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Perspective

Generative artificial intelligence: Pioneering a new paradigm for research and education in smart energy systems

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ABSTRACT

Promoting low-carbon energy systems as a centerpiece of global sustainable development goals is essential. As part of this low-carbon transition, smart energy systems have been an active area of research and education, where artificial intelligence (AI) intersects with energy science. It is an emerging area where research and education face new challenges as new knowledge keeps coming in. During this process, generative artificial intelligence (GAI) plays a critical role in education and research activities. However, GAI's impact on smart energy systems research and education is less discussed. Especially, its impact on education is rarely discussed when compared to research. GAI reshapes both the research process and the roles of teachers and students in the course. This perspective offers insights into the ongoing research and education paradigm shifts observed in the smart energy system. This perspective synthesizes existing studies on "GAI for Science" and "GAI for Education" practices in the field of smart energy systems. In research, the impact of GAI is discussed from both macro and micro levels. In education, this perspective examines how a GAI-driven teaching approach addresses the challenges of teaching smart energy systems compared to the traditional approach. This perspective could benefit the discussion of GAI-reshaped research and education in energy science.

1. Introduction

Amid the escalating global energy demand and the intertwined climate crisis, smart energy systems[1], pivotal for achieving carbon neutrality, have grappled with the persistent challenge of insufficient "smartness" despite decades of development. Traditional technological frameworks primarily rely on automated instrumentation and information-communications technology, which are essentially an integration of mature technologies. In recent years, groundbreaking advancements in generative artificial intelligence (GAI) have injected new momentum into smart energy systems. Unlike traditional AI, which builds a separate dataset and model for each task, GAI draws on broad pre-trained knowledge. It can tune a task-specific model with less data and effort. For smart energy systems, this means faster data handling. More importantly, the shared knowledge opens new ways to solve complex, interdisciplinary problems. Nowadays, leveraging its capabilities in multimodal information processing, semantic understanding, and creative generation, GAI is progressively being integrated into the smart energy systems technological framework[2,3]. This perspective systematically explores the cognitive revolution in smart energy systems driven by GAI, unveils innovative pathways in smart energy systems research and education, and offers references and insights for the low-carbon transition.

For research, influenced by economic and demographic developments, the scale of energy systems is rapidly expanding. This growth is accompanied by the challenge of traditional technological frameworks becoming inadequate due to increased scale and complexity. Simultaneously, the integration of new elements such as hydrogen, electricity trading, and vehicle-to-grid interactions has rendered energy systems not only physically complex but also

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increasingly intricate at the informational level. GAI, through extensive pre-training on vast prior knowledge, effectively addresses this dual complexity in both physical and informational dimensions.

For education, the traditional approach tends to focus on the systematic transmission of theoretical knowledge. However, when confronted with complex interdisciplinary problems, traditional teaching approaches have not effectively fostered students' interdisciplinary integration skills[4]. While students may acquire a solid theoretical foundation, they often struggle to organically integrate knowledge from various disciplines into practical applications. Moreover, the traditional "one-size-fits-all" educational model overlooks individual differences in students' interests, abilities, and learning paces, resulting in a lack of personalized training. This hinders the full realization of students' potential, making it difficult to meet the talent demands of the rapidly evolving smart energy systems field, which requires the integration of multidisciplinary knowledge and the ability to solve creative problems.

For this end, this perspective will primarily focus on the research and education practices of GAI within smart energy systems. Explore the innovative applications of GAI in both research and education for smart energy systems, highlighting its significant role in these domains. Furthermore, this perspective discusses the potential challenges and opportunities that GAI presents for future research in the smart energy systems field. The aim is to inspire more researchers and educators to engage in this critical field, thereby contributing to its advancement and development.

