



The Evolution of Edge Computing in a Data-Driven World

Badahun Kharumnuid¹, Steffy Liza Kharmuti², Lenin Thingbaijam³

^{1,2}BCA, Department of Information Technology, Martin Luther Christian University, Meghalaya, India.

³Associate Professor, Department of Information Technology, Martin Luther Christian University, Meghalaya, India

Email: badakharumnuid6@gmail.com¹, kharmutisteffyliza@gmail.com², lenin.th@gmail.com³

Abstract

Edge computing is revolutionizing data processing and storage by bringing computational and data storage facilities closer to the data sources. This technique tackles the challenges faced by conventional clouds such as high latency and network congestion by employing the concept of data processed at the edge of the network in real-time. This paper discusses the edge computing paradigm and its evolution by covering the relevant concepts, benefits and trends that are changing within various industries. In particular, we assess the factors that make edge computing beneficial in terms of security, performance and efficiency concerns in smart cities, self-driving cars and internet of things (IoT) industries. This paper also reviews and reflects on the challenges of edge computing in terms of security, interoperability and scalability issues and how it can be overcome by integrating edge computing with fog computing, 5G and artificial intelligence (AI).

Keywords: 5G Networks; Artificial Intelligence; Cloud Computing; Edge Computing; Fog Computing; Internet of Things; Real-Time Data Processing.

1. Introduction

According to statistica.com, there are 17.08 billion connected IOT devices as of June 2024, and it is expected to be double by 2030. These devices will generate 79.4 zettabytes (ZB) of data in 2025, a 422% increase from 2019 (Statistica, 2023). This has been the fuel for a radical transformation in how data is created, processed, and analyzed in the digital age. Data handling has been fundamentally changed by the explosion of interconnected devices, sensors, and systems forming the backbone of modern networks- which has led to this explosion of interconnected devices, sensors, and systems [1-5]. Traditionally, cloud computing has been the primary infrastructure for managing the huge data generated by IoT devices. While cloud computing is powerful, it faces a limitation in speed and efficiency, especially for real-time applications. This gap has paved the way for the birth of edge computing, a new paradigm addressing these challenges. In this paper, we discuss on the limitations of cloud computing and how edge computing addresses those limitations. We highlight the different areas where edge computing is used.

Edge computing however has certain limitations and we discuss on integrating with fog computing, 5G and AI to overcome the limitations [6-11].

1.1. Cloud Computing Limitations

Due to the scalable data storage and processing capacity, cloud computing has long been hailed as the basis of modern information technology. It allows for the processing of data at a distance and massive storage of dataset across both personal and business levels without their dependence on local infrastructure [12-17]. However, as an increasing number of devices are being connected to the internet, cloud computing is fast losing serious advantages.

i. High Latency

High latency is one of the critical issues associated with traditional cloud computing models, especially in applications demanding real-time processing of data sensed from connected devices and sensors. The geographical distance between the sources of data and cloud centers can lead to delays that impede application responsiveness (Cosmin &

Schahram,2019; Gessert, Wingerath & Ritter,2020; Wu et al., 2022; Ru, Liming & Cheng,2024) [18-23].

ii. Bandwidth Limitations

Most cloud systems have bandwidth limitations, and such may significantly limit data transfer rates (Hu et al., 2018) [24-29]. This is very challenging in IoT applications with continually generated huge volumes of data (Jansson et al., 2023). Low bandwidth can cause data loss and delays in processing (Tchernykh et al., 2019).

iii. Network Congestion

Network congestion is a common problem in traditional cloud networks, mainly because of the proliferation of connected devices (Mora et al., 2024) [30-37]]. Higher levels of traffic can cause congestion and thus slow down data transmission and processing (Zhang et al., 2024; Chen & Zhao, 2023).

iv. Data Transfer Costs

Conventional cloud services can turn out to be an unnecessary burden on data transfer costs for organizations. Expenses in terms of shifting large amounts of data to and from the cloud could run recklessly high, especially for those applications that tend to need more frequent data synchronization (Atadoga et al.,2024; Wang et al.,2021; Samer et al.,2013) [38-41].

v. Scalability Issues

Scalability is one of the major challenges in traditional cloud computing. Since the number of connected devices and the data they produce increases, traditional cloud infrastructure may become inefficient in scaling up and may face performance degradation (Lorido et al.,2014; Hamann & Reina, 2022) [42-46].

