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Enhancing Smart Building Sustainability with Hybrid Fog–Cloud Architectures: Insights from Simulated IoT Data

Enhancing Smart Building Sustainability with Hybrid Fog–Cloud Architectures: Insights from Simulated IoT Data

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Abstract

The growing demand for energy-efficient urban infrastructure has positioned smart buildings as pivotal in achieving sustainable cities. This study examines the integration of hybrid Fog–Cloud architectures in optimizing energy usage, reducing latency, and managing network bandwidth in smart building environments using simulated IoT data. A mixed-method approach was employed, combining simulations of fixed and scalable scenarios with comparative analysis of Fog and Cloud systems. The key simulators used in this study were the MATLAB Simulink and the iFogSim2 simulation toolkit, to ensure data is generated and analyzed. Key findings reveal latency reductions of over 80% and network bandwidth usage improvements exceeding 30%, with Fog systems consuming significantly less energy and emitting 31% less CO_2 compared to Cloud-only setups. For instance, Fog bandwidth usage ranged from 9.54 Gbps for 20 devices to 75.98 Gbps for 200 devices, compared to Cloud systems at 14.56 Gbps and 110.89 Gbps, respectively. Additionally, energy savings were evident across both fixed and scalable scenarios, with Fog systems consistently outperforming Cloud systems as device counts increased. These improvements align with global sustainability goals, particularly the United Nations Sustainable Development Goal (SDG) 11, emphasizing sustainable cities and communities. This study underscores the transformative potential of hybrid architectures in revolutionizing building operations through resource efficiency and environmental sustainability, paving the way for scalable and resilient IoT ecosystems.

Introduction

Urbanisation has placed immense pressure on energy resources, contributing to global environmental challenges. Buildings account for over 30% of global energy consumption, making them critical targets for energy optimisation and sustainable development (International Energy Agency, 2023). Smart buildings equipped with IoT devices offer transformative potential by enabling data-driven decision-making and adaptive control of energy-intensive systems. However, traditional Cloud-based data processing architectures face limitations, including high latency, network congestion, and significant energy demands.

This study examines a hybrid Fog–Cloud architecture as a solution to these challenges, utilising simulated IoT device data to improve resource management in smart buildings. The research focuses on energy efficiency, latency reduction, and network optimisation, with a particular emphasis on sustainability. By aligning with SDG 11, this work highlights the contribution of innovative building technologies to sustainable urban development.

Ammed et al. (2020) provide a comprehensive overview of the enabling technologies within the IoT technology stack, emphasising the role of middleware platforms in facilitating application development and integration. Their study addresses evolving challenges in IoT ecosystems and proposes strategies to optimise the IoT stack. Notably, the integration of fog/edge networks is examined in depth, highlighting ongoing research gaps and opportunities for further exploration. Apat et al. (2023) focus on application models and resource allocation strategies in IoT environments. Their comparative analysis of various computing paradigms highlights critical features and trade-offs. Additionally, they propose a generalised fog computing architecture, which serves as a foundational framework for advancing resource efficiency and application performance in edge computing scenarios.

McGlinn (2014) investigates the characteristics of different computing paradigms, with particular attention to fog computing. Their work provides a detailed analysis of fog systems, focusing on algorithms and their functionalities within the IoT ecosystem. The study systematically examines challenges faced by fog computing, particularly in its intermediary role between resource-constrained IoT devices and centralised cloud infrastructures. Malkawi et al. (2023) explore the security implications of fog computing within the Industrial Internet of Things (IIoT). Their study identifies specific security requirements in IIoT environments and proposes how fog computing can mitigate risks and enhance system security, making it a critical enabler for industrial applications.

Dave (2024) focused on the role of artificial intelligence (AI) and machine learning (ML) in managing resources within fog and edge computing environments. Their work highlights the potential and challenges of integrating AI/ML algorithms, emphasising scalability, efficiency, and context-awareness in resource-constrained scenarios. Lu et al. (2023) analyse edge computing methodologies employed in signal processing for machine fault diagnosis. Their research demonstrates how real-time signal processing and low-latency fault detection can be achieved using robust IoT systems. This work makes a significant contribution to predictive maintenance strategies, a vital application area for edge computing.

Alowais (2023) addresses the application of edge computing in innovative healthcare. Their study focuses on edge intelligence, leveraging AI to classify and predict patient health states in various scenarios. By integrating advanced edge architectures, they identify challenges and propose solutions for improving healthcare delivery in real-time environments. Hamdan et al. (2023) classify IoT edge computing architectures based on factors such as data placement, orchestration services, security, and big data integration. Their detailed analysis of these architectures highlights their strengths and weaknesses, providing valuable insights into their suitability for various IoT applications.

