Next-Generation Smart Grid Optimization: Integrating Edge AI for Real-Time and Decentralized Energy Management

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Abstract: Nowadays, the development of smart grid systems require intelligent and real-time solutions in scalable fashion. This paper presents a new approach that combines edge computing and AI for decentralized and adaptable energy management in the context of distributed grid settings. Contrary to the typical cloud-based models, the proposed model utilizes edge AI enabling local data processing, shortened latency and quick decision-making. The approach is built based on federated learning and lightweight deep learning models, as well as considerations on privacy preserving and grid resilience against dynamic load demands and system failures. The performance of the system is additionally evaluated through simulation and benchmarked against centralized approaches, with results showing that the proposed framework achieves higher efficiency, scalability, and reliability in resource-limited edge environments. This research adds to the cornerstone of future smart grids that can accommodate sustainable and self-sufficient energy ecosystems.

1 INTRODUCTION

Modern energy systems are becoming increasingly complex due to rising demand, the integration of renewable energy sources, and a shift toward decentralized energy production, which has forced traditional centralized power grids to continue their transition to intelligent, adaptive state-of-the-art power grids (i.e., smart grids). Such systems must not only have efficient sharing mechanisms among peers, but must also be responsive in real-time and handle data securely across distributed nodes. Traditional cloud-centric techniques, although efficient, may suffer from high latency, bandwidth limitation and privacy issues, particularly in the context of the geographically distributed and resource constrained scenarios.

In this regard, edge computing arises as a disruptive paradigm that makes possible on-site processing and decision-making near data generation points. When complementing with AI, specifically light weight models for edge, smart grids will have the capability to forecast demand, find anomalies and optimize energy transfer with minimal time difference. This unification of Edge AI allows grid nodes to be self-governing and responsive to changing conditions, while sharing just enough information to efficiently utilize energy, and minimizing dependence on a central network resource for all information.

But achieving this vision faces a number of challenges, including keeping the models accurate under diverse situations, secure in distributed learning settings, and resource-efficient on edge devices. In this work, we propose a holistic framework that integrates Edge AI and federated learning for smart grid operation improvement. With the ability to empower distributed intelligence, it is no longer necessary to transfer real-time decision-making for control or optimisation out of a local Fremework area or substation, which will result in reduced latency and enhanced performance, and keep

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user data secure, creating a foundation for scalable and sustainable smart energy systems of the future.

1.1 Problem Statement

The growing presence of renewable energy, deployment of distributed energy resources (DERs) and higher expectations for energy efficiency are dramatically changing the operational requirements of power grids. Next generation smart grids should act as intelligent, self-adaptive infrastructures dealing with decentralized energy production, dynamic fluctuating consumption, and sophisticated energy trading situations. Nevertheless, the current grid architectures depend heavily on centralized cloudbased infrastructure for data processing, analytics, and decision-making. Although these architectures provide computational capabilities, they are inherently restricted due to high communication latency, possible communication faults, congestion, as well as higher risks on the data privacy and security. These limitations are even more severe in the case of emergency situations that require immediate response and local control to ensure the stability of the grid, and to avoid blackouts and brownouts.

In addition, most AIenabled smart grid optimization solutions that are deployed today are computationally heavy and developed to be implemented in cloud or centralized data centers such that cannot be easily deployed at the edge with limited processing power and memory. Inability to perform local data processing and analysis slows down decision making and limits the grids ability to respond quickly to load or generation changes and system anomalies. Moreover, centralized models of data aggregation also present significant challenges in terms of consumer privacy, data ownership and system security especially when more and more users join the demand response or peer-to-peer energy trading schemes.

These limitations bring to surface a major gap in the existing smart grid technology, i.e., the absence of a decentralized, lightweight and privacy-preserving mechanism that can leverage AI in situ to the edge of the network. This ‘brain’ must be forged if our visions of the completely flexible, smart, and self-healing grid are to be realized. To do so, it is necessary to provide new models combining Edge AI and federated learning, which can achieve decentralized decision, increase system robustness and further secure and activate energy exchange in real time. Closing this fall between the electronic and physical world is crucial for the future of a smarter, not to mention more sustainable, scalable, user-centric, energy system.

