Human-Centric Analytics for Resilient and Modern Power System Control Rooms

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***Abstract*—Power system operators at control centers play a critical role in ensuring grid resilience and reliability during blackouts and other critical events. This paper introduces COGNIZANT, a next-generation human-machine interface platform that integrates advanced power system simulation with artificial intelligence-driven decision support and behavioral analytics. Developed jointly by Texas A&M University and the National Renewable Energy Laboratory (NREL), the platform addresses the critical knowledge gap created by retiring experienced operators while preparing the workforce for increasingly complex grid challenges.**

The platform combines PowerWorld Dynamic Simulator and GE's Advanced Energy Management System with large language models fine-tuned using Low-Rank Adaptation and retrieval-augmented generation to create an immersive training environment. It enables simulation of over 1,000 diverse scenarios including extreme weather events leveraging historical ERA5 reanalysis data from 1940-2025, cyber-physical threats, and compound multi-domain events. The system is designed to achieve sub-second alert generation and targets a 20% improvement in operator response times through comprehensive training validated using eye-tracking, cognitive load assessment, and behavioral analysis.

This joint research effort establishes a closed-loop framework where NREL's ARIES platform generates high-fidelity grid scenarios and Texas A&M's Smart Grid Center evaluates operator performance, bridging the gap between grid physics and human factors to accelerate deployment of operator-centered resilience solutions.

***Index Terms*—Power systems, human-machine interface, grid visualization, artificial intelligence, operator training, grid resilience**

I. Introduction

POWER system operators at the control center and their decision-making during grid blackouts are key components in ensuring increased resiliency and reliability of the grid. Recent events underscore this critical need: the February 2021 Texas winter storm resulted in widespread outages affecting 4.5 million customers, while California's recurring wildfire-related Public Safety Power Shutoffs have impacted millions. These events reveal vulnerabilities in both technical infrastructure and operator preparedness, highlighting challenges spanning multiple domains from extreme weather to cyber-physical security [1]. Compounding these challenges, the power industry faces a significant workforce transition, with approximately 30% of experienced grid operators approaching retirement by 2030. This impending knowledge loss threatens operational resilience precisely when grid complexity is increasing due to distributed energy resource integration, cyber-physical threats, and climate-driven extreme weather events.

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This paper proposes COGNIZANT, a multi-domain software platform for power system visualization and operator training developed jointly by Texas A&M University and the National Renewable Energy Laboratory (NREL). The operator's behavior, from bulk system control centers to prosumer market interactions, is considered during the design process. This next-generation platform integrates advanced simulation with an AI-driven grid assistant, serving as a state-of-the-art training environment by simulating diverse scenarios—from extreme weather and prosumer behaviors to grid resilience threats—while leveraging AI to analyze operational and historical data for real-time alerts and decision support. Built on established engines like PowerWorld Dynamic Simulator and GE's AEMS, this joint effort aims to expand grid scenario modeling to include complex, simultaneous events (such as cyber-attacks combined with wildfires) and uses fine-tuned large language models to provide contextual decision support and predict future grid instabilities.

The primary contributions of this work include:

- A comprehensive scenario generation framework integrating 500+ operational scenarios with 500 historical weather-driven renewable generation scenarios based on ERA5 reanalysis data (1940-2025)
- An AI decision support architecture employing fine-tuned large language models using Low-Rank Adaptation (LoRA) and retrieval-augmented generation (RAG) designed to achieve sub-second alert generation
- A behavioral analysis framework using eye-tracking, mouse-click pattern analysis, and cognitive load assessment to quantify operator performance
- A validation methodology targeting 20% improvement in operator response times, informed by empirical studies from NREL's ARIES platform
- A closed-loop research framework bridging NREL's cyber-physical scenario generation with Texas A&M's operator-in-the-loop evaluation

A. Background and Related Work

The COGNIZANT platform builds upon and integrates three complementary research streams: comprehensive scenario generation for power system analysis, human factors and operator performance assessment, and AI-driven cyber-physical resilience. This subsection reviews prior work in these areas and positions COGNIZANT's contributions within the existing literature.

1) Scenario Generation and Grid Modeling: Power system visualization tools have evolved from static one-line diagrams and SCADA interfaces to dynamic, interactive systems leveraging wide-area monitoring systems (WAMS), phasor measurement units (PMUs), and advanced computing [2]–[4]. Modern contingency analysis tools such as PSSE, PowerWorld, and DIgSILENT PowerFactory provide simulation-based visualization of cascading failures [5].