vi. Security and Privacy

Security and privacy threats are a dominant concern in traditional cloud computing models [47-52]. Vulnerability to unauthorized access, data breaches, and compliance violations arises in storing sensitive information in the cloud (Subramanian & Jeyaraj, 2018; Abbas, Maennel, & Assar, 2017; Chauhan & Shiaeles, 2023) [53].

vii. Limited Edge Processing Capabilities

Conventional clouds are often unable to provide edge processing devices with the processing power that is needed for effective time processing of data coming

from IoT devices. Such limitation can lead to reliance on centralised processing, which is not even suitable for latency-sensitive applications (Ambalavanar & Hettiarachchi, 2020; Hamdan, Ayyash, & Almajali, 2020; Nair, 2023) [54-63].

1.2. Edge Computing

i. Edge Computing Concepts

Edge Computing is a framework for processing data near its source of origin rather than the Centralized cloud servers [64-69]. Edge computing is a relatively new, distributed computing paradigm that pushes data processing and storage closer to the sources of data, which may include sensors and IoT devices, rather than relying on centralized cloud infrastructure. Shi and Dustdar (2016) believe that the basic motivation behind edge computing is handling data "near the source of its generation," thus reducing the need to transfer it to distant cloud data centers. This proximity to origin data enhances processing efficiency, reduces latency, and diminishes bandwidth use, making it well-suited for real-time applications where fast decisions are critical (Shi & Dustdar, 2016; Satyanarayanan, 2017). Traditional cloud computing actually transfers data for processing and storage into a central cloud server with considerable latency due to the distance between the server and the source of the data (Bonomi, Milito, Zhu, & Addepalli, 2012) [70-74]. As the number of IoT devices continues to increase, this centralized model is causing delays and bottlenecks, making the inefficiencies in handling large amounts of data worse. Edge computing solves this problem by processing data at the "edge" of the network: on the device itself, near to it edge nodes, or even gateways (Satyanarayanan, 2017).

ii. Edge Computing Architecture

The edge computing architecture has layers that have control over data at different points in the network:

- a. **Cloud Layer:** In an edge computing framework, cloud layer is useful when the task requires a lot of computational power or in cases where the data is to be stored in the cloud for a long period of time; otherwise, it is significantly reduced (Satyanarayanan, 2017) [75].
- b. **Edge Layer:** Edge layer with nodes include routers, gateways, and small data centers that act

as intermediaries between the source of the data and the user [76-81]. These edge nodes do more complex processing and provide greater computational power than is available at the edge device (Bonomi et al., 2012).

- c. **Device Layer:** They are basically data sources including sensors, actuators, and IoT [82]. They have constrained computing power so they can only perform the most basic processing operations that include only filtering anomalies or normal data (Shi & Dustdar, 2016). Figure 1 shows the architecture of edge computing.

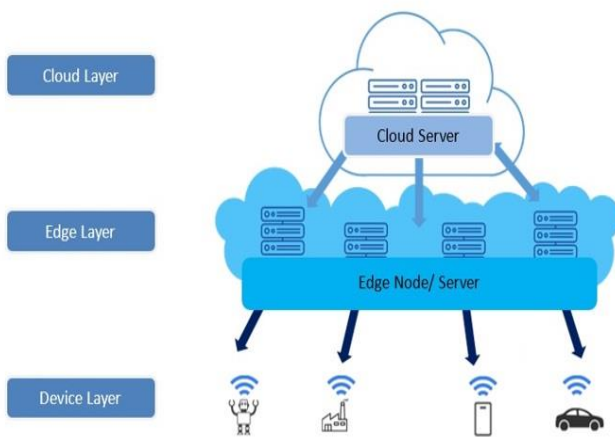


Figure 1 Edge Computing Architecture

2. Edge Computing as a Solution

Edge computing offers a robust framework to tackle the challenges presented by traditional cloud computing models, particularly regarding latency, bandwidth management, network congestion, cost efficiency, scalability, security, and processing capabilities [83-86]. We explore these key aspects in detail:

Low Latency

Latency is significantly reduced by processing data closer to the source. Decentralization calls for direct, real-time processing of data; this is what holds applications like autonomous vehicles and smart city infrastructure together. It reduces the distance data has to travel, thereby making the edge computing system more responsive (Corneo et al., 2021; Huedo et al., 2021; Gheorghe et al., 2019; Varghese & Buyya, 2018).

