Applying Large Language Models to Power Systems: Potential Security Threats

Jiaqi Ruan, Member, IEEE, Gaoqi Liang, Member, IEEE, Huan Zhao, Member, IEEE, Guolong Liu, Member, IEEE, Jing Qiu, Senior Member, IEEE, Junhua Zhao, Senior Member, IEEE, Zhao Xu, Senior Member, IEEE, Fushuan Wen, Fellow, IEEE, and Zhao Yang Dong, Fellow, IEEE

Abstract—Applying large language models (LLMs) to power systems presents a promising avenue for enhancing decision-making and operational efficiency. However, this action may also incur potential security threats, which have not been fully recognized so far. To this end, this letter analyzes potential threats incurred by applying LLMs to power systems, emphasizing the need for urgent research and development of countermeasures.

Index Terms—Power systems, large language models, security threats.

I. INTRODUCTION

N the dynamically evolving landscape of the power sector, characterized by a growing reliance on renewable energy sources and the integration of diverse grid-connected entities, the complexity and openness of power systems have intensified [1]. This evolution presents substantial challenges for power system operators who are tasked with intricate scheduling decisions within an ever-expanding operational scope. In response, the deployment of large language models (LLMs) [2]—sophisticated deep-learning frameworks trained on extensive text corpora—has emerged as a transformative solution. These models excel in understanding and generating human-like linguistic expressions, equipping operators with tailored tools for managing complex scenarios more effectively.

The integration of LLMs signifies a significant advancement in addressing the complexities and decision-making

This work was supported in part by the National Natural Science Foundation of China under Grant 72331009 and Grant 72171206; in part by the Shenzhen Institute of Artificial Intelligence and Robotics for Society (AIRS); in part by the Shenzhen Key Lab of Crowd Intelligence Empowered Low-Carbon Energy Network under Grant ZDSYS20220606100601002; in part by PolyU under Grant YY4T and Grant YY5T; and in part by GRF Project under Grant PolyU15209322. (Corresponding authors: Gaoqi Liang; Zhao Xu.)

Jiaqi Ruan and Zhao Xu are with the Department of Electrical and Electronic Engineering, The Hong Kong Polytechnic University, Hong Kong (e-mail: jiaqi.ruan@polyu.edu.hk; eezhaoxu@polyu.edu.hk).

Gaoqi Liang is with the School of Mechanical Engineering and Automation, Harbin Institute of Technology, Shenzhen, Shenzhen 518055, China (e-mail: lianggaoqi@hit.edu.cn).

Huan Zhao, Guolong Liu, and Junhua Zhao are with the School of Science and Engineering, The Chinese University of Hong Kong, Shenzhen, Shenzhen 518172, China (e-mail: zhaohuan@cuhk.edu.cn; liuguolong@cuhk.edu.cn; zhaojunhua@cuhk.edu.cn). Junhua Zhao is also with the Shenzhen Institute of Artificial Intelligence and Robotics for Society, Shenzhen 518129, China.

Jing Qiu is with the School of Electrical and Information Engineering, The University of Sydney, Sydney, NSW 2006, Australia (e-mail: jeremy.qiu@sydney.edu.au).

Fushuan Wen is with the College of Electrical Engineering, Zhejiang University, Hangzhou 310027, China (e-mail: fushuan.wen@gmail.com).

Zhao Yang Dong is with the School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore 639798 (e-mail: zy.dong@ntu.edu.sg).

challenges of modern power systems. Possessing capabilities in natural language processing, image recognition, and time series analysis [3], LLMs act as powerful, multifaceted tools for navigating the complex data milieu of power systems. They enhance the extraction of critical information from vast datasets, strengthening the foundations of scheduling and policy optimization. Leveraging their robust analytical and logical reasoning capabilities, LLMs facilitate intelligent data retrieval and question-answering, enabling the analysis of various inputs such as historical load data, weather forecasts, and real-time news. This significantly contributes to the formulation of sophisticated optimization strategies. Moreover, LLMs enrich human-computer interactions [4] within power systems, allowing for intuitive presentations of complex data and forecasts, thereby supporting operators in making wellinformed, high-quality decisions. The application of LLMs in power systems not only enhances dispatch accuracy and efficiency but also highlights their role in improving system adaptability and stability, opening new avenues for research and promising commercial prospects.