Recent work has emphasized the importance of representative scenario selection for power system analysis. Methods for selecting diverse operating scenarios that capture system variability while maintaining computational tractability have been demonstrated [6]. Design considerations for operational scenarios have been established, emphasizing the need for scenarios that reflect realistic system stress conditions [7]. Building on this foundation, methodologies for incorporating weather and resilience hazards into power flow modeling have been developed, demonstrating the critical impact of meteorological conditions on transmission planning [8]. These prior efforts establish the technical framework for scenario generation that COGNIZANT extends by integrating historical weather reanalysis data spanning 84 years (1940-2025) from the ERA5 global dataset [9], enabling unprecedented temporal coverage of weather-driven grid scenarios.

2) Human Factors and Operator Performance: Effective operator training and performance assessment require quantitative methods for measuring situational awareness and cognitive load. Eye-tracking technology has emerged as a powerful tool for analyzing operator attention patterns and decision-making processes in control room environments. An eye-tracking assisted platform specifically for power system situational awareness assessment has been developed, demonstrating the technology's capability to identify attention bottlenecks during grid disturbances [10]. Eye-tracking metrics have been validated as reliable indicators of situation awareness in power system control rooms, establishing baseline performance characteristics across operator experience levels [11].

Recent work at NREL's ARIES platform has advanced visualization effectiveness through controlled empirical studies with power system engineers. Rigorous assessments of visualization methods have been conducted, quantifying how design choices impact operator interpretation accuracy and confidence levels [12]. These studies provide validated methodologies for human-centered interface evaluation that inform COGNIZANT's validation framework. The platform extends this prior work by integrating eye-tracking with mouse-click pattern analysis and cognitive load assessment to create a multi-dimensional operator performance evaluation system.

3) AI-Driven Cyber-Physical Resilience: The integration of artificial intelligence into power system operations has accelerated rapidly, particularly for cyber-physical security and resilience applications. Feature extraction and data fusion techniques for improving cyber-physical situational awareness have been demonstrated, showing how machine learning can identify attack patterns across multiple data streams [13]. AI-based approaches for scalable cyber-physical optimal response in large power systems have been developed, establishing frameworks for real-time decision support under attack scenarios [14].

Recent advances in large language models (LLMs) have created new opportunities for power system applications. Retrieval-augmented generation (RAG) techniques enable LLMs to ground responses in verified knowledge bases, improving accuracy for technical domains [15]. Low-Rank Adaptation (LoRA) provides efficient methods for fine-tuning LLMs to specialized vocabularies and contexts while minimizing computational requirements [16]. COGNIZANT leverages these techniques to create an AI assistant specifically adapted to power system operational contexts, combining pattern recognition capabilities with natural language explanation generation.

4) Integration and Gap Analysis: While prior research has advanced individual components—scenario generation, human factors assessment, and AI decision support—existing platforms have not integrated these capabilities into unified training and operational systems. Current tools typically address limited scenario sets, lack AI-driven real-time guidance, and provide insufficient experiential learning opportunities for operators facing the retirement of experienced colleagues. Integration of distributed energy resources and climate-driven extreme events further exacerbates these gaps [17], [18].

COGNIZANT addresses these limitations by establishing a closed-loop research framework that synthesizes comprehensive scenario generation (building on [6]–[8]), rigorous human factors validation (extending [10]–[12]), and modern AI techniques (applying [13]–[16]) within an integrated platform. This multi-domain approach enables operators to develop resilience competencies across technical, cognitive, and decision-making dimensions.

II. Problem Statement and Motivation

Existing grid visualization and simulation tools have critical gaps in technical capabilities, training environments, and decision support systems.

A. Technical and Scenario Limitations

Current platforms focus on narrow operating case ranges and neglect weather-integrated scenarios despite increasing renewable penetration. They cannot simulate compound stress events—simultaneous cyber-attacks and natural disasters—limiting operator preparedness for realistic multi-domain threats.

B. Training and Workforce Challenges

Traditional tools lack immersive training experiences for diverse grid challenges. With approximately 30% of experienced operators approaching retirement, the experiential knowledge gap threatens grid resilience precisely when operational complexity is accelerating.

C. Decision Support and Real-Time Intelligence

Current systems lack AI components capable of processing operational and historical data to provide real-time guidance. They function primarily as reactive tools rather than proactive systems that learn from past events. Human-machine interface design has not adequately incorporated behavioral analysis or cognitive load assessment.

The COGNIZANT platform addresses these challenges through a joint Texas A&M-NREL framework that expands scenario diversity, integrates AI-driven decision support, and provides multi-domain simulation validated through behavioral assessment.