Ruchika and Chhillar (2025) investigate the state of fog computing, identifying gaps in large-scale deployments despite over a decade of research. Their study examines the potential of fog networks in real-time applications and their integration with innovative technologies, such as federated learning and quantum computing, paving the way for future research directions.

The diversity of perspectives and methodologies in these studies underscores the complexity of edge computing and IoT ecosystems. While significant progress has been made, challenges such as scalability, security, resource management, and integration with emerging technologies continue to be areas of active research and innovation.

IoT in Smart Buildings

The Internet of Things (IoT) has revolutionised the way smart buildings operate, offering unprecedented levels of automation, efficiency, and user experience. IoT sensors embedded in smart buildings monitor environmental factors such as temperature, humidity, air quality, and occupancy levels, enabling real-time control over HVAC systems, lighting, and security measures (Abdali et al., 2021). As IoT adoption grows, studies highlight the potential to reduce energy consumption by 20–40% in modern smart buildings (Bashir et al., 2023; Ahmed et al., 2020). However, centralised Cloud architectures often struggle with the sheer volume of data generated by IoT devices, leading to increased latency and energy usage (Shi et al., 2022).

Fog Computing for Sustainable Smart Buildings

Fog computing addresses the limitations of Cloud-only architecture by decentralising data processing and bringing it closer to the network edge. Researchers have demonstrated that Fog nodes significantly reduce latency while improving resource efficiency in innovative environments (Jose et al., 2023; Haldar et al., 2025). For example, Fog-based systems enable real-time decision-making in critical applications, such as security surveillance and energy management, where delays can compromise safety and efficiency (Goyal & Mehta, 2022). Moreover, Fog computing minimises data transfer to centralised Cloud servers, thereby reducing the energy consumption associated with data transmission (Abdala et al., 2021).

Hybrid Fog–Cloud architectures are particularly effective in scalable scenarios, where the number of IoT devices grows exponentially. These systems balance computational workloads between local Fog nodes and the centralised Cloud, achieving a 40% reduction in energy consumption compared to Cloud-only setups. This capability aligns with the need for sustainable solutions in urban infrastructures, as emphasised by Dave (2024).

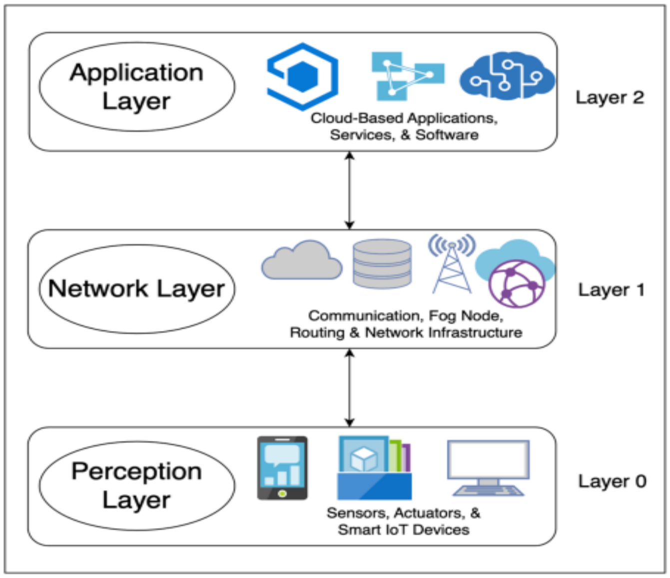

Figure 1: The layered IoT architectural plan for Smart Buildings (Source: Lawal et al. 2023)

Figure 1 illustrates the layered structure of a hybrid Fog–Cloud system, key to enhancing innovative building sustainability. The Perception Layer (Layer 0) collects IoT data from sensors, while the Network Layer (Layer 1) enables efficient data processing through Fog nodes, reducing latency and energy use. The Application Layer (Layer 2) handles advanced analytics in the cloud for real-time control and long-term optimisation, supporting energy efficiency and reduced CO_2 emissions, aligning with the study's goal of improving innovative building sustainability through IoT data.

a) Application Layer: This layer consists of intelligent software programs designed to provide application services in a user-friendly and efficient manner, ensuring they meet the specific needs and requests of users (Rajagopal et al, 2023; Ruiz et al., 2023).

b) Network Layer: This layer includes interconnected wired and wireless systems within public and private networks. Its primary role is to facilitate the transmission of information from the perception layer to the application layer. It employs various protocols and standards, such as Z-Wave, 5G, Bluetooth, LoRaWAN, IPv6, Long-Term Evolution (LTE), ZigBee, and WiFi, to enable seamless connectivity (Alfalouji et al., 2021)

c) Perception Layer: This layer focuses on identifying physical objects and collecting information through monitoring devices like interactive smart devices, actuators, and sensors. These components enable data acquisition from the environment, forming the foundation of IoT systems (Alfalouji et al., 2021; Rajagopal et al., 2023).