However, alongside the growing interest from major power groups in developing LLMs for power systems, this application also introduces significant security concerns [5]. While LLMs offer numerous benefits, their deployment within increasingly open power systems can also lead to potential security threats, particularly in data security and decision-making stability. Currently, there is a notable gap in research and investigation into these issues. This letter aims to address this gap by providing an in-depth analysis of potential threats posed by LLM applications in power systems, thereby enriching the understanding within both academic and industrial communities and steering the development of more secure LLMs for power system applications.

II. POTENTIAL THREATS OF LARGE LANGUAGE MODELS IN POWER SYSTEMS

A. Large Language Models in Power Systems

As traditional power systems evolve into cyber-physical power systems (CPPS), the integration of advanced information and communication technology with physical power systems enables real-time perception, rapid response, and intelligent scheduling [6]. In this context, the introduction of LLMs is a critical step towards enhancing the intelligence features of CPPS and optimizing power system operations, as illustrated in Fig. 1. With their deep understanding and generation of human language, LLMs provide unique advantages

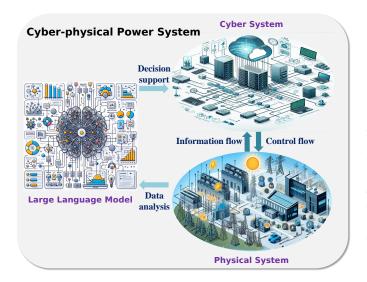


Fig. 1. Illustration of applying the large language model to the cyber-physical power system.

in multimodal data analysis, natural language processing, and intelligent decision support.

Within the CPPS architecture, LLMs are primarily situated in the cyber system's information and application layers. In the information layer, they process and analyze substantial data from sensors, smart meters, and other devices. LLMs can, for example, analyze historical and real-time load data, weather information, and user behavior to forecast electricity demand. In the application layer, LLMs assist in decision-making and optimizing power system operations, generating scheduling strategies and providing valuable insights to system operators. Furthermore, through natural language processing technology, LLMs enhance human-machine interaction, contributing significantly to the overall intelligence of CPPS.

Despite the benefits, the integration of LLMs into CPPS may also face potential threats due to the systems' openness and complexity. These threats include the misuse of LLMs for cyberattacks, data tampering, and issues affecting system stability. At the same time, the decision-making process of LLMs often lacks transparency, which could impact the stability and security of the power system during critical moments. Therefore, a deeper investigation into these potential threats is essential for the safe operation of CPPS.

B. Potential Threats Incurred by Applying Large Language Models

1) Privacy invasion through large language models: The application of LLM in power systems may pose security risks regarding privacy protection. Although the advanced data processing and analysis capabilities of LLM significantly improve the operational efficiency of the power system, they may also pose risks for privacy breaches. This is mainly due to LLMs being designed to improve collaboration efficiency across various departments within the power system and often being deployed as resources widely accessible within the system. Such extensive accessibility makes LLMs potential targets for attackers. Once attackers gain access, they can use

LLMs' intelligent question-answering system to obtain sensitive information about the power system, such as operational data, control strategies, and even security protocols. This kind of privacy theft not only violates data security but also may enable attackers to launch more complex attacks, such as false data injection attacks (FDIAs).

Since FDIA was first proposed in 2009, it has been a hot research topic in academia [7]. However, the implementation of FDIA comes with a strong assumption, wherein attackers have knowledge of the power system's real-time operational conditions, at least partially, to devise effective strategies. Traditionally, obtaining such information has been a significant barrier for attackers, making it difficult to achieve in reality. However, with LLMs in future power systems, this barrier may be significantly lowered. Attackers could use LLMs to obtain detailed operational information and then use this to design FDIA strategies that undermine the power system's stability. Therefore, while LLMs enhance power system intelligence and efficiency, they also introduce privacy breach risks that could be exploited in sophisticated cyberattacks like FDIA.