2. "GAI for science" in smart energy systems research

The primary manifestation of GAI in smart energy systems research lies in its data processing capabilities. Traditional methods, constrained by computational power, often struggle to handle large-scale data processing scenarios. This drawback becomes increasingly pronounced as energy systems expand. GAI effectively addresses this issue because of its excellent data processing capabilities and its ability to fuse multimodal data. Accordingly, this perspective divides the applications of GAI in smart energy systems into micro and macro levels based on the scope of application, as shown in Fig. 1. The reason for adopting this micro-macro classification is to provide a clear analytical framework that corresponds to the different scales and scopes of challenges encountered in smart energy systems. At the micro level, GAI is applied to specific scientific and engineering tasks, such as modeling complex thermal fluid dynamics or accelerating simulations, where improvements are measured in terms of precision and computational efficiency. At the macro level, GAI addresses larger-scale, system-wide problems, such as energy load forecasting, fault diagnosis, and optimization of operational strategies, where the emphasis is on integrating diverse data sources, uncovering cross-domain relationships, and making comprehensive decisions. This two-level classification enables a more nuanced understanding of how GAI contributes both to the advancement of core scientific processes and the transformation of overall system operations in the energy domain. This perspective will explore and analyze the current state of GAI applications at both these levels, delving deeply into the roles and impacts of GAI within these contexts.

At the micro level, the application of GAI in smart energy systems primarily focuses on thermal fluid science, aiming to support complex thermal fluid phenomena, process calculations, and related analyses. According to Matteo's statistics, the number of publications in the field of thermal fluid science and engineering with a focus on AI has grown at an annual rate of approximately 60 % since 2017, whereas the overall growth rate of the entire thermal fluid science and engineering field is only 7 %[5]. This underscores its potential and the enthusiasm for research in this area. Through a review of relevant studies in this field, the role of GAI at the micro level can be summarized as an "engine." Rather than introducing significant innovations in methods or frameworks, GAI primarily leverages existing mature approaches to drive the acceleration and accuracy of thermal fluid modeling, simulation, and computation. Recent advancements in large-scale generative models, such as GPT and diffusion models, have further expanded the capabilities of GAI in thermal fluid science. These models, trained on vast datasets, can generate high-fidelity simulations and predict complex fluid behaviors with unprecedented accuracy. For instance, transformer-based architectures have been adapted to model turbulent flows, leveraging their ability to capture long-range dependencies in fluid dynamics data. This enables more accurate predictions of turbulence and flow patterns, which are crucial for optimizing smart energy systems. Additionally, diffusion models, which are excellent in generating high-quality data, have been applied to create synthetic turbulence datasets, enabling researchers to train more robust models even when experimental data is scarce. Ning[6] *et al.* proposed a non-intrusive fluid simulation acceleration method based on diffusion probability models,

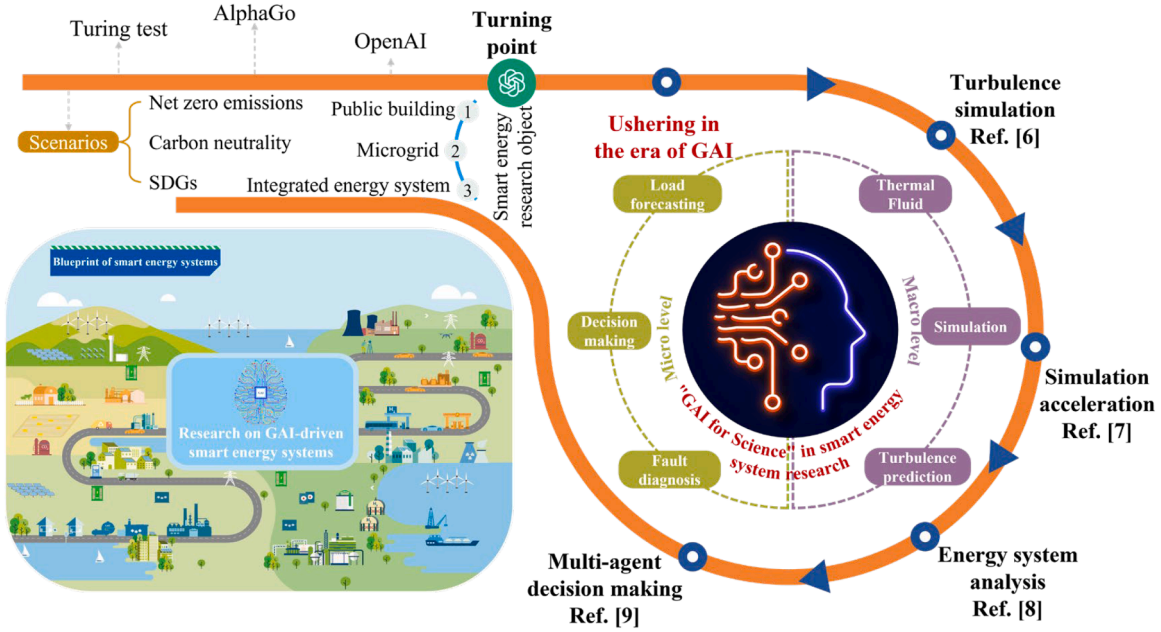

Fig. 1. "GAI for Science" in smart energy systems research.