III. Proposed Technology

A. Proposed platform design features

1) Comprehensive Scenario Generation: The platform will be capable of generating a diverse library of grid scenarios—including weather disruptions, prosumer behavior variations, and simulated grid resilience scenarios (e.g., wildfire plus cyber-attack). Research in human factors demonstrates that operators trained on diverse scenario sets show improved situation awareness and decision accuracy; studies indicate exposure to varied operational conditions can improve diagnostic accuracy by 15–25% compared to narrow training regimes [19], [20].

2) Real-Time Data Processing and Alerting: The AI grid assistant is designed to analyze real-time data streams with target response times under one second, ensuring operators receive prompt alerts to emerging risks. This capability will synthesize data from multiple sources including EMS/SCADA systems, PMU networks, weather services, and market platforms, cross-referencing with historical event libraries to provide contextualized situational awareness.

3) Training Efficacy: Planned validation studies using eye-tracking and behavioral analysis software at Texas A&M's Smart Grid Center will assess operator performance improvements. The platform targets at least 20% reduction in operator reaction times for critical decision-making tasks, informed by human factors research at NREL's ARIES platform [12].

4) Scalability and Robustness: Leveraging PowerWorld Dynamic Studio [21] and GE's AEMS, the platform handles both detailed localized simulations and broader regional grid dynamics without compromising performance.

5) Interdisciplinary Methodology: Effective HMIs for power system operators must address behavioral dynamics, team communication, cascading failures, and cybersecurity. As power systems integrate DERs and new market structures, understanding operator behavior under stress is crucial for decision-making. Combining behavioral insights with power system metrics enables better prediction and mitigation of cascading failures.

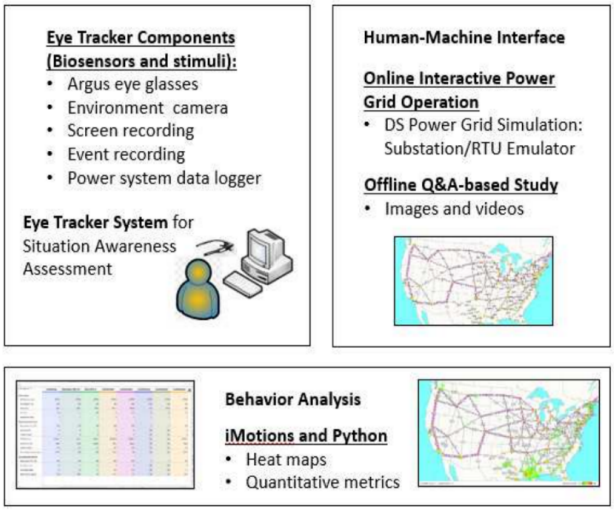

Fig. 1. System components of the COGNIZANT platform showing eye tracker components, human-machine interface modules, and behavior analysis tools including heat maps and quantitative metrics.

B. System Architecture

Figure 1 illustrates the key components of the proposed platform. The system integrates eye tracker components (biosensors and stimuli) including Argus eye glasses, environment cameras, screen recording, event recording, and power system data loggers. These components feed into an eye tracker system for situation awareness assessment. The human-machine interface enables both online interactive power grid operation through DS Power Grid Simulation (Substation/RTU Emulator) and offline Q&A-based studies using images and videos. The behavior analysis module utilizes iMotions and Python software to generate heat maps and quantitative metrics for operator performance evaluation.

C. Technical Implementation

1) AI Decision Support Architecture: The platform employs a hybrid AI architecture combining fine-tuned large language models with complementary machine learning approaches. The core decision support system uses large language models (LLMs) fine-tuned through Low-Rank Adaptation (LoRA) [16], enabling efficient adaptation to power system-specific vocabulary and operational contexts while minimizing computational overhead. Retrieval-augmented generation (RAG) [15] enhances the LLM by grounding responses in verified historical event databases, operational procedures, and real-time grid state information.

Supporting the LLM-based reasoning are specialized machine learning pipelines for pattern recognition and anomaly detection, building on recent advances in feature extraction and data fusion for cyber-physical systems [13], [14]. These include supervised learning models trained on historical disturbance signatures and unsupervised techniques for identifying

novel operational states. The AI module processes inputs from multiple data streams including EMS/SCADA telemetry, PMU measurements, weather forecasts, and market signals to provide contextual alerts and decision recommendations.

Training data comprises operational records from utility partners, synthetic scenarios generated through high-fidelity simulation, and the comprehensive ERA5 weather database described in Section III-C2. The system is designed to achieve alert generation latency below one second for 95th percentile events while maintaining interpretability through natural language explanations of detected anomalies and recommended actions.

