

An Interactive AI-Copilot Platform for Power System Resilience Enhancement

Ankang Deng¹, Liya Ma¹, Hongxun Hui^{1,*}, Ye Chen², and Qingning Lu²

¹State Key Laboratory of Internet of Things for Smart City, Department of Electrical and Computer Engineering
University of Macau, Macao, China

²State Grid Jiangsu Electric Power Company Electric Power Research Institute, Nanjing 211103, China

*Corresponding author: hongxunhui@um.edu.mo

Abstract—Extreme disasters can severely damage power systems and disrupt critical urban services, making rapid disaster awareness, power system repair, and resilience improvement planning essential for power utilities. However, lacking a holistic analytical framework and intuitive result interpretation, existing methods often yield abstract computational metrics that stakeholders struggle to translate into actionable decisions during extreme disasters. This work presents an interactive AI-Copilot platform for enhancing power system resilience. The proposed platform supports resilience enhancement through power system repair optimization and planning suggestions for resilience enhancement. Specifically, the platform integrates disaster scenario description, infrastructure failure-probability assessment, repair scheduling, and resource planning suggestions within a unified Web-based interface. Taking Typhoon Bebinca as a representative disaster, the platform visualizes disaster features and damage distributions, generates repair crew schedules and dispatch routes, and provides investment-oriented resilience suggestions under different observability and repair-resource configurations. The large-language-model-based AI Copilot further translates computational results into interactive explanations for utilities and policymakers. The proposed platform demonstrates the potential of integrating power-system analytics, visual decision support, and AI-assisted interaction to facilitate practical decision-making for power system resilience enhancement.

Index Terms—Power system, extreme disasters, power resilience, AI-Copilot platform

I. INTRODUCTION

Extreme weather events have increasingly threatened modern power systems and urban infrastructures. Hurricane Ian caused more than 47 billion USD in damage in 2022 [1] and led to large-scale power outages across Florida and the Carolinas in the United States [2]. Typhoon Bebinca struck Shanghai in 2024, causing large-scale evacuations, transportation disruptions, and urban infrastructure damage [3]. These events severely damage power facilities, triggering cascading failures across essential public services, such as communication networks. To mitigate these impacts, it is essential to enhance power system resilience through rapid situational

awareness, efficient power system repair, and strategic resilience investments.

To enhance power system resilience under extreme events, existing studies have mainly focused on optimization-based restoration and learning-based decision-making. Lei et al. [4] co-optimized service restoration with repair crew routing and mobile power source dispatch in damaged distribution systems. Shi et al. [5] studied emergency mobile resource scheduling for distribution system restoration, while Zhu et al. [6] focused on repair crew dispatch under post-disaster conditions. In addition, learning-based methods have been investigated to improve the adaptability of restoration decisions in dynamic disaster environments. Wang et al. [7] developed a deep-reinforcement-learning-based framework for mobile resource coordination. Huang et al. [8] investigated learning-based microgrid formation for rapid load restoration, and Vu et al. [9] applied multi-agent reinforcement learning to distributed load restoration under operational constraints.

Beyond technical studies, resilience enhancement has also been supported by policy reports and regulatory guidance. For instance, in the U.S., the Department of Energy has promoted grid resilience grant programs [10]. The Federal Emergency Management Agency provides foundational frameworks for power-outage response planning in [11]. Besides, investment and planning issues are also highlighted by the regulatory agencies. Notably, the National Association of Regulatory Utility Commissioners systematically examines resilience investment evaluation [12]. In China, the National Energy Administration has also emphasized the key sectors for improving power systems resilience. They include emergency management, repair-crew coordination, cross-regional emergency-resource sharing, and backup emergency power supply for critical users [13].

Although the above studies have made significant progress in technological methods and resource investment, two limitations hinder their practical implementation. First, many existing works focus on a single stage of the resilience process, such as repair crew scheduling, mobile resource allocation, or long-term investment planning. Consequently, mapping these interdependencies proves highly challenging. This difficulty prevents planners from formulating a holistic resilience strategy. Second, the results of many advanced methods are pri-

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marily expressed as raw optimization variables, constraints, or numerical indices. These abstract metrics make it difficult for policymakers and utilities to translate into actionable decisions during time-critical emergency responses.