2) Deteriorated performance in large language models: As large-scale neural networks, LLMs require significant computational resources and training investment [8]. Once deployed in power systems, maintaining their performance becomes crucial. However, a shift in the LLM's internal parameters could lead to long-term inappropriate or incorrect decision-making for the power system. The threat of such performance degradation may arise from two main aspects.

Firstly, if the data set (including training, validation, and test sets) is maliciously altered during the training or fine-tuning process, LLMs might learn inaccurate or misleading information. Such errors could lead to deviations in the final model parameters, impacting decision-making accuracy and reliability [9]. Secondly, there is the risk of direct tampering with the LLM's internal parameters. If attackers can access and modify these parameters post-deployment [10], the LLM's output could significantly deviate from expectations, reducing decision-making effectiveness and potentially leading to serious operational issues.

In both scenarios, deteriorating LLM performance may lead to erroneous decisions in power system operations, threatening system stability and security. Therefore, securing LLM data and model parameters is crucial to prevent performance degradation. This necessitates strict security measures at all training, deployment, and operational stages to uphold model integrity and reliability.

3) Threats from semantic divergence: LLM deployment can coordinate operations across various departments and operators, boosting overall power system efficiency. However, this also means that numerous terminals can communicate with the LLM, generating human-machine interactions and creating many interfaces with a high degree of openness. In such an open environment, some interfaces might be exposed to attackers. As LLMs can interact with personnel through intelligent question-answering, attackers may exploit these exposed interfaces to launch semantic divergence attacks (SDAs).

SDAs can be carried out in two ways. The first involves altering the LLM's input data (i.e., query semantics) to elicit

irrelevant or misleading answers. For example, a query about "real-time load" might be manipulated to produce results for "historical load" instead. The second method involves directly altering LLM's outputs to create divergent answer semantics.

Regardless of the method, SDAs can lead to operators receiving incorrect or misleading information, which could then be used in decision-making for power system operations. This misinformation could significantly affect the stability and efficiency of the power system. Therefore, monitoring and protecting LLM inputs and outputs is essential in preventing SDAs. It is necessary to implement strict data validation and security protocols within the power system to ensure information accuracy and consistency, preventing attackers from exploiting LLMs as a tool to attack the power system.

4) Denial of service for large language models: Denial of service (DoS) attacks [11] pose a serious threat to LLMs. These attacks occur when LLMs receive requests exceeding their processing capabilities, rendering the LLM unusable, overloaded, or slow to respond. The attacks can vary, with the most common form being the inundation of the LLM with numerous query requests, depleting computational resources. Beyond ordinary request flooding, attackers might also design particularly complex or lengthy queries, causing the LLM to consume excessive computational resources in processing a single request. The consequences of DoS attacks are severe as they impact the LLM's immediate response capabilities and can paralyze the entire system.

In power systems, this implies that critical decision-support and data analysis functions might be unavailable when needed most. For instance, in emergencies, if operators depend on LLMs for rapid response or decision analysis, a DoS attack could cause delayed or erroneous decisions, affecting the power system's stable operation and safety. Moreover, DoS attacks might be used as part of other attack strategies, such as a diversion or to mask more severe attack activities. Therefore, enhancing LLM security, especially against DoS attacks, is crucial for the safe operation of power systems. This may include effective traffic management, monitoring mechanisms, and designing LLMs with the capacity to resist such attacks.