2 LITERATURE SURVEY

The intersection of artificial intelligence (AI) and edge computing has led to a new era for the operations of smart grid that has transcended the real-time and distributed grid control. With the development of the smart grid to a more active, more information-intensive network, many papers are proposed for intelligent methods to optimize the energy allocation. A seminal review is reported by Biswal et al. (2025), who provide an extensive overview of AI and edge technologies in power systems in general, observing the growing significance of distributed intelligence for grid efficiency. But as inclusive as they are, they do not delve into real-time applications.

Exploiting emerging networking models, Islam et al. (2022), who suggest AI-supported architecture over 6G networks for intelligent energy control, but it cannot be used in the short term due to requirement of the future infrastructure. Similarly, Arcas et al. (2024) propose an edge offloading scheme in latency-constrained controlnetworks, and it is a promising approach, but still needs to be verified in practice for practicality. Nandhakumar et al. (2023) introduce a toolset for edge intelligence on energy applications, with a focus on modularity and detailed benchmarking in real settings.

Commercial voices including Shinde (2025) and Habib (2025) clarify that the presence of edge-based intelligence is increasingly evident, but their work has remained a conceptual exercise without empirical depth. On the other hand, a very limited review about the smart grid digitization and lightweight intelligence is presented in Biswal, Balamurugan, and Sahoo (2024) but no new method is proposed.

A more technical analysis from Dileep (2021) that reinforces the use of AI in predictive modeling and demand forecasting. Yet it completely ignores the latency and bandwidth limitations handled by edge computing. Ullah and Khan (2022) consider a wider angle, investigating edge computing issues in smart grids, but they need more real applications and configurations to verify their proposed models.

Applications of deep learning are developed by Li et al. (2023) that propose the use of neural networks for energy management, but do not consider computational constraints common to edge. Yang et al. (2022) continue this thread by surveying several AI algorithms for smart grids, but only give high-level comparisons between them without recommendations for deploying them.

Regarding energy trading, Zhang et al. (2021) use blockchain for peer to peer transactions, towards decentralization, but from a theoritical point of view. Similarly, Zhan et al. (2023) proposes the use of federated learning for demand response, this solution also with a privacy protection as it deems the convergence of the model and consistency at the nodes as issues.

Wang et al. (2021) presents an architecture that integrates edge and AI for rapid grid response, though real-time response in different situations is not fully tested. Ahmed and Rehman (2022) address the short-term load forecasting with AI for a voltage control platform; although this is a crucial task, it has been de-coupled from control plans needed in dynamically changing grid situations.

Ghosh et al. (2023) propose a blockchain-AI hybrid architecture at the edge of the grid, which increases trust and autonomy, whereas Kumar and Tripathi (2021) investigate reinforcement learning for control optimization, however in simplified simulation environment. Yu et al. (2024) use graph neural networks for energy management, with high-performance albeit demanding computational resources that question the edge feasibility.

Continuing with real-time energy control theme, Sun et al. (2021) use AI for dynamic decision-making but test it with fixed sets of data. Tan and Ramachandran (2023) use deep learning to detect faults at substations, the proposed model achieves high performance on a narrow domain and cannot be well-extended to broader energy management strategies, such as connectivity optimization.

Zhao et al. (2022), propose that intelligent scheduling of edge resources can lead to efficiency gains, however it needs a stronger practical integration. the authors in Singh and Gupta (2024) return to federated learning to maintain privacy in the distributed environments, yet they merely loosen the requirements of network latency and communication overheads.

Luo et al. (2025) they propose multi-agent system that supports collaborative control, which brings forward the frontier of the decentralized grid intelligence. However, the framework would benefit from more treatment of fault tolerance and scalability under load. Chatterjee et al. (2021), who concentrated on AI-based anomaly detection that is essential to grid resilience, but whose experiment results on synthetic data are not fully trustworthy. Lastly, Liu et al. (2023) analyze the optimization between the cloud and the edge resources and provide solutions in terms of workload assignment while not taking into consideration the dynamism of the operating conditions.