i. Enhanced Bandwidth Management

Edge computing solves the problem of bandwidth limitation because it offloads data processing and storage from the central cloud servers [87]. Handling more data at the edge means only necessary information is being sent to the cloud, thus reducing overall data transfer and hence improving the bandwidth usage efficiency (Huedo et al., 2021; Veith, Assuncao, & Lefèvre, 2021).

ii. Mitigation of Network Congestion

Edge computing reduces the load on central servers by sharing computational tasks with edge devices, thereby partially limiting network congestion [88]. It also helps to reduce network congestion, and these will particularly benefit applications that involve high volumes of data transmission, such as video surveillance and IoT monitoring systems (Hossain et al., 2023, Del Gaudio & Hirmer, 2020, Zhang et al., 2020).

iii. Cost-Effective Data Transfer

Edge computing also reduce the costs of data transfer. The edge reduces the costs of transferring data because only relevant information should be transferred to the cloud for further processing, thus reducing the costs of data transfer among many wastes of data that are not relevant (Yin et al., 2019; Fu et al., 2021; Harjula et al., 2021).

iv. Improved Scalability

Scalability is afforded by spreading resources across a number of different edge nodes, rather than solely relying on infrastructure from a single, centralized cloud infrastructure [89]. This flexibility allows for the effective use of new devices and services without having to suffer any radically noticeable degrading in performance (Li et al., 2018; Pudasaini & Abhari, 2020, Wu et Al., 2021; Xu et al., 2023).

v. Enhanced Security and Privacy

Edge computing improved security and privacy of sensitive data through local processing, thus making it expose risks to such information at a reduced level while transferring the data [90]. The location will help mitigate risks such as data breaches and access violations (Gao et al., 2021; Kumar et al., 2022; Xiao et al., 2019)

vi. Increased processing capabilities

With edge computing, a device can process data

locally and hence carry out real-time analytics and response without necessarily relying on more cloud-based resources. This is thus a boon to many applications that require immediate decision-making, such as healthcare monitoring and industrial automation (Bertino & Islam, 2017; Satyanand et al., 2020; Khan et al., 2020).

3. Applications of Edge Computing

Considering the advantages of edge computing, it has several applications and understanding its diverse applications is essential for organizations to stay competitive in the digital landscape. The following are some of the areas:

3.1.Industrial Automation and IoT

Edge computing significantly changes predictive maintenance and real-time control of robotics in industrial tasks. Chen et al. (2016) mentioned that it is applied to alleviate network congestion in industrial video surveillance systems. Vermesan and Coppola (2023) highlights the importance of adequately architecting AI workflow for PdM in industrial applications at the edge. Kristiani et al. (2020) proposed a combination of cloud and edge computing architecture and built a set of an intelligent air-quality monitoring system. Chandramohan et al. (2022) proposed a software defined network-based energy efficient resource management for industrial IoT. SDN-based IIoT architecture with EC outperforms the traditional methods over adaptive computation, effective resource management and latency in industrial wireless networks (IWNs). Zhong et al., 2017 highlighted various intelligent manufacturing through the key technologies including IOT. Intelligent manufacturing requires certain underpinning technologies in order to enable devices or machines to vary their behaviors in response to different situations and requirements based on past experiences and learning capacities and internet of things and edge computing are crucial (McFarlane et al., 2003). Zeng et al. (2019) outlined the application of real-time data processing with edge nodes in industrial factories.

3.2.Healthcare

In healthcare sector, edge computing is transforming patient care by enabling real-time data analytics and remote monitoring. Bertino & Islam (2017) also

mentioned that it was utilized for real-time analytics, healthcare, industrial automation. Liu et al. (2020) discussed real-time data processing for wearable medical devices. Dey et al. (2016) addressed improvements related to latency for telemedicine applications through fog and edge computing. Zhao et al. (2020) discussed benefits related to remote patient monitoring and real-time healthcare analytics. They also highlighted the influence of latency reduction on remote patient monitoring with edge computing. They also took note of diagnostics and real-time monitoring by highlighting the approach of edge computing. Zhou et al. (2021) discussed data security for smart healthcare systems that support edge computing. Alasmary (2024) integrates smart digital health solutions with latency-aware edge computing autoscaling, providing a novel approach to remote patient monitoring