Known limitations include potential degraded performance on rare event types underrepresented in training data, such as novel attack vectors or unprecedented compound disturbances. The RAG architecture mitigates hallucination risks by grounding responses in verified knowledge bases; however, the system may exhibit overconfidence when extrapolating beyond training distributions. Human operator oversight remains essential, with the AI designed as decision support rather than autonomous control.

2) Scenario Generation Framework: The COGNIZANT platform generates diverse operational scenarios through three integrated pathways, building on established methodologies for representative scenario selection and operational design considerations [6], [7]. First, weather-driven scenarios leverage Texas A&M's parallel ERA5 data processing pipeline, which has compiled 84 years of global weather reanalysis data (1940-2025) from the ERA5 global dataset [9] at 0.25° resolution with 27 meteorological variables. The ERA5-derived renewable generation calculations have been validated against independent sources including MERRA2 and HRRR weather models, demonstrating hourly correlations exceeding 0.85 for wind generation and 0.75 for solar generation at major U.S. renewable facilities [22], [23]. Further validation comparing forecast and historical weather data shows wind forecast accuracy improving from approximately 50% at 16 days to over 80% at 7 days before the target date [24]. This historical weather database enables backcasting of renewable generation outputs across different technology vintages and geographic distributions, producing 500 unique weather-driven scenarios that capture extreme events, seasonal patterns, and climate variability impacts on grid operations [8].

Second, cyber-physical scenarios simulate coordinated attacks including false data injection targeting state estimators, denial-of-service attacks on communication networks, and compromised control signals [13], [14]. These scenarios range from single-point intrusions to sophisticated multi-vector campaigns synchronized with physical disturbances. Third, market-driven scenarios model prosumer behavior variations, demand response coordination, and electricity price volatility impacts on distributed resource dispatch.

The platform's distinctive capability lies in compound scenario synthesis, combining elements from all three categories. For example, a winter storm scenario (weather-driven) may be overlaid with generation outages (equipment stress), heightened cyber threats (adversarial timing), and demand surges (market response), creating realistic N-2 and beyond contingencies. The target library exceeds 1,000 scenarios spanning routine operations through extreme multi-domain events.

3) Validation Methodology and Performance Objectives: Validation combines quantitative performance metrics with qualitative behavioral assessment using established eye-tracking methodologies [10], [11]. Eye-tracking captures fixation duration, saccade patterns, and pupil dilation as cognitive load indicators. Mouse-click analysis quantifies decision latency and action sequences, complemented by NASA-TLX cognitive load assessments.

The platform targets a 20% reduction in operator decision time for critical actions. A planned validation study will compare baseline against post-training performance across diverse scenarios, replicating realistic control room conditions while maintaining experimental rigor [12].

IV. Potential Impact

The Texas A&M-NREL platform development is anticipated to have far-reaching impacts:

A. Enhanced Grid Resilience

Simulation of diverse stress scenarios—including complex multi-domain events—helps operators understand system vulnerabilities and develop robust response strategies, expanding capacity to address coordinated threats and compound disturbances.

B. Improved Operator Training

The interactive, AI-assisted training environment provides practical experience handling multi-scenario events, enhancing operator response while mitigating risks from institutional knowledge loss as experienced operators retire.

C. Informed Decision Making

Real-time alerts and predictive insights provide enhanced situational awareness supporting data-driven decisions under high-pressure conditions, reducing cascading failure likelihood through faster, more accurate responses.

D. Industry and Societal Benefits

The integration of advanced simulation with AI techniques sets a new benchmark for grid operation training. A more resilient power grid improves energy security and decreases outages impacting public health, safety, and economic stability.

V. Project Implementation

A. Technology Risk

The availability of data from utilities is a major risk for the development of this platform. Additionally, the current state of HMI development poses another risk. This project has inherently mitigated these risks by partnering with multiple utilities, such as ERCOT, CenterPoint Energy, LCRA, College Station Utilities, United Cooperative Services, and Rayburn Electric Co-Op. Furthermore, comprehensive partnerships with Dell and GE Vernova help mitigate the risks associated with developing this HMI technology.

Fig. 2. The Texas A&M Smart Grid Center Control Room Lab showing the immersive training environment with multiple display screens for power system visualization and operator training scenarios.