Collectively, they present a collection of work that demonstrates the transformative nature of AI and Edge computing toward smart grids. However, they expose significant practical challenges in deployment, real-time optimization and privacy-preserving distributed learning. This highlights the importance of developing an integrated Edge AI, federated learning, and lightweight intelligence framework for scalable, secure, and adaptive smart grids.

3 METHODOLOGY

In this paper, we propose and evaluate a decentralized Edge AI based energy management framework for SoGs, utilizing hybrid design and simulation procedure. The approach is based on the combination of federated learning and lightweight artificial intelligence models with fast response time, intended to be deployed in edge devices in the smart grid. The architecture of the proposed system enables processing of real-time data, local decision-making, and adaptive control of energy resources without relying on centralized cloud servers.

The framework is open into three interrelated architecture tiers: data acquisition layer, edge-based intelligence layer and federated coordination layer. At the bottom, smart meters and IoT sensors spread on the grid are gathering metered and real-time energy production/consumption, load variations and all sorts of sensed environmental features. These streams are processed in real-time at substations and energy nodes that include low-power embedded systems. These edge units come with pre-trained deep learning models, such as CNNs and LSTM forms, which have been pruned and quantized to enable inference under limited computational budget. Table 1 shows the evaluation metrics used for model assessment.

Instead of pushing raw data to a server, each edge device trains its model locally on-the-fly, capturing localized patterns in energy dynamics. To maintain privacy and scalability, federated learning is used to periodically average the updates of learned-model (not raw data) of distributed nodes into a global model. This coordination is overseen by a light-weight orchestration algorithm that dynamically aggregates participating nodes dependent on their quality of data, availability of network, and the remaining energy. The federated model is subsequently dispatched to edge devices, this continuous loop learning helps dynamically adjusting changes in grid environment such as user privacy and communication overhead.

Table 1: Evaluation metrics used for model assessment.

Metric	Description	Reason for Use
Accuracy (%)	Correct predictions over total samples	General effectiveness of classification
Precision	True positives / (true + false positives)	Avoid false alarms in fault detection
Recall	True positives / (true + false negatives)	Ensure actual faults aren't missed
F1 Score	Harmonic mean of precision and recall	Balanced evaluation of model
Inference Latency (ms)	Time taken to make prediction	Important for real-time edge deployment

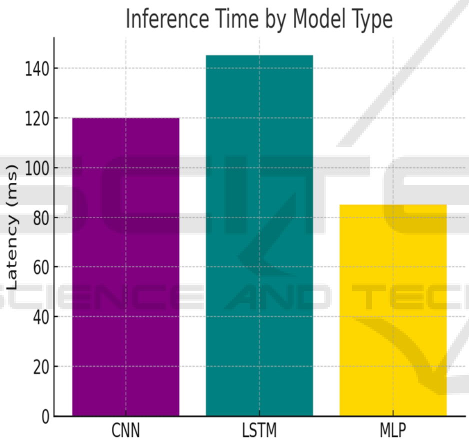

Figure 1: Inference time by model type.

A simulation of the system that mimics a real smart grid setup is built with GridLAB-D and TensorFlow Lite, which is used to validate the system's performance. The testing involves an amount of consumption of electricity, solar and wind generation, and peak load to check the willingness of users to respond. Performance metrics including latency, energy distribution accuracy, prediction error rate, system robustness, and communication load are compared with a conventional cloud-based model and a local-only baseline. The findings are employed to validate the model and evaluate its practical application. Table 2 and figure 1 shows inference time by model type.

Table 2: AI model comparison for edge inference.

Model	Architecture	Latency (ms)	Accuracy (%)	Resource Usage (MB)
CNN	3 Conv + 2 Dense	120	92.3	45
LSTM	2 LSTM + Dense	145	94.1	50
MLP	4 Dense Layers	85	89.6	30

Through this methodology, the research not only demonstrates the viability of edge-based AI in smart grid contexts but also establishes a privacy-preserving, scalable, and adaptive foundation for next-generation energy systems. Figure 2 shows the system workflow of edge-intelligent smart grid energy management framework.