The Role of Real-World IoT Data

The effectiveness of Fog and Cloud architecture in smart buildings is closely tied to the quality of data used in system design and evaluation. Traditional simulation tools often rely on synthetic data, which may not accurately reflect the complexities of real-world scenarios (McGlinn et al., 2014). In contrast, studies using real-world IoT data have provided valuable insights into the performance of hybrid architectures under diverse operating conditions (Li et al., 2022; Malkawi et al., 2023). For instance, Ahmed et al. (2023) found that real-world data from smart sensors improved the accuracy of energy consumption models by 25%, enabling more targeted optimisations.

Sustainability Impacts of Hybrid Architectures

Buildings account for a significant share of global energy consumption, contributing to greenhouse gas emissions and climate change (Ruchika & Chhillar, 2025). Integrating Fog and Cloud computing with IoT systems offers a pathway to mitigate these impacts by enhancing energy efficiency and supporting sustainable building operations. Research by Mohit et al. (2025) highlights the potential of hybrid architectures to align with global sustainability goals, such as the United Nations Sustainable Development Goal (SDG) 11 on sustainable cities and communities. Key benefits include reduced carbon footprints, lower operational costs, and improved system resilience (Obergassel et al., 2023).

While existing research highlights the significant benefits of hybrid Fog–Cloud systems in improving energy efficiency, reducing latency, and optimising bandwidth usage, there are critical gaps that require further exploration. A key concern lies in understanding the long-term sustainability impacts of these systems (Veloso et al., 2021). Although Fog computing minimises energy consumption by reducing reliance on centralised Cloud data centres, limited attention has been given to the lifecycle emissions of Fog and Cloud nodes (Mohit et al., 2025).

The integration of renewable energy sources, such as solar and wind power, into Fog computing remains another underexplored area (Thatigutla, 2025). While renewable energy offers an effective way to lower further the carbon footprint of Fog–Cloud systems, its intermittent nature presents challenges for ensuring consistent performance and reliability. Adaptive energy management strategies and advanced storage solutions are needed to enable Fog nodes to operate seamlessly, even during periods of limited renewable energy availability. Research in this area could drive innovations that make hybrid systems not only more energy-efficient but also more resilient in diverse operational environments (Wang et al., 2020).

Moreover, hybrid architecture must be made scalable and adaptable to support emerging innovative city applications (Syu et al, 2023). These systems hold significant potential for managing real-time, data-intensive tasks such as electric vehicle (EV) charging networks and decentralised energy grids. For instance, hybrid Fog–Cloud systems could efficiently balance EV charging loads and provide predictive analytics to avoid grid overloads, yet few studies have addressed these opportunities. Similarly, the theoretical promise of using localised Fog nodes to manage microgrids and distributed energy resources in decentralised grids requires empirical validation (Walia et al., 2021).

Methodology

This study investigates the management and processing of Internet of Things (IoT) data within a hybrid Fog–Cloud architecture in a simulated innovative building environment. The methodology involves collecting and processing IoT data from sensors that monitor lighting, air quality (including CO2 levels), and security (CCTV). The study is divided into two primary scenarios, each designed to explore different deployment strategies and operational demands within a smart building.

IoT Data Collection and Device Configuration

Data were collected from a set of IoT sensors integrated into an intelligent building system. The study utilised various IoT sensors, including Lighting Sensors to monitor energy consumption and occupancy levels in different rooms, Air Quality Sensors to measure real-time CO2 concentrations and assess air quality, and Security Cameras (CCTV) to capture visual data for security and surveillance purposes within the building.

The devices were strategically placed throughout the simulated environment to reflect both a static deployment (Fixed Scenario) and a dynamically scaling system (Scalable Scenario). The innovative building environment used for simulation was configured to handle varying amounts of data traffic, ranging from low to high levels, simulating both typical and high-demand scenarios for smart buildings.

Simulation Scenarios

Two distinct simulation scenarios were created to assess the performance of the Fog–Cloud architecture under different conditions:

In the Fixed Scenario, IoT devices were placed in predefined positions, reflecting a static deployment typical of conventional smart buildings. This setup enabled the observation of system performance under stable, unchanging conditions, without considering growth in operational demands. In contrast, the Scalable Scenario involved the gradual increase of IoT devices over time to simulate the expansion of operational needs. This scenario provided insights into the challenges of scaling a smart building's IoT infrastructure, including network latency, resource management, and task distribution between fog and cloud layers as the number of devices and data traffic grew.