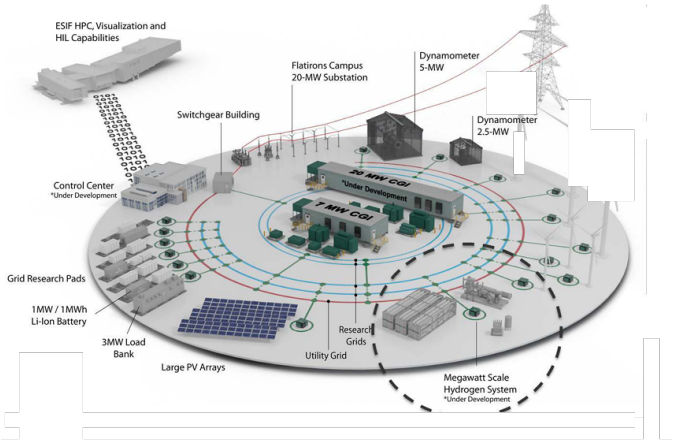

Fig. 3. NREL ARIES platform integrating physical hardware with emulated devices for grid-scale research

B. Project Location Support

The platform will be developed at the Texas A&M Engineering Experiment Station (TEES) Smart Grid Center (SGC), and at NREL's Advanced Research on Integrated Energy Systems (ARIES) lab. Figure 2 shows the SGC Control Room Lab facility. The model creation and scenario development will use the high-performance computing resources available to SGC and Texas A&M University researchers. The human-machine interface (HMI) training and validation will use the SGC Control Room Lab's eye tracking and mouse-click recording technology, and the simulated control room environment.

*1) **NREL ARIES Capabilities for Utility Visualisation Research**:* The National Renewable Energy Laboratory's Advanced Research on Integrated Energy Systems (ARIES) platform provides a national-scale capability for investigating next-generation visualization and situational-awareness tools for utility control centers. ARIES integrates high-fidelity real-time simulation, hardware-in-the-loop experimentation, and multi-site laboratory coupling to recreate complex grid conditions spanning transmission, distribution, and behind-the-meter domains with millisecond accuracy.

ARIES research focuses on advanced visualization concepts including dynamic stability indicators, synchrophasor-informed dashboards, predictive analytics, cyber-situational awareness overlays, and integrated EMS–DERMS–WAMS views. The platform supports systematic assessment of human–machine interface designs, alarm-management strategies, and operator cognitive load through controlled experimentation. By linking physical equipment with prototype control-room interfaces, ARIES enables evaluation of how emerging grid technologies influence operational workflows. ARIES functions as a pre-deployment proving ground where utilities validate visualization strategies and evaluate performance under diverse scenarios before full-scale implementation.

*2) **Complementarity Between NREL's ARIES Platform and the Texas A&M Smart Grid Center Control Room Lab**:* NREL's ARIES platform and the Texas A&M Smart Grid Center (SGC) Control Room Lab offer highly complementary capabilities forming a robust national ecosystem for grid-operations research. ARIES provides large-scale, hardware-in-the-loop, and cyber-physical experimentation spanning transmission, distribution, and multi-energy domains, while the SGC Control Room Lab contributes expertise in operator behavior, human–machine interface evaluation, and EMS- and DMS-level decision-support research.

ARIES excels in creating high-fidelity operational scenarios incorporating inverter-based resources, grid-forming technologies, DER aggregation, and cross-domain interactions. These ARIES-generated datasets enable comprehensive assessments of how operators interpret and respond to future grid conditions. Conversely, the SGC Control Room Lab provides a mature environment for studying operator cognition, interface usability, and alarm design through rapid prototyping under operator-in-the-loop conditions, enabling evaluation of whether visualization strategies improve situational awareness and support accurate decision-making.

Together, the facilities form a **closed-loop research framework**: ARIES generates the physical and cyber-physical reality of next-generation grid conditions, and the SGC Control Room Lab evaluates how those conditions should be presented and acted upon in modern control centers. This combination bridges the gap between grid physics and operator performance, ensuring visualization innovations are tested for both technical accuracy and human factors.

C. Key Technical Risks and Mitigation

Key technical challenges include integrating simulation engines with the AI module for seamless real-time data flow, ensuring access to comprehensive, high-quality grid data, managing scalability for multi-domain real-time scenarios, and rigorously validating system performance using eye-tracking and reaction-time tools. We will mitigate these risks through thorough testing, robust data-sharing agreements with utility partners, and leveraging high-performance computing resources from A&M and Dell.

VI. Conclusion

The proposed platform represents a significant advancement in power system operator training and grid resilience enhancement. By integrating advanced simulation capabilities with AI-driven decision support, the platform addresses critical gaps in current grid visualization and training tools. The comprehensive approach encompasses scenario generation, real-time data processing, behavioral analysis, and operator training in an immersive environment. The successful deployment of the proposed platform will contribute to improved grid resilience, better-trained operators, and enhanced decision-making capabilities, ultimately benefiting society through more reliable and secure electric power systems.

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