To address these limitations, this work proposes an interactive AI-Copilot platform for power system repair scheduling and resilience-oriented planning in power systems. Unlike isolated analytical tools, the proposed platform links disaster impact assessment, repair-strategy generation, and planning-oriented resilience evaluation within a unified decision-support workflow. Furthermore, by leveraging Large Language Model (LLM)-assisted interpretation, the AI Copilot translates complex computational results into actionable guidance, facilitating the practical implementation of these strategies. The technical novelty of this work lies primarily in the platform-level integration of power-system repair and resilience analytics with LLM-assisted human interaction. The main contributions of this work are summarized as follows:

- **A platform-level integration framework for power resilience enhancement:** The proposed platform integrates and visualizes disaster features, potential infrastructure damage risks, repair strategies, and investment recommendations within a unified Web-based framework. This integrated workflow enables users to map the complex interdependencies across different stages, from disaster scenarios, repair performance, to resilience enhancement decisions, thereby improving overall operational efficacy.
- **An AI Copilot for interactive results interpretation and decision support:** The platform provides AI-assisted interpretation for different user groups. For policy makers, it translates technical results into intuitive information for disaster prevention and mitigation decisions. For utilities, it explains repair schedules, sensitivity results, and investment strategies, supporting more transparent operational and planning decisions.

II. SYSTEM PLATFORM DESCRIPTION

A. Overview

This section describes the architecture of the AI-Copilot assisted platform, designed to enhance power system resilience through an integrated decision-support workflow. The platform supports three primary functions: 1) disaster scenario characterization; 2) power system repair strategy optimization; and 3) planning suggestions for future resilience improvement.

To achieve these functions, the platform operates through a systematic, end-to-end workflow in Fig. 1. Specifically, the operational process begins with multi-source data acquisition, sequential advancing through disaster scenarios, repair-task analysis, and resilience evaluation. Historical typhoon-track data, grid topology, communication base-station information, and substation risk references are first imported into the platform. Based on these inputs, the system constructs the disaster scenario by estimating hazard exposure and infrastructure damage risks. The generated scenario is then linked with the repair optimization engine, which produces structured crew-task sequences and outage-related indicators. Furthermore,

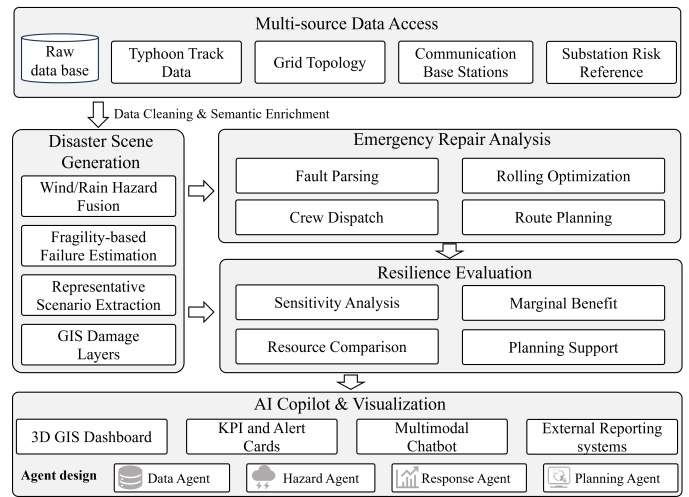


Fig. 1. Overall system workflow of the AI Copilot platform, from multi-source data access and disaster-scene generation to repair analysis, resilience evaluation, and bilingual visual interaction.

an offline sensitivity-analysis module evaluates power system resilience across varying observability and crew resource configurations. The final results are presented through a bilingual visual interface with AI Copilot functions for explanation and interaction. Notably, the AI-Copilot translates complex analytical findings into accessible language for diverse audiences, ranging from industry professionals to end consumers. Consequently, the platform equips policymakers and system operators with straightforward, expert-level recommendations.

To maximize usability for a wide range of audiences, from academics to industry utilities, the framework is integrated as a web-based system divided into frontend and backend components. This architecture effectively combines modular implementation with seamless integrated operation. The front end provides a single-page visualization dashboard for disaster progression, repair routing, and resilience performance. Conversely, the back end is organized around Python-based analytical modules and FastAPI services. It manages data acquisition, repair strategy optimization, and performance simulations for various resilience requirements. This design allows the hazard-analysis, repair-analysis, and interaction components to be developed independently, while still maintaining a continuous end-to-end workflow for practical use.

