Generative AI-Assisted Risk Assessment and Planning for Distribution Networks

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***Abstract*—This paper proposes an LLM-based multi-agent framework to address critical challenges in distribution network planning, including operational data scarcity, limited risk identification, and non-standardized decision-making planning. The generative AI-assisted framework integrates three specialized agents that collaboratively automate the entire workflow from the construction of physics-ready models to the generation of optimized planning scheme: the Operational Risk Assessment Agent converts non-standardized distribution system data into pre-designed simulation-ready formats for power flow calculation and risk identification; the Planning Requirements Analysis Agent generates specific preliminary measures for distribution network upgrades and constructs formal model specifications through pre-prepared context learning; following the models construction, the Auto-Coding Agent codes executable scripts by leveraging customized formal model specifications, solver APIs, and data interfaces. By integrating prompt engineering and contextual learning, the framework establishes a reliable workflow. Cross-scale validation demonstrates that the framework achieves over 70% accuracy in both data conversion and code generation, enabling precise risk identification and effective planning solutions while maintaining robust generalization across diverse grid scales and LLM engines.**

Keywords*—*Generative Artificial Intelligence; Multi-Agent; Large Language Models; Distribution Network Planning

I. Introduction

Although numerical methods for distribution network planning are mature, their practical implementation is hindered by the vast scale and non-standardized nature of real-world grid data, which traditional tools cannot autonomously convert into physics-consistent models. To bridge this "automation gap," this study utilizes the semantic reasoning and code generation capabilities of Large Language Models (LLMs) as an intelligent interface between unstructured data and deterministic solvers. By automating the transition from fragmented engineering records to executable optimization models, the proposed multi-agent framework effectively overcomes obstacles across the levels of raw data processing, planning analysis, and planning solution generation.

Firstly, at the data level, distribution networks universally face the core bottleneck of missing historical operational data and poor data quality. Their extensive geographical coverage and dispersed monitoring points make incomplete collection or low precision of critical operational data common occurrences. As noted in [2], incomplete data is a primary cause of inaccurate state estimation in distribution networks. Direct analysis based on incomplete, noisy raw data can easily lead to inaccurate risk assessment [3]. Although the utilization of static equipment records and predicted load data provides a viable method to address data gaps, the traditional manual conversion of heterogeneous, non-standard records into simulation-ready formats is cumbersome and error-prone. More importantly, conventional automated scripts struggle to map inconsistent or incomplete textual descriptions to simulation-ready parameters. To address this, LLMs are introduced for their unique ability to perform automated component mapping and parameter extraction.

Secondly, at the planning analysis level, existing methods fail to adequately diagnose operational risks driven by the complex coupling of aging grid structure, load fluctuation, and distributed generation output, making potential cause diagnosis extremely difficult. While conventional sensitivity analysis struggles with such multi-dimensional interdependencies, LLMs offer a unique capacity for semantic reasoning to process massive, unstructured datasets By integrating pre-prepared context learning, LLMs can analyze power flow results alongside natural language prompts to derive rigorous formal model specifications, reducing the complexity of manual problem definition and model building. However, this potential remains underutilized. Literature [4-5] further points out that the current LLMs in network planning is more advanced in the solution phase, whereas the crucial preliminary stages of “problem definition” and “model construction” still heavily rely on planners. Therefore, empowering LLMs with the capacity for autonomous problem structuring and model construction is crucial.

Finally, at the planning solution level, the conversion from an optimization model to executable code remains heavily reliant on manual effort, resulting in low automation. Even given a reasonable mathematical model, accurately encoding it into executable scripts for solvers (e.g., Gurobi) is a complex and time-consuming task. Although generative artificial intelligence (AI) shows great potential in code generation, literature [6] points out that general-purpose LLMs often produce logical errors or API misuse when generating optimization-centric customized code involving complex mathematical modeling and specific library calls, due to a lack of precise domain-specific constraints. Currently, there is a lack of high-quality automatic code generation methods that understand the particularities of power system optimization problems and strictly adhere to coding specifications. This gap prevents the translation of mathematical formulations into executable scripts, thereby impeding the automated acquisition of optimal planning schemes via numerical model solution [7-9].

