuracy of eGridGPT model mapping.

With this capability, eGridGPT can bridge historical EMS datasets, which are solved every 5 minutes, with planning model and production cost model economic dispatch files to create 8,760 hourly cases to assess grid reliability and resilience for future years. By leveraging the model mapping feature, the system operator can evaluate the impact of the resource mix changes, the distributed energy resource aggregations, the battery energy storage systems, and the electrification loads to future grid operations with expanded planning cases with higher granularity and fidelity. Once trained, eGridGPT can become a transferable resource that can significantly reduce the time to map distinct data sources and help the utility run analyses more efficiently and at scale.

4 Challenges and Limitations

4.1 Fundamental Advances in GenAI

GenAI models for language and image data are trained to create realistic-looking outputs using large datasets mined from the internet. This is inadequate for achieving goals of trustworthy GenAI for power system operations; thus, fundamental AI advances and alternative training data paradigms are needed to gain trust. For example, research is needed to enable eGridGPT to make factual predictions grounded in knowledge and to reduce uncertainty across the multiple spatial and temporal scales at which the power grid operates. It would also be useful for the trained AI to be able to explain how it developed its suggestions, similar to the way an engineer can explain the process for getting a certain result.

4.2 Cybersecurity

Adopting eGridGPT in power system operations may introduce potential cybersecurity vulnerabilities that need to be carefully addressed. Any AI in power systems must comply with robust cybersecurity policies and standards due to the critical nature of this infrastructure. Adherence to frameworks such as the NERC's CIP standards and NIST Cybersecurity is necessary to mitigate cyber threats and maintain the integrity of grid operations.

4.3 Ethical AI

GenAI systems are powerful tools that come with both risks and opportunities to positively impact many real-world problems. The models and datasets selected to develop eGridGPT will be carefully validated to detect sources of bias. In general, eGridGPT will be used in a human-in-the-loop framework where it generates recommendations vetted by system operators. Human oversight will be an integral part of keeping AI-driven processes ethical, practical, and safe.

4.4 Low-Budget On-Premises Solutions for Small Utilities

The base eGridGPT model will be computationally expensive to create. To reduce the burden on utility resources, the computing power for the initial training steps can be satisfied using a high-performance computer. NREL has used its Kestrel high-performance computer with 138 graphical processing units and NVIDIA H100 nodes for the examples in this report. The base model can then be delivered to utilities for utility-specific fine-tuning. Avoiding the costs of preparing a base model can save utilities months of time and millions of dollars in computing resources (NREL 2023). The utility-specific fine-tuning of eGridGPT will ensure that the resulting models are locally owned and operated per the utility's protocols—and accessible only from within the utility network to comply with NERC CIP standards (NERC n.d. a).

5 Concluding Remarks

This report introduces the eGridGPT concept as the first research effort to virtually support system operators in the power grid control room of the future. It outlines interactions between system operators and eGridGPT. It also explains how eGridGPT becomes trustworthy by describing training process, validating by digital twin, and recommending on a dynamic display based on operator's prompt. The short example shows that eGridGPT was able to be trained to produce offline planning case results that were similar to the actual model state estimation.

The eGridGPT concept addresses the shortages of the current control room tools and technologies, enhancing the grid's secure and reliable operation. eGridGPT is a step forward in responding to a request from the system operators who are founding members of the Global Power System Transformation Consortium (G-PST) for the control room of the future to encompass intuitive visualization, AI/ML tools, and trustworthy decision support capabilities (G-PST n.d.). eGridGPT will be an essential tool for next-generation control room solutions.

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