Data Processing and Simulation Tools

The collected data were processed using MATLAB Simulink and the iFogSim2 simulation toolkit. Both tools were chosen for their strengths in simulating and analysing innovative environments and Fog–Cloud architectures.

MATLAB Simulink was selected for its comprehensive modelling capabilities, particularly in the simulation of control systems, signal processing, and real-time data processing. Its integration with IoT tools makes it a versatile platform for processing large volumes of data generated by the IoT sensors in this study. Additionally, Simulink’s ability to model complex systems and visualise system behaviour makes it an excellent tool for real-time analysis of sensor data in innovative building applications. Furthermore, Simulink's extensive support for integration with other platforms allows for seamless incorporation of the iFogSim2 toolkit into the simulation environment.

iFogSim2, a simulation toolkit designed explicitly for Fog Computing, was chosen for its ability to model hybrid Fog–Cloud systems accurately. The toolkit is widely used in the research community for simulating the deployment of fog nodes and cloud servers, task offloading, and resource management in IoT-based environments. It supports the evaluation of latency, throughput, and the distribution of computing tasks between the fog and cloud layers, making it an ideal tool for investigating the performance of Fog–Cloud architectures in smart buildings. The use of iFogSim2 allows for a detailed simulation of various deployment strategies and their impact on system performance under both static and scalable conditions.

Together, MATLAB Simulink and iFogSim2 provide a robust simulation framework that enables detailed, accurate, and reproducible analysis of IoT-based innovative building systems under varying operational scenarios. The combination of these tools ensures that the study’s findings are both reliable and relevant for real-world applications. Key performance metrics included energy consumption (MJ), latency (ms), and network bandwidth usage (Gbps). The Fog nodes were modelled using Raspberry Pi 4 devices, while Cloud computations were simulated with high-capacity servers.

Results

Energy Efficiency

The hybrid Fog–Cloud architecture demonstrated notable energy efficiency improvements across both fixed and scalable scenarios. In fixed setups, where the number of IoT devices remained constant, energy consumption savings were modest, reflecting the inherent overhead of maintaining active Fog nodes. However, in scalable scenarios with device counts ranging from 20 to 200, energy savings became increasingly significant, peaking at **4.35%** for 200 devices (Figure 1). This trend highlights the efficiency of decentralised processing as device density increases, where Fog nodes effectively offload computational tasks from energy-intensive Cloud servers.

Latency Reduction

Latency reduction emerged as the most striking advantage of Fog computing in the hybrid architecture. By situating Fog nodes closer to IoT devices at the network edge, data processing and response times were significantly improved. For scenarios involving 200 devices, latency was reduced by an impressive 82% compared to Cloud-only setups. This improvement is crucial for applications that require real-time responsiveness, such as security systems that rely on CCTV-triggered alerts and automated decision-making systems in industrial settings. This capability positions hybrid architectures as essential for latency-sensitive IoT applications, from innovative traffic management to real-time health monitoring systems.

Network Bandwidth Optimisation

Bandwidth optimisation was another significant benefit observed under the hybrid Fog–Cloud architecture. In scenarios with high data traffic, the localised data processing capabilities of Fog nodes reduced the volume of data transmitted to Cloud servers. For example, light sensor data showed a 38% reduction in bandwidth usage compared to Cloud-only systems. This improvement highlights the effectiveness of Fog computing in mitigating network congestion, a common challenge in IoT deployments that involve large volumes of heterogeneous data streams. By preprocessing and aggregating data locally, Fog computing not only enhances bandwidth efficiency but also supports the scalability of IoT networks, ensuring smooth operation even under peak data loads. This is particularly beneficial in urban innovative building environments, where multiple devices generate continuous streams of data requiring real-time analytics.

Sustainability Implications

The sustainability implications of hybrid Fog–Cloud architectures extend beyond immediate operational efficiencies. By reducing the reliance on centralised Cloud data centres, Fog computing lowers the energy demands associated with long-distance data transmission and the maintenance of large-scale server farms. This shift not only decreases the carbon footprint of IoT systems but also aligns with global sustainability goals, such as the United Nations Sustainable Development Goals (SDGs). According to the International Telecommunication Union (2023), transitioning to energy-efficient digital infrastructure is crucial for combating climate change. The hybrid architecture's ability to minimise energy usage and improve processing efficiency supports this vision, making it an ideal framework for sustainable smart building operations. Furthermore, the localised nature of Fog computing enhances system resilience, reducing the environmental impact of outages and promoting the adoption of green energy solutions for edge devices.