To bridge these gaps, this study proposes a LLM-based multi-agent collaborative framework. This framework aims to systematically tackle three major challenges through specialized, cooperative agents: automatic data format conversion and simulation-based data completion, context-learning-based risk causation analysis and model formulation, and specification-constrained automatic coding. To enhance the effectiveness and generalization of this framework, prompt engineering, in-context learning, and workflow design are strategically employed to guide these agents toward precise task execution and robust collaboration. Specifically, a standardized data structure is designed to provide a unified

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prompt template, enabling LLMs to accurately convert disorganized raw data into simulation-ready formats. Furthermore, distribution network-related domain knowledge base is constructed as contextual information, empowering agents to perform potential cause diagnosis of operational risks, generate specific preliminary measures, and construct formal model specifications. Additionally, this paper also introduces a rigorous coding specification that decomposes complex optimization problems and models into machine-interpretable components, thereby enabling the reliable auto-generation of executable solver code.

II. Generative AI-Driven Multi-Agent Framework

To enhance the intelligence and automation level of distribution network planning, this paper presents a multi-agent framework including three specialized agents: (1) Distribution Network Operational Risk Assessment Agent (ORA Agent), (2) Distribution Network Planning Requirements Analysis Agent (PRA Agent), and (3) Planning Model Auto-Coding Agent (MAC Agent), as illustrated in Fig. 1. Before the automatic planning, users first collect and provide distribution system data of the target distribution network. This dataset serves as critical input for both the ORA Agent to execute power flow calculations and the MAC Agent for distribution network planning script generation. Upon receiving execution commands, the ORA Agent automatically transforms non-standardized distribution system data into input formats compatible with power flow simulation tools such as PandaPower and OpenDSS scripts. Utilizing these standardized data and predicted load profiles, the ORA Agent performs power flow simulations and analyzes the results to derive operational risk evaluations. Subsequently, the PRA Agent utilizes these power flow and risk assessment outcomes to diagnose potential network weaknesses. By drawing on its integrated knowledge base for in-context learning, the Agent demonstrates the capacity to provide appropriate planning recommendations, such as using capacitor compensation or conductor replacement to resolve voltage violations. Based on these recommendations, the PRA Agent systematically constructs formal model specifications that explicitly define objectives, decision variables, and constraints. Finally, the MAC Agent translates the proposed planning suggestions and mathematical models into executable code. To ensure reliable code generation, three fundamental elements are established for automated LLM processing: (1) explicit model descriptions combining natural language with mathematical formulations, (2) standard format distribution network parameters, and (3) rigorous coding standards that integrate solver APIs specification. Based on these elements, the Agent generates executable scripts to solve optimization models and retrieve results. Upon verifying the solution via simulation, an integrated 'assessment-analysis-optimization' workflow is realized."

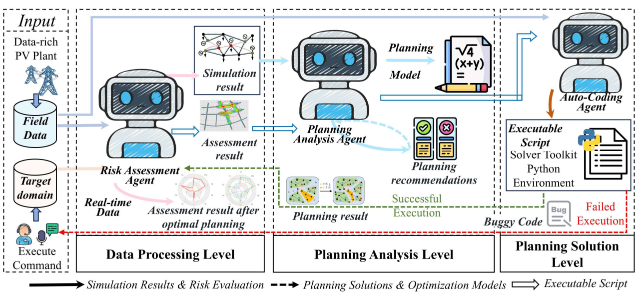


Fig. 1. Mult-Agent Framework

While multi-agent frameworks enable intelligent assessment and planning for distribution networks, general-purpose architectures often suffer from insufficient stability and generalization capabilities. The core challenge lies in the lack of distribution system domain knowledge in generic LLMs. Specifically, inadequate understanding of optimal power flow workflows may lead to erroneous conclusions from the ORA and PRA Agents, while insufficient familiarity with network modeling parameters can prevent the MAC Agent from generating valid scripts. To address these limitations, this study develops specialized optimization strategies through prompt engineering, workflow design, and contextual mechanisms, including a standardized data structure for power flow simulation, contextual information for planning recommendation generation, and standardized formats for improving auto-coding accuracy. These strategies receive specialized implementation across different agents: the ORA Agent employs customized prompts and workflows (Section III.A), the Planning Analysis Agent benefits from contextual knowledge enhancement (Section III.B), and the MAC Agent utilizes prompt engineering to enforce the standardized formats (Section III.C).