B. Platform Architecture

As illustrated in Fig. 2, the platform is organized into four logical layers that connect the main business functions with their corresponding user-interface (UI) modules. The data access layer provides the required disaster, grid, communication, and substation data for all downstream functions. The disaster scene layer supports disaster description, failure-probability assessment, and damage visualization. The core function layer implements repair scheduling and resilience analysis, while the AI Copilot and visualization layer presents analytical results through interactive interface modules. In this design, the

business workflow of disaster scenario characterization, repair mission assignment, and resilience enhancement suggestion is mapped onto a clear layered architecture and further exposed to users through dedicated UI modules.

1) *Data Access Layer*: This foundational layer is responsible for ingesting and processing multisource heterogeneous data. It integrates data regarding power grid topology, communication infrastructure, and meteorological hazard. To improve reproducibility and portability, the current implementation relies on structured, CSV-based utility datasets and verified external sources for physical world modeling. Furthermore, the system's analytical components utilize academic licenses for computational solvers (e.g., Gurobi) and authorized API keys for LLMs.

2) *Disaster Scene Layer*: This layer maps the hazard data onto the physical infrastructures. Specifically, it tracks the spatial and temporal progression of the extreme event. Based on this progression, it calculates the expected damage to facilities according to their specific physical vulnerability and exposure conditions. Through this process, the platform transforms raw hazard inputs into interpretable damage datasets. These datasets directly support downstream decision-making and integrate with the visualization layer to provide clear, visual representations of the disaster impacts.

3) *Core Function Layer*: Acting as the analytical engine, this layer encompasses the algorithmic modules. Primarily, it dynamically generates optimal repair strategies to facilitate post-disaster recovery. Additionally, it conducts sensitivity analyses to evaluate resilience performance under varying communication availability and resource capacities. The algorithms are encapsulated as independent services, ensuring that the platform remains scalable.

4) *AI Copilot and Visualization Layer*: This layer serves as the primary interface between the system and the human operator, functioning across two key dimensions: operational interaction and result interpretation. Operationally, operators can import specific disaster scenarios and physical infrastructure data to generate optimal repair strategies. Furthermore, users can configure resilience preferences and resource capacities to simulate the performance improvements of hypothetical investments. Interpretatively, the layer integrates a conversational AI-Copilot. Through this interactive dialogue module, operators can seamlessly query the technical details of repair strategies and easily interpret the effectiveness of proposed investment plans. These dual functions are supported by a GIS-based bilingual visualization module that displays comprehensive maps and charts.

C. Implementation Details

The implementation details are designed around three practical considerations: 1) LLM security and reliability, 2) computational efficiency, and 3) user accessibility.

- 1) **LLM security and reliability**: LLM API keys are managed through encrypted backend storage rather than being exposed on the frontend. API connectivity testing, alternative API-base candidates, and retry mechanisms

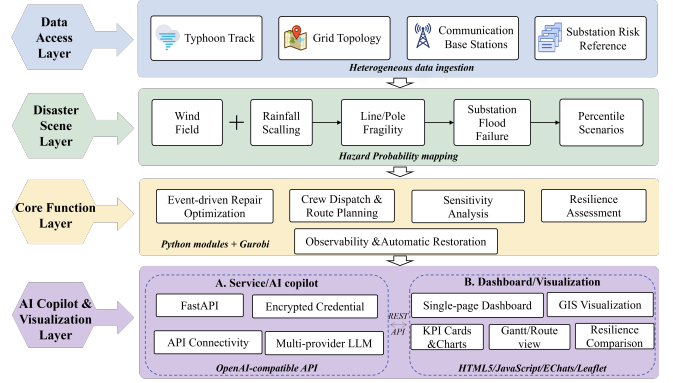


Fig. 2. Four-layer platform architecture, including data access, disaster-scene generation, core analytical functions, and AI Copilot plus visualization interface.

are also provided to improve access stability under unstable network conditions.

- 2) **Computational efficiency**: The platform integrates a lightweight Python/FastAPI backend with an HTML5, JavaScript, and ECharts frontend, separating backend computation from frontend visualization to support efficient processing and responsive interaction.
- 3) **User accessibility**: The interface supports persistent Chinese/English switching without page refresh, improving usability for operators, planners, and users with different technical backgrounds.

III. CORE FUNCTIONS

A. Disaster Scene Description

Accurately describing disaster characteristics is the first step for power system resilience analysis. Taking a typhoon disaster as an example, the platform describes the disaster scene through typhoon trajectory, wind-field intensity, rainfall intensity, and flood-related indicators. Specifically, typhoon wind exposure is estimated using the Batts wind-field model, while rainfall-induced flood risk is represented using a Chicago rainfall profile approximation. These disaster features are mapped onto the geographical layout of power grids, communication stations, and substations, thereby providing a spatial-temporal basis for subsequent infrastructure vulnerability assessment.