utilizing GAI techniques to expedite the convergence process of computational fluid dynamics simulations. Their study demonstrates that applying GAI not only achieves a speedup factor of up to 2.4 but also significantly enhances the solution accuracy for traditionally challenging-to-converge samples in simulations. This provides an efficient and robust acceleration strategy for complex flow simulations. Du [7] *et al.* employed conditional neural field encoding and latent diffusion models to achieve high-fidelity, stochastic turbulence generation by performing the diffusion process in a compact latent space. Experiments demonstrate that this model is excellent in various complex geometries and turbulent conditions, significantly outperforming traditional methods and existing deep-learning models.

At the macro level, the application of GAI focuses more on novel solutions to emerging problems. Typical examples include load forecasting, fault diagnosis, and optimization of energy system decisions. Unlike the emphasis on data processing capabilities at the micro level, GAI's macro-level applications lean more toward leveraging the ability to uncover potential connections among various elements, supporting energy system operational decisions and providing forward-looking recommendations. For instance, Lai[8] et al. successfully transferred a pre-trained BERT model to a wind power prediction dataset by aligning language models with spatiotemporal data, effectively applying it to downstream load forecasting tasks. Similarly, Feng[9] et al. utilized the T5 model to predict carbon emissions from industrial users, achieving a generalizable model across multiple targets through prompt engineering and minimal fine-tuning. The precision and broad applicability of generative language models are important for optimizing resource allocation in distributed energy systems and adapting to more complex and diverse scenarios.

Compared to subtasks, system-level operational decisions better demonstrate the logical analysis and reasoning capabilities of GAI. While providing approaches for optimizing decision-making in distributed energy systems, traditional reinforcement learning and other machine learning methods often encounter challenges such as convergence difficulties and high training costs. These methods typically require extensive trial-and-error processes to learn optimal action strategies, leading to resource wastage or unnecessary risks in highly complex and uncertain energy environments. In contrast, GAI, particularly GAI based on large pre-trained models, can achieve effective decision-making outcomes without requiring additional large-scale training. They can be quickly transferred to specific tasks and optimized through targeted fine-tuning. Moreover, the strong generalizability of GAI models allows them to be flexibly applied to diverse scenarios, not limited to a single type of energy system. Whether optimizing power dispatch, managing energy storage facilities, or planning renewable energy output portfolios, GAI can provide effective optimization solutions. For example, Xiao [9] *et al.* proposed an LLM-based multi-agent framework that automatically optimizes building energy systems through a three-stage process, delivering reliable optimization results at a lower cost.

3. "GAI for education" in smart energy systems course

As the global construction of new energy system frameworks accelerates, the current isolated and outdated foundational knowledge systems in the energy sector are increasingly inadequate to meet the talent development needs for future advancements in smart energy systems. For instance, the configuration of energy storage in the power system often involves a wide range of knowledge, including electrochemistry (battery selection), control science (battery temperature control), thermodynamics (efficient heat exchange), and economics (cost accounting). There is an urgent need to cultivate a group of interdisciplinary professionals in the smart energy systems field who possess both digital and informational expertise, as well as the ability to integrate knowledge across multiple disciplines.

The current teaching approach delineates knowledge boundaries along single-discipline lines, with course content struggling to keep pace with the rapid advancements in smart energy systems. Course instruction predominantly follows a one-way knowledge transmission model, and students are confined within standardized evaluation frameworks. This fragmented approach fails to foster cross-domain thinking and falls short of cultivating the creative problem-solving skills essential for the development of smart energy systems. GAI, with its robust knowledge integration capabilities, innovative problem-solving abilities, and human-machine collaboration and interaction features, can inject new vitality into the traditional teaching approach, as shown in Fig. 2. It can break disciplinary boundaries, enhance teaching efficiency, optimize evaluation systems, and promote the development of students' cross-domain thinking and innovation capabilities, thereby providing strong support for cultivating interdisciplinary talents in the field of smart energy systems. Numerous examples of GAI for education already exist. Platforms like Knewton[10], which are based on artificial intelligence, offer real-time feedback and dynamically adjust learning paths based on student interactions, creating more interactive and self-paced learning experiences. Similarly, tools such as Gradescope[11] utilize GAI to assess student progress and identify trends, reducing the administrative burden on educators while providing richer insights into student learning. Additionally, Wu[12] *et al.* developed a web-based K-12 GAI education platform named "Mo", to address two key challenges: the transition of GAI practices from higher education to K-12 education and the uneven distribution of GAI education resources. By offering features such as an online learning environment, resource sharing, and community support, the platform has been piloted in multiple schools, receiving positive feedback and demonstrating significant impact. These examples of GAI for education initiatives highlight how GAI is reshaping traditional education models, paving the way for a more inclusive, adaptive, and effective learning ecosystem.