Sustainability on Energy Consumption

Table 1 emphasises the comparative energy consumption and CO_2 emissions of Fog and Cloud simulations for various IoT devices, particularly showcasing differences as the number of devices increases.

Table 1: Sustainability on Energy Consumption

Number of Devices	**CCTV Fog Energy (MJ)**	**CCTV Cloud Energy (MJ)**	**CCTV Energy Difference (%)**	**CCTV Fog CO_2**	**CCTV Cloud CO_2**	**CCTV CO_2 Difference (%)**	**Light Fog Energy (MJ)**	**Light Cloud Energy (MJ)**	**Light Energy Difference (%)**
20	2778	2765	0.47	2790	2785	0.18	2785	2790	-0.18
40	2805	2835	-1.06	2880	2865	0.52	2835	2845	-0.35
60	2845	2865	-0.70	2890	2895	-0.17	2875	2885	-0.35
80	2888	2925	-1.27	2915	2940	-0.85	2900	2925	-0.85
100	2900	2970	-2.36	2930	2990	-2.01	2920	2975	-1.85
120	2915	2995	-2.67	2940	3015	-2.49	2945	2995	-1.67
140	2935	3015	-2.65	2965	3035	-2.31	2960	3020	-1.99
160	2958	3040	-2.70	2980	3060	-2.61	2985	3050	-2.13
180	2967	3065	-3.20	2998	3080	-2.66	3010	3080	-2.27
200	2995	3100	-3.39	2972	3105	-4.29	3035	3105	-2.26

Summary of the Findings on Sustainability and Energy Consumption

Energy consumption and CO_2 emissions trends for both Fog and Cloud systems remained stable with 20 to 200 devices, with notable differences emerging as device counts exceeded 100. For CCTV, the Fog-Cloud hybrid simulation showed slightly lower energy consumption, with a peak difference of -3.39% at 200 devices, indicating greater efficiency as device counts grew. Similarly, CO_2 emissions were consistently lower in Fog-Cloud hybrid simulations, with a percentage difference ranging from 0.18% at 20 devices to -4.29% at 200 devices, emphasising the environmental benefits of Fog computing. For light sensors, Fog-Cloud hybrid simulations also outperformed Cloud-only setups in both energy consumption and CO_2 emissions, with a peak energy consumption difference of -2.27% at 180 devices, highlighting the efficiency of localised data processing in environmental monitoring.

The data reveal an apparent disparity in latency performance, with cloud-based configurations demonstrating significantly higher latency (907.22 ms for CCTV and 861.78 ms for Light) compared to their fog counterparts (181.87 ms for CCTV and 81.89 ms for Light). These findings affirm the lower end-to-end delay advantage of fog computing, which is critical in real-time and near-real-time applications. Furthermore, the chart illustrates notable CO_2 emission differentials, with cloud deployments contributing to substantially higher CO_2 levels. This environmental disparity underscores the growing concern regarding the carbon footprint of centralised cloud infrastructures. Overall, the radar plot substantiates the suitability of fog computing in latency-sensitive and environmentally constrained application domains. This evidently shows that the cloud-based scenarios are better in comparison to fog.

Table 2: Sustainability on Latency (ms) Analysis for Device Data Handling

Number of Devices	CCTV Fog Latency (ms)	CCTV Cloud Latency (ms)	CCTV Latency Difference (%)	CCTV Fog CO2	CCTV Cloud CO2	CCTV CO2 Difference (%)	Light Fog Latency (ms)	Light Cloud Latency (ms)	Light Latency Difference (%)
20	220.12	755.45	70.85	104.55	678.32	84.59	102.65	688.45	85.10
40	225.67	779.89	71.06	88.67	735.12	87.94	98.23	744.23	86.81
60	199.32	829.56	75.97	81.34	824.56	90.13	84.34	810.76	89.60
80	193.45	870.13	77.77	78.65	848.45	90.73	75.78	852.34	91.11
100	181.87	907.22	79.95	83.91	875.43	90.41	81.89	861.78	90.50
120	171.23	910.47	81.19	85.12	891.76	90.46	83.12	900.12	90.77
140	174.09	916.58	81.01	93.67	917.45	89.79	94.78	908.34	89.56
160	168.32	928.46	81.87	98.32	919.76	89.31	96.56	911.45	89.41
180	166.87	950.67	82.45	104.87	911.23	88.49	106.32	921.56	88.47
200	172.34	953.91	81.93	122.45	927.45	86.79	120.45	929.78	87.05

Observations on the Sustainability on Latency (ms) Analysis for Device Data Handling

Fog computing consistently reduced latency for both CCTV and light sensors, with differences exceeding 80% across all device counts, especially at higher device numbers, demonstrating its scalability for large-scale IoT deployments. CO_2 emissions were significantly lower in Fog systems compared to Cloud setups, with reductions stabilising above 85% at high device counts, showcasing the sustainability benefits of localised data processing in Fog nodes.