III. Multi-Agent Framework Optimization Strategies

A. Specialized Data Structure for Power Flow Simulation

To resolve assessment difficulties caused by missing and heterogeneous operational data in networks, this paper designed a standardized distribution network data structure (Fig. 2) that bridges raw distribution system data and power flow simulation software. Organized in a hierarchical JSON format, this structure provides a unified mapping target that simplifies the extraction of critical parameters from multi-source heterogeneous data. More importantly, it serves as a structural constraint during the MAC Agent's modeling process. By grounding the agent's reasoning within this predefined schema, the framework effectively prevents arbitrary generation and ensures that the extracted parameters remain physically consistent, thereby providing a reliable foundation for subsequent code generation [10-11].

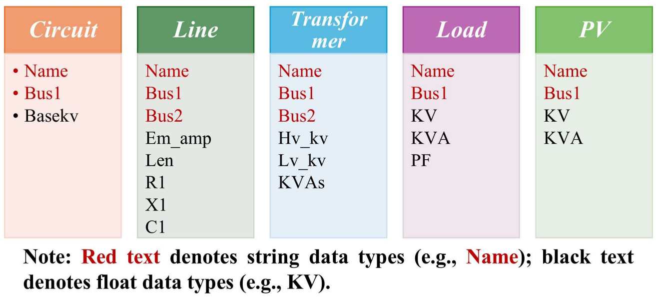


Fig. 2. Layered Nested Entity-Relationship Diagram

In Fig. 2, the Circuit layer defines global distribution grid settings, while the component layers (Line, Transformer, Load, and PV) categorize topology and electrical parameters, such as RLC data, rated voltages, and capacities. Moreover, device names in the Load and PV layers serve as unique keys to link these static network models with external time-series Excel files, enabling the integration of dynamic operational profiles for simulation. Consequently, the Agent leverages this structured foundation to construct physics-based simulation models from non-standard records. Simultaneously, it synthesizes an operational dataset that integrates historical observations and LLM-predicted profiles, effectively capturing the stochastic variability of loads and distributed energy resources. This synthesized data underpins the batch simulations essential for the automated operational risk assessment.

B. *Contextual Information for Planning Analysis*

For precise risk assessment and planning analysis of distribution networks, this paper constructed a domain knowledge base as contextual information for the PRA Agent. This knowledge base integrates documents from technical regulations, typical fault analysis reports, academic literature, and historical planning cases, comprising two main categories: "Network Problem Summaries" systematically documenting common issues like terminal low-voltage, line/transformer overloading, high network loss, and seasonal load fluctuations along with their root causes; and an "Optimization Method Library" detailing mathematical models, applicable conditions, and constraints for various planning measures. The PRA Agent draws upon the Optimization Method Library to select appropriate mitigation measures, thereby generating preliminary planning recommendations. Subsequently, these recommendations are translated into formal mathematical models by leveraging the domain expertise encapsulated in Network Problem Summaries, which enables the PRA Agent to explicitly define objective functions and constraints. The structure and formulation of these model paradigms are elaborated as follows:

$$\min_{\substack{x \in \Phi \\ a \in A \\ m \in M \\ \varsigma \in \Gamma}} / \max \begin{cases} f_{1,S_\Sigma}(x_t, a_t, m, \varsigma) = 0 \\ \ldots\ldots \\ f_{n,S_\Sigma}(x_t, a_t, m, \varsigma) = 0 \end{cases} \tag{1}$$

$$s.t. P(x_t, m) = 0 \tag{2}$$

$$a_t = h(x_t, m, \varsigma) \tag{3}$$

$$q(x_t, a_t, m) \le 0 \tag{4}$$

$$\Phi(q(x_t, a_t, m) \le 0) \le \xi \tag{5}$$

Equation (1) represents the objective function, where f_1 to f_n denote n distinct optimization objectives. The variable x_t captures time-varying state variables such as power and voltage, while a_t reflects external indicators or decision inputs. The parameter m characterizes attributes of the planning objects, and ς represents stochastic elements. The sets Φ, A, M, and Γ denote the state space, indicator space, attribute space, and stochastic factor space, respectively. Equation (2) defines the equality constraints, which enforce fundamental physical laws governing system operation, primarily encompassing energy balance and power flow equations. Equation (3) specifies the indicator computation functions. Equation (4) describes the inequality constraints that establish safety margins and physical limits for system operation. Equation (5) formulates a chance constraint, where α indicates the confidence level.