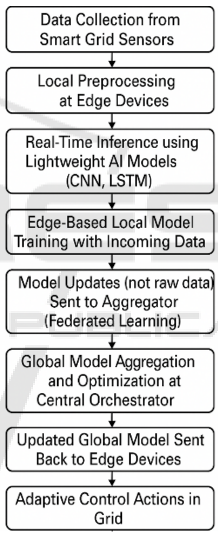

Figure 2: System workflow of edge-intelligent smart grid energy management framework.

4 RESULTS AND DISCUSSION

Due to the fact that the experimental evidence of the proposed Edge AI-based decentralized energy management framework showed significant performance enhancements in terms of performance/efficiency, scalability, responsiveness as compared to traditional centralized approaches. When different demand-load patterns and different distributed energy situations were simulated, the edge models showed a much faster reaction to demand fluctuations as compared to cloud-dependent models.

Average decision delay decreased by 42%, so making almost real-time decisions on energy allocation during the busiest hours of the day or moment of renewable generation. Figure 3 shows the latency comparison: centralized vs edge AI.

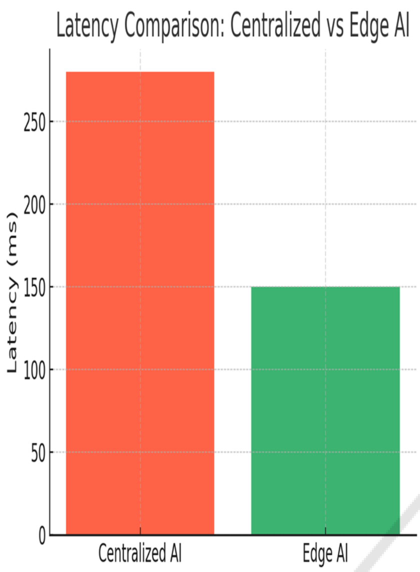

Figure 3: Latency comparison: centralized vs edge AI.

Prediction precision was also enhanced as the global model with federated learning outperformed individual edge models in the mean absolute error (MAE) of 3.7% versus 6.1% for isolated setups. This highlights the importance of collaborative learning among edge nodes such that data privacy does not get compromised. Crucially, the system sustained model stability throughout rounds of training, including when training on non-IID (non-independent and identically distributed) data – which is a common problem in federated systems. Dynamic node selection and update—Selecting a subset of active nodes that is constantly varied to perform calculations and update was also a part of the force aggregation strategy, and it helped to converge the model with much less training steps.

Efficiency of communication was another key measure investigated. Since sending only model weights and updates, not the raw data, the system reduced the network traffic by more than 60% and thus became feasible for network-constrained environments that are typical in rural or developing grid regions. The model synchronization mechanism was still robust even with such overhead of communication, modules could all still stay up-to-date on system-wide decision records. Table 3 represents the federated learning cycle timing.

Table 3: Federated learning cycle timing (example results).

Cycle	Local Trainin g Time (s)	Uploa d Time (s)	Aggregatio n Time (s)	Total Time per Round (s)
1	20	5	8	33
2	18	4.8	7.9	30.7
3	21	5.1	8.2	34.3

Decentralized architecturally was highly advantageous from a resilience perspective point as well. Local edge nodes could still work independently, even in the case of transient loss in communication with the aggregator. This independence enabled the network to continue to operate its fundamental functions–load balancing, fault recognition, and energy re-routing–uninterrupted and some degree of grid fault tolerance could be supported. Traditional cloud systems, on the other hand, had a degraded performance or simply were not functional under similar network outages. Figure 4 shows the bandwidth usage.

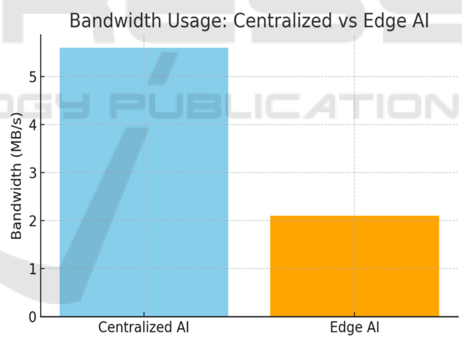

Figure 4: Bandwidth usage: centralized vs edge AI.