Based on the described disaster scene, the platform further estimates infrastructure failure probabilities. A vulnerability-based assessment is used to translate wind exposure into the failure probabilities of power lines, poles, and stations. Rainfall and flood-related indicators are used to evaluate the interruption risk of substations. In addition to direct physical damage, the platform also considers the indirect functional outage of communication base stations caused by the loss of power supply from affected substations. In this way, the disaster scene is transformed from a spatial-temporal feature description into a failure-probability map of coupled power and communication infrastructures.

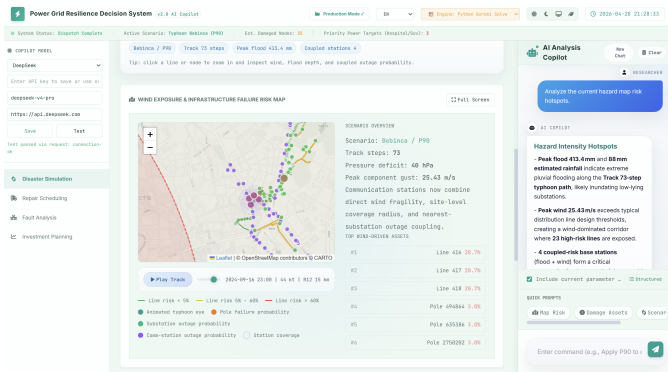


Fig. 3. GIS-based disaster damage distribution interface, showing wind-risk lines, flood-related substations, and coupled communication-station outage layers.

The failure-probability map is then used to generate representative damage distributions for repair and resilience analysis. In the scenario analysis workflow, Monte Carlo sampling is first used to produce multiple deterministic damage realizations from the estimated failure probabilities. Then, a percentile-based selection rule extracts a representative scenario of interest, such as a median or high-percentile damage case. In the current Web-based demonstration, the selected scenario is presented as a deterministic damage distribution and used as the input for downstream repair scheduling. This process enables dispatchers to examine statistically meaningful damage patterns without being exposed to complex probabilistic details.

B. Power System Repair Strategy Optimization

Once the damage distribution is established, rapid power system repair becomes the primary objective. The power system repair strategy module formulates the repair scheduling task as a Gurobi-based mixed-integer optimization problem within an event-driven rolling simulation framework. It takes the damage scenario, grid topology, fault observability, crew resources, and cost parameters as inputs, and outputs crew-task assignments, dispatch routes, restoration states, and outage-related indicators.

A key feature of this module is its event-driven rolling optimization mechanism. Rather than generating a single, static plan, the platform dynamically adjusts repair priorities in response to newly discovered faults, task completions, automated restoration events, and fluctuating crew availability. Based on these conditions, the system computes structured crew-task sequences, routing plans, and restoration priorities that can be directly interpreted as repair work orders.

The generated strategy is further connected to the visual interface. Repair routes, task sequences, and restoration priorities are displayed through map overlays, schedule views, and key performance indicators. This visualization enables system operators to monitor both the spatial dispatch of repair crews and the temporal evolution of the restoration process. Ultimately, the platform combines real-time computation with

direct visual feedback, effectively addressing the slow and inefficient nature of manual dispatch in practical recovery efforts.

C. Resilience-Oriented Resource Planning

Beyond managing active disaster recovery, the platform supports resource planning for utilities and policymakers, in order to enhance power resilience. Since resilience investment depends on how additional resources improve restoration performance, the resilience enhancement module compares different resource allocation options under user-specified performance targets, such as maximum outage duration and total outage loss. Accordingly, it is implemented as a sensitivity-based resource comparison under a selected representative damage scenario. With communication observability, repair-crew capacity, and cost-related parameters as inputs, the module outputs restoration-time indicators, outage-loss indicators, total cost, heat maps, and investment-oriented recommendations.

The primary objective of this module is to conduct sensitivity analyses evaluating the impact of communication and repair resources on overall resilience performance. Specifically, the current implementation quantitatively compares restoration outcomes across varying levels of communication observability and repair crew capacities. Through this mechanism, users can systematically evaluate how enhancing communication observability, expanding repair crew capacities, or adjusting resource combinations impact overall resilience performance. This performance is evaluated using metrics such as maximum outage duration, direct outage costs, and total system expenses (encompassing both repair and routing costs). Ultimately, this capability transforms resilience enhancement planning from qualitative discussions into rigorous quantitative evaluations.