C. *Standardized Formats and Safety Mechanism for Improved Auto-Coding*

To address accuracy and reliability issues in generating professional optimization code, this paper developed a rigorous coding specification for the MAC Agent. The core concept involves decomposing complex distribution network planning optimization problems into standardized components that are both machine-interpretable and LLM-learnable, comprising three key elements: 1) data interface standards, 2) model definition templates, and 3) solver API specifications. The designed solver API specifications adhere to the standard syntax of solvers like Gurobi, utilizing commands from the gurobipy package for model construction, while data interface standards ensure grid parameters are automatically retrieved from structured JSON files, facilitating the generation of highly detailed model descriptions as illustrated in Fig. 3. Under this framework, provided that the mathematical models constructed by the PRA Agent satisfy physical constraints, the MAC Agent's structured translation guarantees that the generated code precisely preserves these physical laws without logical distortion. This paradigm allows engineers to pivot from the technical intricacies of mathematical modeling and manual coding toward a more strategic analysis of the planning problem itself.

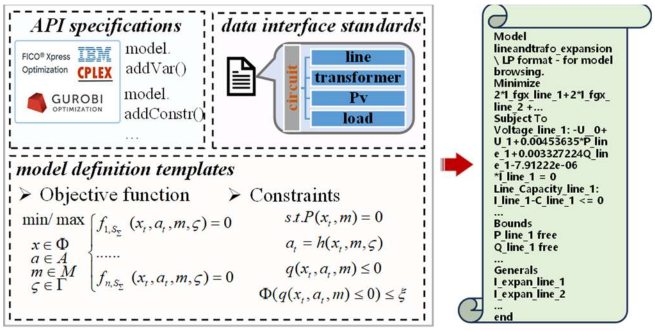


Fig. 3. Auto-Encoding Specification Format of the Optimization Model

To further bolster execution reliability, a feedback-driven safety layer is implemented as a fallback mechanism. Upon executing the generated script, an automated verification mechanism checks the solver's output. If a syntax error is detected, the agent captures the error logs to iteratively modify the code for up to five attempts, after which the task is referred to a human engineer if the error persists. Furthermore, if the solver returns an "Infeasible" status—indicating the model designed by PRA Agent conflict rather than a coding error—the system immediately bypasses further iterations and returns the model to the engineer for manual correction of the underlying optimization logic.

IV. CASE STUDY

This section validates the proposed framework by assessing its data conversion and coding accuracy, evaluating the risk assessment and planning effectiveness, and verifying its overall reliability and generalization across diverse distribution networks and heterogeneous data sources.

A. *Accuracy of the Data Conversion and Code Generation*

To evaluate the proficiency and robustness of the proposed framework, this section conducts a rigorous assessment focusing on the accuracy of both data conversion and code implementation. A validation dataset comprising 80 independent test cases is established to simulate diverse engineering environments. These cases are categorized into four groups based on network scale: 30–50 buses, 50–70 buses, 70–90 buses, and 90–110 buses, with each group containing 20 distinct distribution network. To verify the framework's generalization capability, the input data are derived from four heterogeneous sources: structured tabular ledgers, unstructured technical reports, mixed data sources, and legacy system logs. The ORA Agent converts these heterogeneous formats into the structured data shown in Fig. 2 for power flow calculation in OpenDSS or pandapower. Conversion is deemed accurate if the deviation from actual values remains within 5%, with the resulting accuracy rates presented in Fig. 4. Following the formulation of planning models, the MAC Agent automatically generates code based on formal mathematical models. Successful execution by the solver indicates coding precision, with the corresponding success rates illustrated in Fig. 5.

