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From Agent to Swarm and Decentralized Collaboration: Rethinking Power System Collaboration Driven by Large Language Models

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Abstract. With the increasing deployment of renewable energy and distributed energy resources, the power system is becoming more complex and distributed in its operation. Recently, large language models (LLMs) have attracted much attention due to their strong domain knowledge and flexible decision-making abilities, and various forms of multi-agent and decentralized methods have also been introduced to support distributed intelligent organizations. However, the application of these methods to problems in power systems has not been fully realized. Organization structure and coordination mode are the two research topics examined in this paper's theoretical exploration of LLM-based agents. This paper studies the application of LLMs in power-system agents and multi-agent systems, and analyzes the development of swarm and decentralized collaboration based on LLMs in this field. The relationship between the two research directions and the basic conditions under which they can be applied in power system scenarios are investigated. Based on the above analysis, this paper outlines the current research landscape and provides a theoretical basis for future research on integrated intelligent collaboration in complex power system environments.

Keywords: Large Language Models, Multi-Agent Systems, Swarm and Decentralized Organization, Power Systems, Intelligent Agents

1. Introduction

Given the world's "dual carbon" goals, modern power systems are undergoing structural changes, they will no longer be planned and centrally operated but will be more uncertain and have a more distributed structure. With the large-scale application of renewable energy and the rapid development of distributed energy resources, the control boundary of the power system has also been gradually extended from a few large power plants to numerous end-use devices. Major power blackouts have also shown that the traditional centralized scheduling framework based on operating modes is no longer suitable for dealing with the increasingly complex operational characteristics of the new power system.

Although a variety of artificial intelligence methods have been investigated and applied in power system scenarios, these methods still face inherent limitations. Traditional machine learning is

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constrained by limited cross-task generalization capability, deep learning demands large-scale labeled datasets and suffers from poor interpretability, reinforcement learning is confronted with the challenge of low sample efficiency. Since 2025, Large Language Models (LLMs) have exhibited strong performance in semantic understanding, commonsense reasoning, and few-shot learning, achieving encouraging results in load forecasting, domain knowledge question answering, and other power system applications [1, 2].

However, the power system is essentially a multi-agent, multi-objective, and multi-timescale system. A standalone large language model (LLM) is incapable of realizing large-scale system-level coordination. In comparison, multi-agent systems (MAS) are well suited to the distributed "source-grid-load-storage" architecture of power systems, and have been applied to microgrid coordination and distributed optimization tasks [3]. However,traditional MAS agents operate based on rigid rules or task-specific models, lacking sufficient cognitive flexibility.

Two mainstream technology combinations have gradually emerged in existing research: the LLM enhanced multi-agent system applied to the power system and the LLM driven decentralized group organization frameworks. Despite significant initial progress, the paradigm of integrating LLM, decentralized group organizations, and power systems is still under explored.

This paper presents a structured overview of this research and investigates the theoretical feasibility of integrating large language models, decentralized organization and power system multi-agent coordination. It provides a theoretical basis for future research on integrated intelligent collaboration in complex power system environments.

2. Basic theory

2.1. Basic theory of Large Language Models

Large Language Models (LLMs) are artificial intelligence models that have been trained on vast amounts of data and use deep neural networks to learn language rules and world knowledge. The foundation of these models is large-scale pre-training and parameterized knowledge learning, which enable them to learn how to process language and knowledge within a single parameter space. They can obtain basic knowledge representations and use in-context learning and knowledge augmentation to generate information and perform logical reasoning based on input data, helping them handle different tasks. Therefore, LLMs can process large amounts of knowledge, understand semantics, reason over knowledge, and generate content through parameterized learning [1, 2, 4].

2.2. Basic theory of multi-agent systems

A multi-agent system consists of multiple independent intelligent agents that can perceive, reason and act. Each agent in the system has its own goals, an internal state and the ability to choose actions, and can observe and assess the world based on the information it has gathered. When multiple agents work together to achieve a goal, they communicate and exchange information among themselves, divide the work, negotiate, and coordinate their actions toward the shared goal. The defining feature of a multi-agent system is the interaction and coordination among its agents, rather than their number. Therefore, the basic characteristics of agents can be summarized as agent autonomy, interaction with the environment, communication among agents, task coordination and goal orientation [5-8].