Based on comprehensive sensitivity analyses, the platform outputs comparative charts, summary heat maps, and investment-guided recommendations. These outputs enable planners to identify resource allocation strategies that yield the highest marginal returns, providing actionable support for future resilience enhancement. Consequently, this module transcends basic post-event analysis, functioning as a strategic interface that bridges operational recovery performance with long-term resource investment.

IV. INTERFACE MODULES AND DEMONSTRATION

The functions introduced in Section III represent the core capabilities of the platform, including disaster assessment, repair optimization, and resilience analysis. These functions are exposed to end users through dedicated UI modules in the visualization layer. Accordingly, this section focuses on the UI modules and demonstrates how the underlying functions are presented and interacted with in the Web-based platform.

A. Disaster and Damage Module

Accessed through the dashboard, this disaster and damage module empowers users to visually analyze complex hazard impacts within a unified GIS environment. Upon

selecting a scenario of interest, the interface renders the hazard on a GIS-based map using layered visual elements, dynamically linking with official meteorological data sources (such as the China Typhoon website referring to <https://typhoon.nmc.cn/mobile.html>). This module can simultaneously display two key data streams: 1) dynamic disaster features, such as typhoon track animations, the spatial distribution of maximum wind speed, estimated rainfall distribution, and peak flood depth; and 2) associated infrastructure damage risks, including failure probabilities for power lines and poles, flood impacts on substations, and cascading functional outages in communication base stations caused by power loss. All the information is seamlessly integrated into a single view. Operators can click map objects to inspect local attributes, which makes the damage pattern more interpretable than a conventional text-based list. Additionally, the dashboard provides scenario overview panels that allow users to inspect various hazard layers without leaving the main screen.

The practical value of this module lies in facilitating rapid situational awareness. Rather than manually aggregating topology data, meteorological forecasts, and risk assessments, dispatchers can instantly visualize critical damage hotspots and prioritize vulnerable assets. This significantly accelerates the transition from hazard perception to recovery preparation, establishing an intuitive foundation for subsequent dispatch operations.

B. Repair Scheduling Module

Building upon the established disaster scenario, the repair scheduling module generates dynamic recovery plans. Users first configure key operational parameters, including the communication observability level, the number of available repair crews, and their initial locations. Upon selecting the optimization engine (e.g., the Python Gurobi API), the platform initializes the computational environment and executes the simulation. Within seconds, the system outputs an optimal schedule for all crews, visualized through a Gantt-style task chart. Concurrently, their routing sequences are tracked on a live, OpenStreetMap-based monitor [14]. This interface dynamically highlights vehicle trajectories, fault nodes, active repair statuses, completed tasks, and priority loads. To further enhance execution efficiency, the module includes a dedicated dispatch function, enabling operators to instantly transmit finalized task directives to on-site crews. Specifically, this module provides the visualization of the power system repair strategy in two dimensions: 1) a temporal repair schedule, detailing task sequences, durations, and crew allocations; and 2) a spatial repair schedule, visualizing dispatch routes and dynamic restoration states.

Through this module, users, particularly utility operators, can directly review executable dispatch schedules through the UI. This visualization significantly enhances the clarity of complex repair strategies. Furthermore, the automated generation of these schedules alleviates the burden of manual coordination, thereby substantially improving overall execution efficiency.

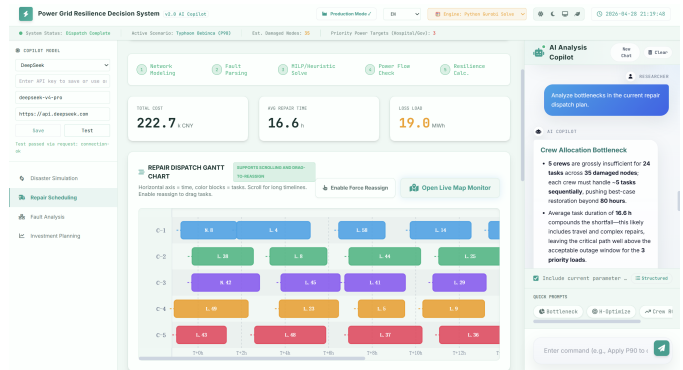


Fig. 4. Repair work-order generation interface, including crew-task timeline, KPI cards, and map-based dispatch routing.

