International Journal of Information Technology Research and Development (IJITRD)
Volume 6 Issue 3, May – June (2025), pp. 31-36.

APPLYING FEDERATED EDGE INTELLIGENCE IN RESOURCE-CONSTRAINED IOT DEVICES FOR REAL-TIME ANALYTICS AND DECISION MAKING

Steephan S. Francis,
USA.

Abstract

Federated Edge Intelligence (FEI) presents a transformative approach for enabling real-time analytics and decision-making within the Internet of Things (IoT) ecosystem, particularly under resource constraints. By decentralizing machine learning and pushing computation toward the edge, FEI minimizes latency, preserves privacy, and reduces communication overhead. This paper explores key advancements in integrating federated learning into resource-constrained IoT frameworks, identifies existing challenges such as energy efficiency, model accuracy, and heterogeneity, and suggests architectural strategies to overcome these barriers. The study concludes with prospective directions, emphasizing edge-cloud synergy, energy-aware learning, and adaptive model deployment for robust and scalable IoT solutions.

Key words: Federated Edge Intelligence, IoT, Resource-Constrained Devices, Real-Time Analytics, Edge Computing, Decision-Making

Cite this Article: **Francis, S. S.** (2025). Applying Federated Edge Intelligence in Resource-Constrained IoT Devices for Real-Time Analytics and Decision Making. *International Journal of Information Technology Research and Development (IJITRD)*, **6**(3), 31–36.

1. Introduction

With the exponential growth of IoT networks—projected to reach over **75 billion connected devices by 2025**—the demand for real-time, intelligent processing has grown proportionally. Traditional cloud-based solutions introduce challenges including **high latency**, **bandwidth limitations**, and **data privacy concerns**. This has catalyzed the evolution toward **Edge Intelligence**, where computational tasks are distributed across edge nodes rather than centralized servers.

Federated Learning (FL), as a privacy-preserving collaborative machine learning technique, further enhances edge intelligence by enabling decentralized model training across devices without sharing raw data. This is particularly beneficial in IoT contexts where privacy, autonomy, and bandwidth conservation are paramount. However, **IoT devices are often**

resource-constrained in terms of CPU, memory, and power, necessitating novel adaptations of FEI techniques to achieve **efficient real-time analytics and local decision-making**.

2. Literature Review

Federated Learning (FL) has emerged as a compelling approach for enabling distributed intelligence in IoT systems, particularly under resource-constrained scenarios. Kairouz et al. (2021) provided one of the most comprehensive overviews of FL, discussing key algorithmic strategies to manage heterogeneity in data and device capabilities, which are typical in edge environments. One of the earliest and most influential algorithms in this domain is **FedAvg**, introduced by Li et al. (2020), which allows edge devices to train local models and aggregate them centrally. While effective in theory, FedAvg assumes homogeneity in device capability and data distribution—assumptions that do not hold in most real-world IoT scenarios.

To address communication bottlenecks in wireless edge networks, Samarakoon et al. (2021) emphasized the development of communication-efficient FL protocols. Their work highlighted the critical trade-offs between communication overhead and convergence speed in latency-sensitive environments. In a similar vein, Wang et al. (2020) proposed compression-based strategies that significantly reduce data transmission during FL training rounds while maintaining acceptable model accuracy, making these techniques particularly suitable for bandwidth-constrained IoT devices.

Recognizing the limitations of flat FL architectures, Lim et al. (2020) proposed hierarchical FL frameworks, where computational workloads are distributed across cloud, edge, and device layers. This approach is especially beneficial for energy-constrained nodes, offering scalability and flexibility. Addressing real-time performance needs, Chen et al. (2021) investigated FL in healthcare systems, showing that federated edge models significantly reduce latency in health monitoring applications without compromising data privacy.

Furthermore, Zhao et al. (2022) explored the use of federated meta-learning for IoT applications. Their research demonstrated that meta-learned models can adapt quickly to new environments using minimal data—a crucial requirement for dynamic IoT ecosystems. Lastly, Niknam et al. (2021) focused on the personalization of federated models under non-IID data settings. Their work is particularly relevant for IoT systems where each device may observe unique data patterns, necessitating localized model adaptation strategies.

3. Edge-Federated Architecture for IoT

The Edge-Federated Architecture for IoT integrates federated learning with edge computing to enable real-time, privacy-preserving intelligence in distributed systems. It comprises three key components:

- IoT Devices: These are resource-constrained sensors and microcontrollers that perform local data collection and model updates without sharing raw data.