In the energy science sector, Stecyk[13] et al. focus on the temporal alignment of GAI with smart energy education, reviewing the evolution of energy education—from engineering disciplines in the early 20th century to mid-century energy research projects and further to sustainable development and energy systems engineering in the early 21st century. In recent years, with the integration of AI and GAI technologies, energy education has begun to shift towards intelligence and interdisciplinary approaches. A more illustrative example is the work of Popadić et al. [14] who explored how GAI and knowledge graph technologies can address data management and interoperability challenges in the energy sector, demonstrating their potential applications in energy education and management. Pan[15], in his new book "Artificial Intelligence 2.0″, provides a case study on the application of GAI in education within the smart energy systems field. In this case, students are categorized into three types: the first group is familiar with AI but lacks knowledge of the energy sector; the second has a strong background in energy but lacks coding skills; and the third possesses both areas of knowledge and is eager to take on challenges. Taking the distinct characteristics of these three groups into consideration, an integrated energy advisor (IEA) is developed. The IEA is actually a large language model assistant used for teaching smart energy. It is obtained by fine-tuning the pre-trained model with knowledge within the field of smart energy. In teaching, it is open to students to assist in answering questions and exploring innovative solutions to complex problems. These endeavors in GAI for smart energy systems education all highlight its immense potential in driving educational innovation, enhancing students' interdisciplinary capabilities, and tackling the complex challenges of smart energy systems.

4. Challenges and opportunities

GAI-driven smart energy system education remains an emerging field that urgently needs innovations. Still, significant challenges and future opportunities exist, ranging from educational transformation to technological innovation and talent cultivation. The three major challenges of GAI in the field of smart energy from application, research and

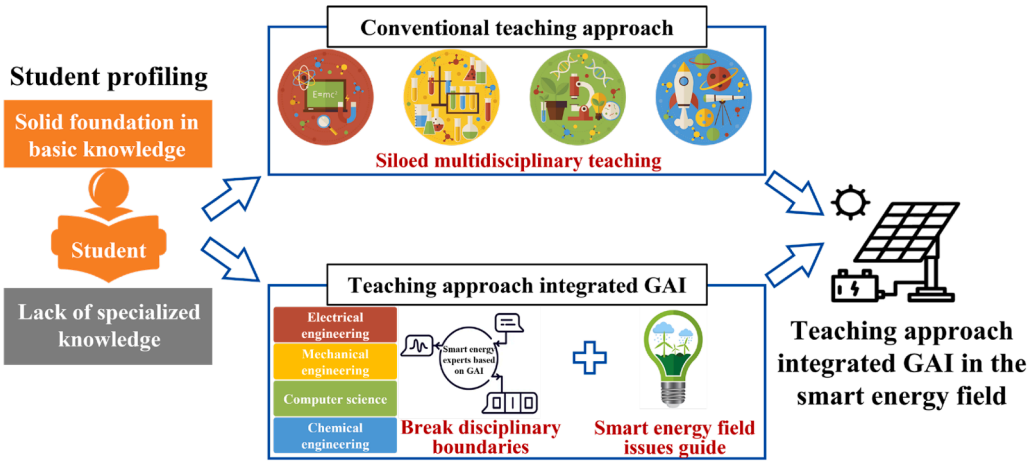

Fig. 2. "GAI for Education" in smart energy systems course.

development to teaching were listed in this perspective as shown in Fig. 3.