C. Resilience Suggestion Module

The resilience suggestion module provides strategic guidance to help policymakers and utilities improve overall power system resilience. This module features two primary components: 1) a quantitative comparative analysis of key performance indicators under different communication-observability and repair-crew configurations, including restoration time, outage loss, total cost, and weighted planning scores. This output enables users to systematically evaluate how restoration performance changes when communication observability or repair crew availability is adjusted. 2) Evidence-based investment recommendations for long-term planning, tailored to diverse resilience objectives. For instance, policymakers typically prioritize minimizing outage durations, whereas power utilities often focus on reducing overall economic costs. Consequently, the module generates distinct, customized investment strategies to address each stakeholder's specific priorities.

Based on these quantitative comparisons, this module evaluates the marginal benefits of various resource configurations. The results are delivered through structured visualizations and investment-guided recommendations, helping users determine whether limited budgets should be allocated to enhancing communication observability, expanding repair crews, or pursuing a balanced combination of both. This capability strengthens the practical value of the platform by linking restoration-performance indicators with actionable resilience-planning decisions.

D. AI Copilot Interaction Module

The AI Copilot serves as the platform's primary interactive interface, accessible via a dedicated module on the right side of the dashboard. This interface allows users to manage chat histories, such as initiating new conversations or clearing message histories, and dynamically integrate current parameter data into the conversation context. The module connects to a pluggable, multi-provider LLM configuration layer that supports various model options, secure credential management, and pre-interaction connectivity testing. Furthermore, the platform incorporates a persistent, one-click bilingual

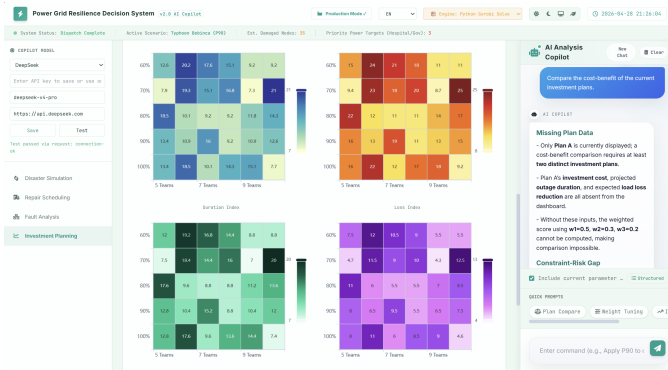


Fig. 5. Resilience suggestion interface, including sensitivity curves, heat-map comparison, weighted plan scores, and recommendation outputs.

toggle (English/Chinese) at the global UI level to ensure broad accessibility.

From the user perspective, the interaction flow is highly streamlined. Operators first select a model provider and authenticate their credentials. Once connectivity is verified, they can submit queries directly via the chat interface. The Copilot can be prompted to analyze resilience performance, evaluate crew-allocation tradeoffs, or formulate investment suggestions for specific resilience demands.

This module significantly reduces operational complexity and enhances overall accessibility. Specifically, the integration of multi-LLM switching, API verification, configuration reuse, and bilingual support ensures seamless adoption for users with diverse technical backgrounds and linguistic preferences. For instance, for on-site crews, the Copilot translates complex, sequential repair schedules into clear, time-slotted task directives. For utility operators, the underlying LLM automates the generation of comparative reports detailing performance improvement rates across various strategies. Finally, for policymakers, who may lack familiarity with raw optimization outputs, the module serves as an interactive assistant, distilling dense computational results into accessible, actionable insights.

V. CONCLUSION

In conclusion, this work presents an interactive AI Copilot platform dedicated to power system repair and resilience management under extreme disasters. The platform is engineered to comprehensively visualize disaster impacts, compute optimal repair strategies, and guide resilience planning. To achieve these functionalities, we have developed the system with three core features: 1) we establish an intuitive, GIS-based interface that provides comprehensive visibility across the physical grid, significantly accelerating operator decision-making during critical emergencies; 2) a robust API architecture is established to bridge the frontend and backend, ensuring that heavy computational workloads are offloaded to the server to maintain interface fluidity; and 3) a specialized, LLM-driven AI Copilot is integrated to provide interactive, bilingual support across all operational modules. By providing

end-to-end operational support through an accessible interface, this platform serves as a vital hub, translating complex mathematical optimizations into practical, actionable tools for power utility operators and policymakers.

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