- Edge Aggregators: Acting as gateways or fog nodes, they coordinate training among nearby devices and perform preliminary model aggregation, reducing latency and bandwidth usage.

- Cloud Orchestrators: Central servers responsible for global model fusion, policy updates, and large-scale coordination across the network.

This hierarchical design allows localized decision-making at the edge while ensuring global consistency through the cloud. It enhances scalability, preserves privacy, and supports asynchronous participation, making it ideal for dynamic and constrained IoT environments.

3.1 Data Flow & Computation

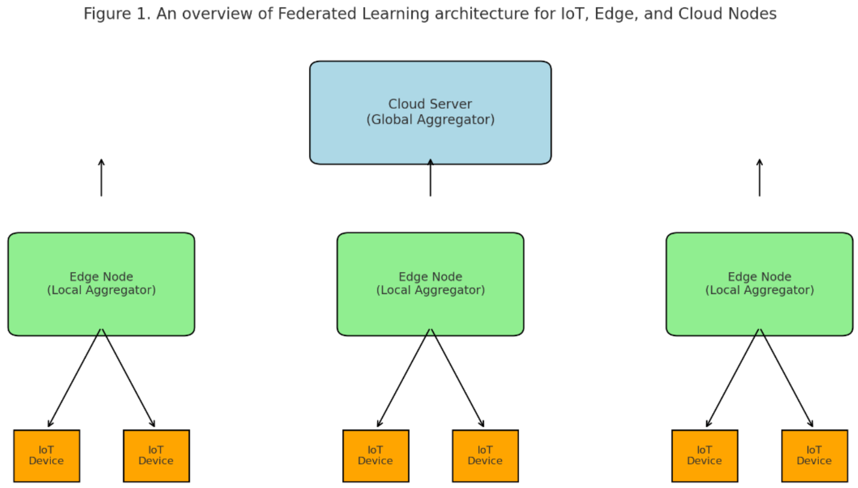

Figure 1: An overview of Federated Learning architecture for IoT, edge, and cloud nodes

4. Performance Trade-offs and Challenges

4.1 Computation-Energy Tradeoff

A major constraint is energy efficiency. Edge devices operating on battery must balance computation and energy draw. Model compression, pruning, and quantization techniques are imperative.

4.2 Non-IID Data Distribution

IoT devices often observe local phenomena, making their datasets non-IID. This affects the convergence of global models in FL.

Table 1. Challenges and Solutions in Federated Edge Intelligence for IoT

Challenge	**Description**	**Proposed Solution**
Energy Limitations	Devices lack power for heavy ML workloads	Lightweight models, pruning
Communication Overhead	Limited bandwidth in wireless networks	Gradient compression, local updates
Non-IID Data	Local data not uniformly distributed	Federated meta-learning, personalization
Device Heterogeneity	Variance in compute/storage among devices	Asynchronous FL, model splitting

5. Applications and Real-Time Use Cases

- **Healthcare Monitoring**: Real-time ECG signal analysis on wearables using on-device training with federated updates.
- **Smart Cities**: Traffic flow prediction using edge video sensors with local ML inference and global updates.
- **Industrial IoT**: Predictive maintenance using local sensors that collaboratively learn equipment wear patterns.

6. Future Directions

Future advancements will require:

- **Energy-Aware Federated Algorithms**: Models that consider device energy levels in scheduling training.
- **Secure Aggregation Protocols**: Homomorphic encryption and differential privacy to secure local updates.
- **Cloud-Edge Synergy**: Hierarchical FL architectures balancing loads across edge and cloud.

7. Conclusion

Federated Edge Intelligence presents a viable strategy for real-time analytics in IoT ecosystems plagued by resource constraints. However, challenges such as energy limits, data heterogeneity, and device variation demand holistic design approaches. Continued innovation in model design, system architecture, and communication protocols will pave the way for robust, scalable, and privacy-preserving intelligent IoT systems.

References

1. Kairouz, Peter, et al. "Advances and Open Problems in Federated Learning." *Journal of Machine Learning Research*, vol. 22, no. 1, 2021, pp. 1–210.