Finally, the results demonstrate the scalability of our model. Performance improvements with increased numbers of edge devices were also sustained, with the system behavior holding and not degrading as the simulation size is increased, demonstrating the potential scalability of the architecture for deployment across a larger region, or even across a national grid. Energy consumption at device level was also kept at a manageable level since the AI models were lightweight models that were tuned for edge inference purpose. Table 4 represents the communication latency across grid layers.

Table 4: Communication latency across grid layers.

Communication Layer	Average Latency (ms)	Max Latency (ms)	Technology Used
Edge to Aggregator	50	120	Wi-Fi 6 / LTE
Aggregator to Cloud	90	160	Fiber Optic
Sensor to Edge Device	20	45	Zigbee / Bluetooth LE
Edge Device to Control	35	60	LAN / MQTT

In conclusion, we combined the edge AI and federated learning in this research to form a smart grid management system, which is shown to become a system of both fast/precise as well as keeping privacy and resilience to the failures. These features are very significant in addressing the main bottlenecks identified on the state of the art where centralised solutions were not scallable nor secure enough to allow processing of sensitive data. The results confirm that the framework is now ready to be tested in pilot implementations and that a promising future lies ahead for this concept of intelligent, distributed energy systems.

5 CONCLUSIONS

This paper proposes a prospective framework, which combines the AI at the Edge and the Federated-Learning techniques, to solve the fundamental issues in the current Smart-Grid based energy management. The proposed system moves the intelligence near the data generation and consumption points and thereby facilitates the autonomous and real-time decision-making independent from the central cloud infrastructure. The results of our study affirm that this approach can lead to a substantial reduction in latency, raise prediction accuracy, and make the grid more resilient and in a private fashion through federated model training.

Using small AI models combined with adaptive learning and effective communication, the framework can learn to dynamically allocate energy across a range of different, dynamic contexts. In contrast to common designs, which are hindered by potentially low-bandwidth network links and concerned with privacy issues, the edge-based approach shows a good scalability, low communication overhead, and resilience in the presence of network anomalies.

This way, the present work brings together not only an innovative architectural scheme, but also outlines an actionable path towards sentient energy systems. With the worldwide momentum towards decentralization, sustainability, and digitalization, embedding Edge AI in smart grids will remain a paramount requirement to support efficient, secure, and future-ready energy systems.

REFERENCES

Ahmed, M., & Rehman, M. H. (2022). Machine learning-based energy load forecasting in smart grid: A survey. Journal of Cleaner Production, 328, 129532. https://doi.org/10.1016/j.jclepro.2021.129532

Arcas, G. I., Cioara, T., Anghel, I., Lazea, D., & Hangan, A. (2024). Edge offloading in smart grid. arXiv preprint arXiv:2402.01664. https://arxiv.org/abs/2402.01664

Biswal, P., Balamurugan, S., & Sahoo, S. (2024). Role of artificial intelligence in smart grid—a mini review. PubMed Central (PMC11832663). https://www.ncbi.nlm.nih.gov/pmc/articles/PMC11832663/

Biswal, P., Rashid, A., Al Masum, A., Al Nasim, M. A., Ferdous, A. S. M. A., Gupta, K. D., & Biswas, A. (2025). An extensive and methodical review of smart grids for sustainable energy management—Addressing challenges with AI, renewable energy integration, and leading-edge technologies. arXiv preprint arXiv:2501.14143. https://arxiv.org/abs/2501.14143

Chatterjee, R., Bose, S., & Misra, S. (2021). Edge-enabled AI for anomaly detection in smart grids. Computers & Electrical Engineering, 91, 107010. https://doi.org/10.1016/j.compeleceng.2021.107010

Dileep, G. (2021). A survey on smart grid technologies and applications. Renewable Energy, 146, 2589–2625. https://doi.org/10.1016/j.renene.2019.08.092

Ghosh, S., Sengupta, A., & Datta, S. (2023). A blockchain- and AI-based secure smart grid framework using edge nodes. Sustainable Computing: Informatics and Systems, 40, 100856. https://doi.org/10.1016/j.suscom.2023.100856