The cloud infrastructure exhibits superior throughput, with bandwidth reaching 65.49 Gbps (CCTV) and 66.78 Gbps (Light), in contrast to fog counterparts registering 50.32 Gbps and 45.89 Gbps, respectively. While this denotes a cloud advantage in terms of data handling capacity, the CO_2 difference percentages hovering around 31% suggest a significant environmental trade-off. The consistent performance patterns across both sensor types emphasise the systemic impact of architectural choice on both efficiency and sustainability.

Observations on the differences for CCTV and light sensor data management

The Fog scenario consistently used less bandwidth than Cloud, demonstrating the efficiency of localised data processing. As device numbers increased, the bandwidth gap between Fog and Cloud slightly narrowed, reflecting scalability challenges in both setups. Fog systems also exhibited lower CO_2 emissions across all device counts, maintaining a significant reduction compared to Cloud systems, highlighting the environmental benefits of decentralised Fog computing.

Cloud-based deployments demonstrate higher energy use, 2970 MJ for CCTV and 2975 MJ for Light, compared to fog-based values of 2900 MJ and 2920 MJ, respectively. The CO_2 difference percentages (−2.01% for CCTV and −1.85% for Light) further highlight the elevated environmental cost of cloud computing in terms of carbon emissions. The compact clustering of fog-based values near the chart's centre illustrates their relative efficiency and lower environmental burden. These findings reinforce the argument that fog computing offers a viable, energy-conscious alternative to traditional cloud infrastructures, particularly in resource-sensitive contexts such as educational, industrial, and smart city environments.

These results collectively highlight the transformative potential of hybrid Fog–Cloud architectures in enhancing energy efficiency, reducing latency, and promoting sustainability in IoT-driven environments. Future research should explore the integration of renewable energy sources into Fog nodes and the optimisation of resource allocation algorithms to enhance these benefits further.

Discussion

The findings of this study highlight the transformative potential of Fog computing in addressing the challenges associated with traditional Cloud systems in IoT environments. By processing data closer to the network edge, Fog computing consistently demonstrated lower latency, reduced energy consumption, and decreased network bandwidth usage compared to Cloud-only setups. For instance, network bandwidth usage reductions exceeded 30% across various device counts, highlighting the efficiency of localised processing in alleviating congestion and ensuring real-time responsiveness. These results align with Jose et al. (2023) and Ruchika & Chhillar (2025), who both emphasise the critical role of decentralised architectures in improving resource utilisation and supporting latency-sensitive IoT applications. Additionally, the scalability benefits of Fog computing were evident, as the system maintained its performance advantages even as the number of devices increased, reinforcing findings from Obergassel et al. (2023), who noted the adaptability of hybrid architectures in high-density IoT deployments.

In addition to these findings, the study identifies key areas for future exploration, including interoperability challenges and the integration of AI-driven solutions for IoT optimisation. Interoperability remains a significant hurdle in environments with diverse IoT devices and platforms, and future research should focus on developing universal communication protocols and middleware frameworks to address this issue. Mohit et al. (2025) and Li et al. (2024) emphasise the importance of seamless integration in enhancing IoT scalability and usability. Moreover, leveraging AI and machine learning techniques for real-time analytics, predictive maintenance, and resource optimisation presents transformative opportunities for IoT networks. Studies by Abdali et al. (2021) and Haldar et al. (2025) suggest that incorporating edge AI capabilities can not only enhance system performance but also reduce the reliance on centralised Cloud systems, further supporting the scalability and sustainability of IoT ecosystems. These research directions are pivotal for advancing next-generation IoT systems that are efficient, user-centric, and environmentally responsible.

Despite their advantages, hybrid Fog–Cloud systems face challenges related to security, scalability, and interoperability. Ensuring the seamless integration of diverse IoT devices and platforms remains a critical hurdle, particularly in large-scale deployments (Rajagopa et al., 2023; Oma, 2023; Ruiz et al. 2023). Furthermore, the computational limitations of Fog nodes can constrain their ability to handle high data volumes, necessitating efficient workload distribution strategies (Ahmed et al., 2023 & Razaque et al., 2022).

Achieving interoperability between diverse IoT devices requires developing universal standards, middleware, and protocols. Additionally, integrating renewable energy sources and adaptive energy management frameworks can improve sustainability. At the same time, AI and machine learning can optimise scalability, predictive maintenance, and resource allocation in large-scale IoT deployments.