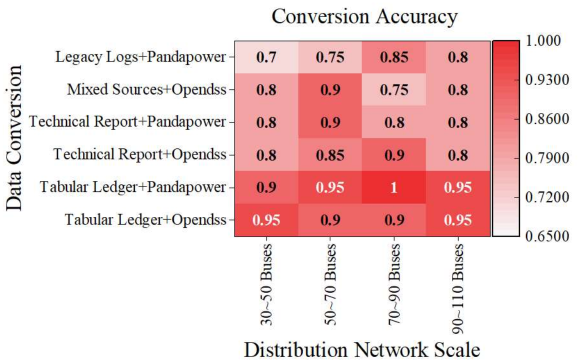


Fig. 4. Data Conversion Accuracy Across Different Grid Scales

As illustrated in Fig. 4, the data conversion accuracy remains robust across all test scenarios, with values typically ranging between 70% and 100%. Structured data sources, such as tabular ledgers, yield the highest precision, achieving a peak accuracy of 100% for the 70–90 bus system. Although unstructured formats like technical reports and legacy logs exhibit slightly lower performance due to their inherent data fragmentation, the accuracy consistently remains above 70%.

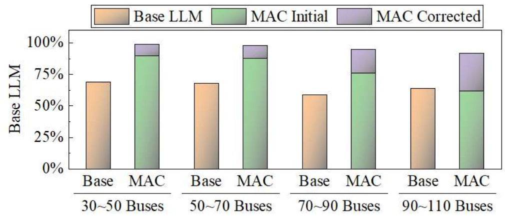


Fig. 5. Code Generation Accuracy of MAC Agent

As shown in Fig. 5, the MAC agent consistently outperforms the base LLM across all network scales. For systems with 30–50 buses, the MAC agent achieves a 90% initial success rate, significantly higher than the 70% of the base LLM. Moreover, the fallback mechanism provides a substantial boost in complex scenarios, yielding a 30% improvement for the 90–110 bus scale and achieving a cumulative success rate of 90%. These results validate the efficacy of the safety layer in ensuring high-fidelity code implementation for large-scale distribution networks.

TABLE I. SUMMARY OF IDENTIFIED OPERATIONAL RISKS AND CORRESPONDING PLANNING RECOMMENDATIONS

Feeder	Operational Risk Assessment Agent		Planning Requirements Analysis Agent		
	Power Flow Results	***Identified Issues***	***Planning Recommendation***	***Optimization Objective***	***Decision Variables***
Feeder 1	Reverse power flow: 527.7kW Voltage rise: 0.203p.u. …	Seasonal load fluctuations causing reverse power flow and overvoltage	Mobile energy storage deployment	Minimize energy storage configuration cost	ESS location and capacity
Feeder 2	Overloading of transformers:141% Overloading of lines:61% …	Overloading of lines and transformers due to high load density	Line upgrading and transformer capacity expansion	Minimize total investment cost	Line types, transformer ratings
Feeder 3	Minimum bus voltage: 0.530p.u. Average bus voltage: 0.804p.u. …	Low voltage issues due to long feeders and thin conductors	Reactive power compensation combined with line replacement	Minimize total investment in line upgrades	Compensation device parameters, line types

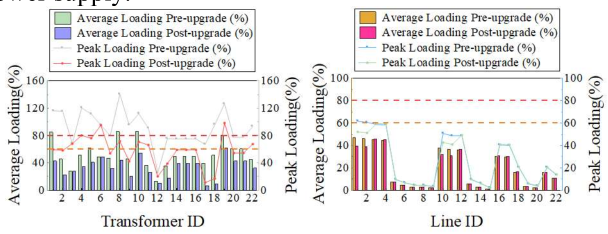
B. Effectiveness of the Risk Assessment and Analysis

The proposed multi-agent framework demonstrates significant efficacy in distribution network risk assessment, as validated through comprehensive testing on three distinct 10 kV feeders. As summarized in Table I, when processing field-surveyed network data, the ORA Agent precisely identified critical vulnerabilities through detailed power flow analysis that quantified specific operational parameters. For Feeder 1, analysis revealed significant reverse power flow (3.85 MW) and substantial voltage rise (0.203 p.u.) during low-demand periods. In Feeder 2, the ORA Agent accurately identified transformer and line overloading issues under high load density conditions. For Feeder 3, the ORA Agent correctly diagnosed voltage drop issues along extended 400V lines. Building on these diagnostics, the PRA Agent leverages strategic prompt engineering to generate targeted planning recommendations and structured optimization models. The MAC Agent subsequently generated executable scripts based on the formulated optimization models. These scripts were executed to obtain optimal planning schemes for the three respective feeders. The following subsections present a detailed simulation-based analysis of the grid performance corresponding to these derived planning suggestions, validating the effectiveness of the proposed solutions.