III. CONCLUSION AND SUGGESTIONS

While LLMs significantly enhance the operational efficiency and decision-making capabilities in modern power systems, they also introduce vulnerabilities. These risks, ranging from data security breaches to threats like SDAs and DoS attacks, emphasize the necessity for the need for robust security measures throughout LLMs' lifecycle. The integration of LLMs into power systems thus presents a dual challenge: leveraging their advanced capabilities for complex power system operations while ensuring resilience and integrity against cyber threats. This letter advocates for ongoing research, vigilant implementation, and the development of secure, transparent systems. Addressing these challenges is pivotal for the evolution of power systems that are not only intelligent and efficient but also secure and reliable. The future of power systems relies on striking a balance between harnessing the potential of LLMs and safeguarding against the associated risks.

REFERENCES

- [1] D. Wang, F. Chen, B. Meng, X. Hu, and J. Wang, "Event-based secure H∞ load frequency control for delayed power systems subject to deception attacks," *Applied Mathematics and Computation*, vol. 394, p. 125788, Apr. 2021.
- [2] S. Porsdam Mann, B. D. Earp, N. Møller, S. Vynn, and J. Savulescu, "AUTOGEN: A Personalized Large Language Model for Academic Enhancement—Ethics and Proof of Principle," Am. J. Bioeth., vol. 23, no. 10, pp. 28–41, Oct. 2023.
- [3] N. Carlini, F. Tramèr, E. Wallace, M. Jagielski, A. Herbert-Voss, K. Lee, A. Roberts, T. Brown, D. Song, Ú. Erlingsson, A. Oprea, and C. Raffel, "Extracting Training Data from Large Language Models," in 30th USENIX Security Symposium (USENIX Security 21), 2021, pp. 2633– 2650.
- [4] T. Wu, M. Terry, and C. J. Cai, "AI Chains: Transparent and Controllable Human-AI Interaction by Chaining Large Language Model Prompts," in *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*, ser. CHI '22. New York, NY, USA: Association for Computing Machinery, Apr. 2022, pp. 1–22.
- [5] L. Weidinger, J. Uesato, M. Rauh, C. Griffin, P.-S. Huang, J. Mellor, A. Glaese, M. Cheng, B. Balle, A. Kasirzadeh, C. Biles, S. Brown, Z. Kenton, W. Hawkins, T. Stepleton, A. Birhane, L. A. Hendricks, L. Rimell, W. Isaac, J. Haas, S. Legassick, G. Irving, and I. Gabriel, "Taxonomy of Risks posed by Language Models," in *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*, ser. FAccT '22. New York, NY, USA: Association for Computing Machinery, Jun. 2022, pp. 214–229.
- [6] H. Wang, J. Ruan, B. Zhou, C. Li, Q. Wu, M. Q. Raza, and G.-Z. Cao, "Dynamic Data Injection Attack Detection of Cyber Physical Power Systems With Uncertainties," *IEEE Trans. Ind. Inform.*, vol. 15, no. 10, pp. 5505–5518, Oct. 2019.
- [7] G. Liang, J. Zhao, F. Luo, S. R. Weller, and Z. Y. Dong, "A Review of False Data Injection Attacks Against Modern Power Systems," *IEEE Trans. Smart Grid*, vol. 8, no. 4, pp. 1630–1638, Jul. 2017.
- [8] E. M. Bender, T. Gebru, A. McMillan-Major, and S. Shmitchell, "On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?" in Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, ser. FAccT '21. New York, NY, USA: Association for Computing Machinery, Mar. 2021, pp. 610–623.
- [9] J. Ruan, G. Liang, J. Zhao, H. Zhao, J. Qiu, F. Wen, and Z. Y. Dong, "Deep learning for cybersecurity in smart grids: Review and perspectives," *Energy Convers. Econ.*, vol. 4, no. 4, pp. 233–251, 2023.
- [10] L. Yang, G. Liang, Y. Yang, J. Ruan, P. Yu, and C. Yang, "Adversarial false data injection attacks on deep learning-based short-term wind speed forecasting," *IET Renew. Power Gener.*, 2023.
- [11] A. Huseinović, S. Mrdović, K. Bicakci, and S. Uludag, "A Survey of Denial-of-Service Attacks and Solutions in the Smart Grid," *IEEE Access*, vol. 8, pp. 177 447–177 470, 2020.