References

Abdali, T.-A. N., Hassan, R., Aman, A. H. M., & Nguyen, Q. N. (2021). Fog Computing Advancement: Concept, Architecture, Applications, Advantages, and Open Issues. *IEEE Access*, *9*, 75961–75980. https://doi.org/10.1109/ACCESS.2021.3081770

Alowais, S. A., Alghamdi, S. S., Alsuhebany, N., Alqahtani, T., Alshaya, A. I., Almohareb, S. N., Aldairem, A., Alrashed, M., Bin Saleh, K., Badreldin, H. A., Al Yami, M. S., Al Harbi, S., & Albekairy, A. M. (2023). Revolutionizing healthcare: The role of artificial intelligence in clinical practice. *BMC Medical Education*, *23*(1), 689. https://doi.org/10.1186/s12909-023-04698-z

Ammad, M., Shah, M. A., Islam, S. U., Maple, C., Alaulamie, A. A., Rodrigues, J. J. P. C., Mussadiq, S., & Tariq, U. (2020). A Novel Fog-Based Multi-Level Energy-Efficient Framework for IoT-Enabled Smart Environments. *IEEE Access*, *8*, 150010–150026.

Bashir, M. R., & Gill, A. Q. (2017). IoT enabled smart buildings: A systematic review. *2017 Intelligent Systems Conference (IntelliSys)*, 151–159. https://doi.org/10.1109/IntelliSys.2017.8324283

Dave, K. (2024). *An IoT-Based Approach of Synthetic Data Generation With Reduced Reality Gap—ProQuest*. https://www.proquest.com/openview/271a70bda8525d7819270f493332567e/1?pq-origsite=gscholar&cbl=18750&diss=y

Haldar, A., & Sethi, N. (2025). Energy Efficiency, Energy Access, and Climate Solutions. In A. Haldar & N. Sethi (Eds.), *Reconciling Energy Poverty and Climate Change: Universal Energy Access and Net-Zero Emission* (pp. 121–154). Springer Nature. https://doi.org/10.1007/978-981-96-6145-9_3

Jose, B., Emanuele, B., Luciano, C., Kelly, C., Faran, R., & Jacob, T. (2023). *The Breakthrough Agenda Report 2023*. 65–98.

Kumar, H. A., J, R., Shetty, R., Roy, S., & Sitaram, D. (2020). Comparison Of IoT Architectures Using A Smart City Benchmark. *Procedia Computer Science*, *171*, 1507–1516. https://doi.org/10.1016/j.procs.2020.04.161

Lawal, K. N., Olaniyi, T. K., & Gibson, R. M. (2024). Leveraging Real-World Data from IoT Devices in a Fog–Cloud Architecture for Resource Optimisation within a Smart Building. *Applied Sciences*, *14*(1), Article 1. https://doi.org/10.3390/app14010316

Li, J., Liu, Z., Han, G., Demian, P., & Osmani, M. (2024). *The relationship between Artificial Intelligence (AI) and Building Information Modeling (BIM) technologies for sustainable building in the context of smart cities*. https://doi.org/10.3390/su162410848']

Malkawi, A., Ervin, S., Han, X., Chen, E. X., Lim, S., Ampanavos, S., & Howard, P. (2023). Design and applications of an IoT architecture for data-driven smart building operations and experimentation. *Energy and Buildings*, *295*, 113291.

McGlinn, K., Hederman, L., & Lewis, D. (2014). SimCon: A context simulator for supporting evaluation of smart building applications when faced with uncertainty. *Pervasive and Mobile Computing*, *12*, 139–159. https://doi.org/10.1016/j.pmcj.2013.02.003

Mohit, K., Guatam, S., Ashutosh, K., & Kalka, D. (2025). *AI-Based Advanced Optimization Techniques for Edge Computing—Google Books*.

Obergassel, W., Xia-Bauer, C., & Thomas, S. (2023). Strengthening global climate governance and international cooperation for energy-efficient buildings. *Energy Efficiency*, *16*(8), 100. https://doi.org/10.1007/s12053-023-10177-7

Oma, R., Nakamura, S., Duolikun, D., Enokido, T., & Takizawa, M. (2018). An energy-efficient model for fog computing in the Internet of Things (IoT). *Internet of Things*, *1–2*, 14–26. https://doi.org/10.1016/j.iot.2018.08.003

Rajagopal, S. M., Supriya, M., & Buyya, R. (2023). Resource Provisioning Using Meta-Heuristic Methods for IoT Microservices With Mobility Management. *IEEE Access*, *11*, 60915–60938. https://doi.org/10.1109/ACCESS.2023.3281348