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2.3. Basic theory of decentralized organizations

A decentralized organization is one that does not have a single central body for decision-making and control, instead, it is organized by distributing decision-making authority and coordinating the actions of various relatively independent units to achieve the goals of the entire organization. A centralized organization collects information, makes decisions at the top, and then instructs the various parts of the organization. In contrast, a decentralized organization has relatively independent units that can operate independently based on local information, and coordination is achieved through direct communication, sharing of information, negotiation, etc. Over time, the entire structure and behavior of the organization will gradually emerge as a result of the actions of many individuals. Therefore, the main features of a decentralized organization are the distribution of power and decision-making, entity autonomy, the use of local information, horizontal interaction and self-organization [9].

3. Research status of LLM-enabled intelligent agents in power systems

3.1. Traditional multi-agent collaboration in power systems

Before the emergence of large language models, multi-agent systems were widely applied to distributed power-system coordination. Zhou et al. systematically reviewed multi-agent applications in microgrid optimization, demand response, and electricity market simulation [1]. Du et al. further analyzed the evolution of power-system intelligence from traditional multi-agent coordination toward LLM-enhanced collaboration [4]. However, agent roles, decision rules, and communication mechanisms are generally predefined, limiting their adaptability to complex and dynamic environments [1, 4].

3.2. LLM-based intelligent agents in power systems

Recent research has introduced LLMs into power-system analysis and decision-making. Several review studies have summarized the applications of LLMs in forecasting, fault analysis, operation, control, decision support, and agentic AI frameworks for smart grids [1-4]. In terms of specific applications, Zhao et al. proposed a large language model-based power dispatch agent and demonstrated its application in economic dispatch, congestion management, and contingency analysis [10]. Dong et al. investigated customized large-model agents for smart-grid operation, while Rojas et al. proposed solver-grounded architectures that use LLMs for task decomposition and external solvers for numerical calculations [8, 11]. Taken together, these studies show a shift from LLM-based information assistance toward task-oriented power-system agents, although multi-agent interaction and decentralized organization remain limited [3, 8, 10, 11].

3.3. LLM-enhanced multi-agent collaboration

Researchers have further combined LLMs with multi-agent systems and reinforcement learning. Chen et al. proposed MAPPO-LLM, introducing LLM-guided prior knowledge into multi-agent reinforcement learning for coordinated smart-grid control [5]. Xia et al. embedded LLMs into multi-agent reinforcement learning for low-carbon scheduling of integrated energy systems [6]. Zhang et al. surveyed LLM-enhanced reinforcement learning methods for smart grids and discussed their potential for coordinated optimization [12]. Dong et al. also developed a mixture-of-agents architecture in which specialized agents handle load, generation, safety, and market tasks under a

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supervisor agent [11]. These studies demonstrate the feasibility of incorporating LLM-based knowledge and guidance into multi-agent decision-making, but the agent roles and organizational structures remain largely predefined [5, 6, 11, 12].

3.4. LLM-based swarm and decentralized collaboration in related fields

LLM-based swarm collaboration has also been explored in robotics and UAVs. Jiang et al. investigated spontaneous social interaction among LLM-powered swarm robots, demonstrating the potential for collective interaction and emergent behavior [9]. Cui et al. developed an LLM-based multi-agent method for UAV swarm inspection path optimization and defect identification, including energy-infrastructure inspection scenarios [13]. These studies demonstrate the emerging use of LLM-based agents for collective task coordination and optimization, but their application to power-system operation and control remains limited [9, 13].

3.5. Research gaps

Existing research has progressively developed from traditional multi-agent coordination to LLM-based power agents, LLM-enhanced multi-agent learning, and LLM-based swarm collaboration in related fields [1-15]. However, existing power-system intelligent agents generally rely on predefined roles and coordination structures, while autonomous organization and dynamic decentralized collaboration remain insufficiently explored [1, 5, 6, 11]. Systematic evaluation of decentralized collaboration is also limited. Trashchenkov proposed an executable benchmark covering 41 power-engineering tasks for quantitative evaluation of AI agents under power-system constraints [14], but decentralized swarm coordination is not specifically addressed. These gaps motivate further investigation of integrated intelligent collaboration frameworks that combine LLM-based cognitive capabilities, decentralized organization, and power-system multi-agent coordination while satisfying physical, reliability, and real-time constraints.

4. Comparative analysis and theoretical outlook of integrated frameworks

4.1. Comparative analysis of LLM–multi-agent and LLM–decentralized collaboration frameworks

Based on the research reviewed in Section 3, two core research directions can be identified: the integration of large language models with traditional multi-agent systems for power-system applications, and their integration with swarm intelligence or decentralized collaboration. Both directions use LLMs for reasoning and decision support, but differ in their organizational structures and coordination mechanisms.