Challenge #1 in GAI for education: Multi-modal general "large" language model integrated with professional "small" language models

The current energy domain education lacks top-level systematic integration courses to help students connect multiple professional courses and apply them in an integrated project. Therefore, professional "small" language models and general "large" language models are needed to change the traditional classroom teaching mode of teachers. Additionally, the development of such complex systems requires collaboration among top-tier universities, leading industry enterprises, GAI technology companies, and hardware companies.

Challenge #2 in GAI for science: Interpretable GAI-driven new paradigm for scientific research and interdisciplinary knowledge integration

The current AI-driven new paradigm for scientific research lacks closed-loop validation from law discovery and logical deduction to experiments or simulation. E pointed out that it is necessary to strengthen the top-level design of China's GAI for Science[16]. In the future, smart energy systems will extend beyond the energy scope and urgently require interdisciplinary collaboration among mechanics, control, artificial intelligence, etc. Another challenge is ensuring privacy and security in GAI for science. This involves data encryption and storage isolation, as well as realizing the GAI system's security reinforcement and data traceability throughout the full life cycle.

Challenge #3 in GAI for students: Student-in-the-loop personalized learning and multi-dimensional learning quality assessment tools

It is necessary to utilize the GAI education system to break through the traditional teaching dilemmas and design personalized teaching content at multiple levels, namely basic, advanced, and innovative. Through data analysis, the hierarchical relationships of common difficulties among students can be visualized and the characteristics of important knowledge points can be quantified. The GAI-based teaching assessment tools can conduct multi-dimensional evaluations of students' learning processes, innovative ideas, teamwork, and knowledge mastery. However, objective assessment criteria and systems are still lacking.

With the further development of GAI technology, a transformative revolution will be achieved in the education and science of future smart energy systems. Foundational models in various subdivided professional fields will be built by GAI. How GAI can be integrated to achieve interdisciplinary innovation and integrated applications in smart energy systems will become more important, as it can greatly break through the traditional energy scope and address challenges of global climate change and environmental sustainability.

CRediT authorship contribution statement

Xiaojie Lin: Writing – review & editing, Supervision, Project administration, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Zheng Luo:** Writing – original draft, Visualization,

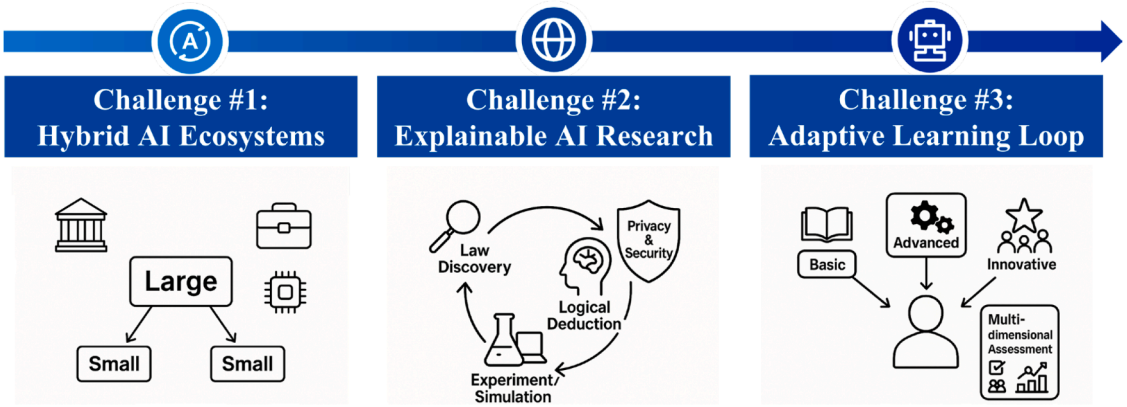

Fig. 3. The challenges that GAI brings to the smart energy field.

Validation, Software, Resources, Investigation, Formal analysis. **Liuliu Du-Ikonen:** Writing – review & editing, Project administration, Data curation. **Xueru Lin:** Writing – review & editing, Methodology, Investigation. **Yihui Mao:** Writing – original draft, Supervision, Resources, Project administration, Data curation. **Haoyu Jiang:** Writing – original draft, Methodology, Investigation. **Shuai Wang:** Writing – review & editing, Project administration, Funding acquisition, Data curation. **Chongshuo Yuan:** Writing – original draft, Resources, Formal analysis. **Wei Zhong:** Writing – review & editing, Funding acquisition, Conceptualization. **Zitao Yu:** Writing – review & editing, Project administration, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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