a) Mobile Energy Storage for Seasonal Fluctuations

b) To address the impact of seasonal load variations, the PRA Agent recommended deploying mobile energy storage and formulated a corresponding optimization model. The model, which aimed to minimize total cost while satisfying power flow and operational constraints, was automatically converted into executable code by the MAC Agent. The optimization results demonstrated a scenario-dependent configuration, where no storage was allocated for closure days and weekdays, while a 200 kWh/50 kW unit (cost: 28×10⁴ CNY) and a 1075 kWh/300 kW unit (cost: 150.5×10⁴ CNY) were required for weekends and holidays, respectively.Capacity Expansion for Overload Mitigation

For the transformer overloading issues of Feeder 2, the PRA Agent constructed an optimization model for capacity expansion, which was coded and solved by MAC Agent. The resulting scheme involved coordinated capacity expansion for a majority of transformers and selective reinforcement of the most severely loaded lines. The results, depicted in Fig. 6, show a significant improvement: transformers that were previously severely overloaded (with maximum load ratios exceeding 120%) were alleviated, with their post-expansion load ratios all reduced to below 100%. The average load ratio across transformers decreased by approximately 30–50%, substantially enhancing the security and reliability of the power supply.



(a) (b)

Fig. 6. Impact Analysis of Capacity Expansion on Transformer/Line Load Rates

c) Coordinated Measures for Low-Voltage Issue

The ORA Agent identified widespread low-voltage issues on Feeder 3, for which the PRA Agent proposed a coordinated solution: relocating transformers and replacing 24.07 km of lines. With an estimated 1.2036 million RMB investment, the optimized scheme raised node voltages from a minimum of 0.55 p.u. to above 0.9 p.u. This demonstrates the framework's effectiveness in integrated problem diagnosis and solution generation.

C. Analysis of Stability and Generalization Enhancement

To assess the stability and generalization of the multi-agent framework, we constructed three ablated versions (Schemes 1–3) by successively removing one of the proposed improvement strategies, and compared them against the complete framework (Scheme 4). Each variant was evaluated on three core capabilities: power flow analysis, planning-oriented model formulation, and automatic code generation.

TABLE II. COMPARISON OF RESULTS FROM DIFFERENT ENHANCEMENT SCHEMES

Enhancement Scheme	Power Flow Computation	Risk Assessment & Modeling	Auto-Coding
1	No power flow results	Unable to generate conclusions	Missing parameters
2	Multi-tool support	Misaligned with core grid issues	Impractical code
3	Multi-tool support	Accurate overload identification	Lacks code comprehension
4	Multi-tool support	Accurate overload identification	Fully operational

As summarized in Table II, Scheme 1 failed during power flow computation, preventing all subsequent functions. Scheme 2 performed flow calculations but generated impractical recommendations and faulty code, reflecting poor semantic comprehension. Scheme 3 succeeded in analysis and modeling but failed in code generation, indicating a breakdown in model-to-code translation. Only Scheme 4 achieved seamless integration across all stages, demonstrating robust tool compatibility, accurate problem identification, and reliable code generation.

Finally, to evaluate the framework's reliability across different underlying LLMs, the end-to-end planning task—comprising data conversion, risk diagnosis, and model formulation—was tested on 20 independent grid samples using various state-of-the-art LLM engines, including GPT-4, Claude 3, and Llama 3. The experimental results revealed high consistency across these platforms, with all engines achieving similar success rates when integrated into the proposed multi-agent cooperative structure. This uniformity suggests that the framework's performance is primarily driven by its systematic multi-agent coordination and specialized prompt engineering rather than the specific choice of the underlying model. Consequently, the framework demonstrates strong technical portability and methodological robustness, ensuring stable and reliable planning outcomes regardless of the specific LLM engine employed.

V. CONCLUSION

This study establishes a generative AI-based multi-agent collaborative framework for distribution network risk assessment and planning. Comprehensive validation demonstrates that the framework achieves high accuracy in both data conversion and code generation, enabling precise risk identification and effective planning across diverse scenarios. The integration of structured workflows and prompt engineering ensures remarkable methodological robustness and generalization across varying grid scales and different LLM engines. Future work will focus on deeper integration with real-time data platforms and extending the framework's decision-making capabilities to accommodate complex scenarios involving distributed energy resources.

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