Razaque, A., Jararweh, Y., Alotaibi, B., Alotaibi, M., Hariri, S., & Almiani, M. (2022). Energy-efficient and secure mobile fog-based cloud for the Internet of Things. *Future Generation Computer Systems*, *127*, 1–13. https://doi.org/10.1016/j.future.2021.08.024

Ruchika, & Chhillar, R. S. (2025). Performance Evaluation of Hybrid Cloud-Fog Computing Architectures in Smart Home IoT Environments: A Comparative Simulation Study Across Multiple Tools. *Journal of Grid Computing*, *23*(2), 14. https://doi.org/10.1007/s10723-025-09802-9

Ruiz, D. P., Vasquez, R. A. D., & Jadan, B. V. (2023, November 15). *Predictive Energy Management in Internet of Things: Optimization of Smart Buildings for Energy Efficiency. | EBSCOhost*. https://doi.org/10.54216/JISIoT.100201

Syu, J.-H., Lin, J. C.-W., Srivastava, G., & Yu, K. (2023). A Comprehensive Survey on Artificial Intelligence Empowered Edge Computing on Consumer Electronics. *IEEE Transactions on Consumer Electronics*, *69*(4), 1023–1034. https://doi.org/10.1109/TCE.2023.3318150

Thatigutla, N. R. (2025). The Evolution of Cloud Architecture: Navigating Security and Sustainability in the Hybrid Era. *Journal of Computer Science and Technology Studies*, *7*(5), Article 5. https://doi.org/10.32996/jcsts.2025.7.5.10

Veloso, A. F. da S., de Moura, M. C. L., Mendes, D. L. de S., Junior, J. V. R., Rabêlo, R. A. L., & Rodrigues, J. J. P. C. (2021). Towards Sustainability using an Edge-Fog-Cloud Architecture for Demand-Side Management. *2021 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, 1731–1736. https://doi.org/10.1109/SMC52423.2021.9658962

Walia, N. K., Kaur, N., Alowaidi, M., Bhatia, K. S., Mishra, S., Sharma, N. K., Sharma, S. K., & Kaur, H. (2021). An Energy-Efficient Hybrid Scheduling Algorithm for Task Scheduling in the Cloud Computing Environments. *IEEE Access*, *9*, 117325–117337.

Wang, H., Liu, T., Kim, B., Lin, C.-W., Shiraishi, S., Xie, J., & Han, Z. (2020). Architectural Design Alternatives Based on Cloud/Edge/Fog Computing for Connected Vehicles. *IEEE Communications Surveys & Tutorials*, *22*(4), 2349–2377.

APPENDIX

```
import matplotlib.pyplot as plt
import numpy as np
# Data for energy efficiency
devices = np.arange(20, 220, 20)
energy_savings = [0.5, 1.0, 1.5, 2.1, 2.7, 3.3, 3.8, 4.1, 4.2, 4.35]

# Data for latency reduction
latency_cloud = [750, 776, 825, 865, 903, 905, 911, 923, 945, 949]
latency_fog = [218, 221, 197, 190, 178, 170, 171, 165, 164, 170]

# Data for bandwidth optimization
bandwidth_cloud = [20, 25, 30, 35, 40, 45, 50, 55, 60, 65]
bandwidth_fog = [12, 15, 18, 20, 23, 26, 28, 30, 33, 37]

# Energy Efficiency Diagram
plt.figure(figsize=(8, 5))
plt.plot(devices, energy_savings, marker='o', label='Energy Savings (%)')
plt.title("Energy Efficiency Improvement")
plt.xlabel("Number of Devices")
plt.ylabel("Energy Savings (%)")
plt.grid(True)
plt.legend()
plt.show()

# Latency Reduction Diagram
plt.figure(figsize=(8, 5))
plt.plot(devices, latency_cloud, label='Cloud Latency (ms)', linestyle='--', marker='o')
plt.plot(devices, latency_fog, label='Fog Latency (ms)', linestyle='-', marker='s')
plt.title("Latency Comparison")
plt.xlabel("Number of Devices")
plt.ylabel("Latency (ms)")
plt.grid(True)
plt.legend()
plt.show()

# Bandwidth Optimization Diagram
plt.figure(figsize=(8, 5))
plt.plot(devices, bandwidth_cloud, label='Cloud Bandwidth Usage (Gbps)', linestyle='--', marker='o')
plt.plot(devices, bandwidth_fog, label='Fog Bandwidth Usage (Gbps)', linestyle='-', marker='s')
plt.title("Bandwidth Usage Comparison")
plt.xlabel("Number of Devices")
plt.ylabel("Bandwidth Usage (Gbps)")
plt.grid(True)
plt.legend()
plt.show()
```