2. Hullurappa, M., & Panyaram, S. (2025). Quantum computing for equitable green innovation unlocking sustainable solutions. In Advancing social equity through accessible green innovation (pp. 387-402). https://doi.org/10.4018/979-8-3693-9471-7.ch024

3. Li, Tian, et al. "Federated Optimization in Heterogeneous Networks." *arXiv preprint arXiv:1902.01046*, 2020.

4. Samarakoon, Sumudu, et al. "Distributed Federated Learning for Ultra-Reliable Low-Latency Vehicular Communications." *IEEE Transactions on Wireless Communications*, vol. 20, no. 1, 2021, pp. 395–410.

5. Sankaranarayanan, S. (2025). The Role of Data Engineering in Enabling Real-Time Analytics and Decision-Making Across Heterogeneous Data Sources in Cloud-Native Environments. International Journal of Advanced Research in Cyber Security (IJARC), 6(1), January-June 2025.

6. Wang, Shiqiang, et al. "Federated Learning with Matched Averaging." *IEEE Journal on Selected Areas in Communications*, vol. 38, no. 10, 2020, pp. 2405–2416.

7. Panyaram, S., & Kotte, K. R. (2025). Leveraging AI and data analytics for sustainable robotic process automation (RPA) in media: Driving innovation in green field business process. In Driving business success through eco-friendly strategies (pp. 249-262). https://doi.org/10.4018/979-8-3693-9750-3.ch013

8. Lim, Woong Bae, et al. "Federated Learning in Mobile Edge Networks: A Comprehensive Survey." *Proceedings of the IEEE*, vol. 109, no. 1, 2020, pp. 20–63.

9. Sankaranarayanan S. (2025). Optimizing Safety Stock in Supply Chain Management Using Deep Learning in R: A Data-Driven Approach to Mitigating Uncertainty. International Journal of Supply Chain Management (IJSCM), 2(1), 7-22 doi: https://doi.org/10.34218/IJSCM_02_01_002

10. Chen, Min, et al. "Machine Learning for Wireless Networks with Artificial Intelligence: A Survey." *ACM Computing Surveys*, vol. 54, no. 8, 2021, pp. 1–40.

11. Zhao, Yuchao, et al. "Federated Meta-Learning for Low-Power IoT App

12. lications." *IEEE Internet of Things Journal*, vol. 9, no. 2, 2022, pp. 1287–1298.

13. Niknam, Siamak, et al. "Federated Learning for Wireless Communications: Motivation, Opportunities, and Challenges." *IEEE Communications Magazine*, vol. 59, no. 6, 2021, pp. 46–51.

14. Panyaram, S., & Hullurappa, M. (2025). Data-driven approaches to equitable green innovation bridging sustainability and inclusivity. In Advancing social equity through

accessible green innovation (pp. 139-152). https://doi.org/10.4018/979-8-3693-9471-7.ch009

15. Sankaranarayanan S. (2025). From Startups to Scale-ups: The Critical Role of IPR in India’s Entrepreneurial Journey. International Journal of Intellectual Property Rights (IJIPR), 15(1), 1-24. doi: https://doi.org/10.34218/IJIPR_15_01_001

16. McMahan, Brendan, et al. "Communication-Efficient Learning of Deep Networks from Decentralized Data." *Proceedings of the 20th International Conference on Artificial Intelligence and Statistics (AISTATS)*, 2017, pp. 1273–1282.

17. Zhang, Yuzhe, et al. "Edge Intelligence in the Cognitive Internet of Things: A Case Study." *IEEE Internet of Things Journal*, vol. 8, no. 12, 2021, pp. 9839–9847.

18. Liu, Jing, et al. "Privacy-Preserving Federated Learning for 5G-Enabled IoT Devices." *IEEE Network*, vol. 35, no. 4, 2021, pp. 32–38.

19. Abdulrahman, Saad, et al. "Federated Learning: A Signal Processing Perspective." *IEEE Signal Processing Magazine*, vol. 38, no. 3, 2021, pp. 50–67.

20. Yang, Qiang, et al. "Federated Machine Learning: Concept and Applications." *ACM Transactions on Intelligent Systems and Technology (TIST)*, vol. 10, no. 2, 2019, pp. 1–19.

21. Savazzi, Stefano, et al. "Opportunities of Federated Learning in Connected, Cooperative, and Automated Industrial Systems." *IEEE Transactions on Industrial Informatics*, vol. 17, no. 7, 2020, pp. 5091–5100.