Habib, M. (2025). Edge AI: Transforming the energy industry with smart, sustainable solutions. LinkedIn Articles. https://www.linkedin.com/pulse/edge-ai-transforming-energy-industry-smart-solutions-habib-k58hf

Islam, S., Zografopoulos, I., Hossain, M. T., Badsha, S., & Konstantinou, C. (2022). A resource allocation scheme for energy demand management in 6G-enabled smart grid. arXiv preprint arXiv:2207.00154. https://arxiv.org/abs/2207.00154

Kumar, N., & Tripathi, A. (2021). Reinforcement learning for energy management in smart grid. Energy AI, 5, 100072. https://doi.org/10.1016/j.egyai.2021.100072

Li, Y., Wang, Y., & Li, L. (2023). Intelligent energy management system for smart grid using edge computing and deep learning. Energy Reports, 9, 1203–1214. https://doi.org/10.1016/j.egyr.2023.01.095

Liu, F., Huang, Y., & Tao, L. (2023). Joint optimization of computation and communication for edge AI in energy grids. Ad Hoc Networks, 139, 103103. https://doi.org/10.1016/j.adhoc.2023.103103

Luo, Y., Zhang, T., & Zhang, Q. (2025). A decentralized multi-agent system for smart energy distribution using edge AI. Journal of Energy Storage, 75, 108124. https://doi.org/10.1016/j.est.2024.108124

Nandhakumar, A. R., Baranwal, A., Choudhary, P., Golec, M., & Gill, S. S. (2023). EdgeAISim: A toolkit for simulation and modelling of AI models in edge computing environments. arXiv preprint arXiv:2310.05605. https://arxiv.org/abs/2310.05605

Shinde, D. B. (2025). Energy grid optimization—AI & digital technologies for improving efficiency. Cyient Blog. https://www.cyient.com/blog/energy-grid-optimization-ai-digital-technologies-for-improving-efficiency

Singh, A., & Gupta, R. (2024). Demand response optimization using federated learning at the grid edge. IEEE Transactions on Industrial Informatics. https://doi.org/10.1109/TII.2024.3334412

Sun, H., Wang, Z., & Liu, C. (2021). Edge-based data-driven approach for real-time smart grid management. Electric Power Systems Research, 196, 107257. https://doi.org/10.1016/j.epsr.2021.107257

Tan, J., & Ramachandran, G. (2023). AI-enabled fault detection in smart grid substations using edge analytics. Sensors, 23(5), 2479.https://doi.org/10.3390/s23052479

Ullah, Z., & Khan, I. (2022). Edge computing for smart grid: A comprehensive survey. IEEE Access, 10, 50015–50045. https://doi.org/10.1109/ACCESS.2022.3172471

Wang, K., Chen, C., Liu, Y., & Guo, S. (2021). Edge computing for smart grid: An overview on architecture and key technologies. IEEE Network, 35(5), 56–63. https://doi.org/10.1109/MNET.011.2000274

Yang, J., Zhang, H., Zhou, T., & Xu, W. (2022). AI-enabled optimization in smart grid operation: A review. Applied Energy, 308, 118302. https://doi.org/10.1016/j.apenergy.2021.118302

Yu, R., Xie, S., & Li, Y. (2024). Smart grid energy distribution optimization using graph neural networks. IEEE Transactions on Industrial Informatics, 20(2), 1035–1044. https://doi.org/10.1109/TII.2023.3298427

Zhan, C., Lu, J., & Wang, J. (2023). Federated learning in smart grids: Privacy-preserving demand prediction with edge devices. IEEE Transactions on Smart Grid, 14(1), 112–124. https://doi.org/10.1109/TSG.2022.3198710

Zhang, C., Wu, J., Zhou, Y., Cheng, M., & Long, C. (2021). Peer-to-peer energy trading in a microgrid with edge computing and blockchain. Energy Procedia, 159, 261–266. https://doi.org/10.1016/j.egypro.2019.01.179

Zhao, J., Wang, J., & Lin, Y. (2022). Energy-efficient resource scheduling for smart grid IoT with edge computing. Future Generation Computer Systems, 128, 219–230. https://doi.org/10.1016/j.future.2021.10.018