The integration of LLMs with traditional multi-agent systems has been relatively well explored in power systems [5, 6, 10-12]. These frameworks combine the reasoning and knowledge-processing capabilities of LLMs with predefined agent roles and coordination mechanisms. Their main advantage is that agent responsibilities and interactions can be explicitly designed, facilitating the incorporation of power-system constraints and domain-specific optimization objectives. However, many existing frameworks still depend on predefined roles, hierarchical supervision, or fixed coordination structures [5, 6, 11].

In contrast, LLM-based swarm and decentralized collaboration emphasizes local interaction, collective coordination, and potentially emergent organizational behavior [9, 13, 15]. Compared

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with predefined multi-agent architectures, decentralized collaboration offers greater potential for dynamic task allocation and organizational adaptation. However, its application to power-system operation and control remains limited [9, 13, 15]. Therefore, the two approaches exhibit complementary characteristics: power-system multi-agent frameworks provide stronger domain constraints and established coordination mechanisms, whereas decentralized collaboration offers potential for more flexible organizational adaptation.

4.2. Theoretical feasibility of integrating LLMs, decentralized organization, and power-system multi-agent coordination

The analysis in Section 3 suggests that integrating LLMs, decentralized organization, and power-system multi-agent coordination is theoretically feasible because the three components address different functional requirements. LLMs can provide language-based knowledge processing, contextual reasoning, and decision support, while multi-agent systems provide explicit agent-level task allocation and coordination mechanisms [1, 3-6]. Decentralized organization can distribute decision-making authority, and agents can make decisions based on local information and coordinate their actions rather than relying on a single supervisory agent.

Existing studies provide support for some of these components. MAPPO-LLM and LLM-embedded multi-agent reinforcement learning have shown that LLM-derived knowledge can be used to coordinate decisions [5, 6]. Meanwhile, swarm-oriented studies have shown that LLM-based agents can participate in collective interaction and optimization [9, 13, 15]. These studies suggest that the three functional components can complement each other, although their full integration into power-system operation and control remains insufficiently explored.

4.3. Theoretical challenges of the integrated framework

Several theoretical challenges remain. First, because of severe weather and other adverse conditions in the power system, decentralized decision-making cannot be carried out. Local agents should coordinate their actions to achieve the goals of power balance, stability, security and reliability for the system.

Second, agents need mechanisms for communication, task assignment and coordination. Unlike systems with fixed multi-agent architectures, decentralized systems must determine when agents should cooperate, which agents should communicate, and how to distribute responsibilities based on current system conditions.

Third, LLM-based decision support requires verification. Recently, more attention has been paid to autonomous, safe and explainable agentic AI in smart grids [3], and solver-grounded architectures have begun to use external numerical solvers for reliable computation [8]. LLMs should not be used as independent numerical controllers, rather, their outputs need to be combined with physical models, optimization algorithms and verifiable constraints.

Finally, systematic evaluation remains limited. The Power Systems Agent Benchmark is an executable framework for evaluating AI agents on 41 power-engineering tasks , but it does not cover decentralized collective behavior and dynamic organizational adaptation. Therefore, future evaluation frameworks should consider the performance of individual agents as well as the coordination efficiency, adaptability, reliability, safety and overall system performance [14].

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5. Conclusion

This paper introduces the development of large language model-based agents in power systems and examines the prospects for combining large language models with multi-agent coordination and decentralized organization. Research has gradually expanded from traditional multi-agent coordination to LLM-based power-system agents and LLM-enhanced multi-agent coordination. Research on swarm intelligence in related fields has also provided new insights into decentralized coordination. However, existing approaches still face limitations, including fixed agent roles, relatively rigid organizational structures, and limited dynamic coordination capabilities, while the systematic evaluation of decentralized group behavior remains insufficiently explored. Based on the above comparison, this paper argues that integrating the cognitive capabilities of large language models with decentralized organization and multi-agent coordination in power systems is theoretically feasible, as these components can complement each other in decision-making, task allocation, and distributed collaboration. Nevertheless, the full integration of these components and the effectiveness of the resulting framework under practical power-system constraints remain open research questions.

The paper's contributions are to summarize the progress of the previous studies, identify gaps in large language model-based multi-agent systems and decentralized coordination, and provide theoretical support for building integrated frameworks in the future. Future research could improve the present large language model-based multi-agent architecture, introduce decentralized and swarm intelligence mechanisms for powering the operation of power systems, and develop communication, security, coordination and evaluation mechanisms for the integrated framework. One problem of this paper is that it is only a theoretical study and has not yet built a model, designed an algorithm or carried out independent numerical tests. Therefore, the following studies will extend the theoretical basis of this paper through models, simulations and experiments.

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