3.3.Smart Cities

The domain of smart cities has gained advantages from edge computing in traffic regulation, environmental surveillance, and energy optimisation. Harsha and Gobi (2024) illustrated real-time optimization of urban traffic and infrastructure. Taleb et al. (2017) discussed its role in smart cities and traffic management. Wang et al. (2024), highlighted the applications of edge computing in smart city transportation. Sahil and Sood (2021) developed an IoT-based smart traffic management system using Edge Cloud technology to optimize traffic flow and enhance safety at urban intersections. Xu et al. (2024) proposed utilizing edge computing to alleviate stop-and-go traffic patterns and their negative effects on urban transportation systems.

3.4.Agriculture

Edge computing in precision agriculture supports real-time data analysis and automation. Feng (2022), examines the integration of edge computing and blockchain in smart agriculture systems to enhance data security and integrity, addressing vulnerabilities in centralized databases that could lead to information leaks and product quality issues. It proposes a smart agriculture architecture (Fig. 2) that utilizes blockchain for secure data storage and efficient image detection algorithms to improve matching speed, while also acknowledging the

limitations of blockchain's immutability and the need for global optimal matching in image stitching. Akhtar et al. (2021), emphasizes the integration of smart sensing and edge computing technologies in developing nations to improve precision agriculture, stressing the necessity for cost-effective infrastructure and better internet connectivity to foster agricultural growth.

3.5. Smart Homes

Edge computing functions, including device automation, help benefit the smart home environment in aspects of privacy protection. Aliero, Qureshi, & Pasha (2021) discuss smart home energy management systems in IoT networks for green city demands and services (Figure 2). Chamola et al. (2020) explored edge computing for smart parking automation and device coordination. Fernandes, Jung, & Prakash (2016) also conduct a security analysis of emerging smart home applications.

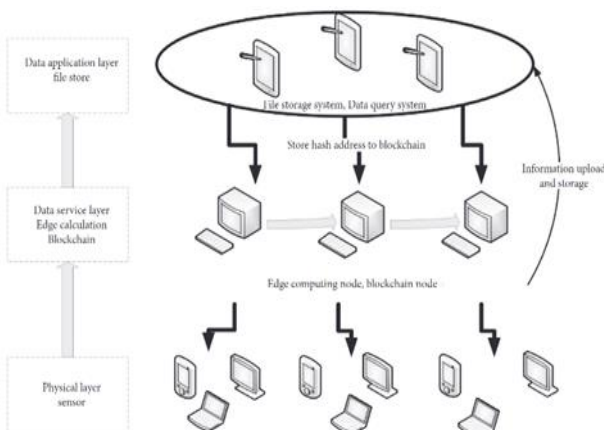


Figure 2 Smart Agriculture Architecture Design

3.6. Virtual Reality

Edge computing mitigates the high computational requirement in these technologies. Wang and Zhao (2022), discussed how edge computing facilitates immersive experiences. They identified edge intelligence in virtual reality (VR) and augmented reality applications. Deng et al. (2020) further discussed edge computing for immersive VR applications. They divided edge intelligence by distinguishing between AI for edge, which enhances edge computing solutions with AI technologies, and AI on edge, which focuses on model training and inference at the edge, while outlining core concepts

and a research roadmap for future initiatives.

3.7. Telecommunications

The telecommunication industry uses edge computing to improve the scalability and efficiency of 5G networks. Carvalho, Cabral, Pereira, and Bernardino (2021), highlighted scalability through edge computing to enhance the management of data and connectivity more efficiently. Mao et al. (2017) discussed how mobile edge computing accelerates services through reduced network congestion and decreased latency. They also presented a comprehensive survey of mobile edge computing research, emphasizing joint radio and computational resource management, while addressing challenges and future directions in areas like deployment, caching, mobility, green practices, and privacy, alongside recent standardization efforts and application scenarios.

3.8. Smart Grids

In smart grids, edge computing manages energy resources and ensures scalability. Minh et al. (2022), outlined how it enables efficient scaling. They discussed enhancing smart grids for energy management. Sena, Ullah, and Nardelli (2021), emphasized improving smart grid infrastructure through edge computing.

3.9. Robotics

In the field of robotics, edge computing enables low-latency control and real-time decision-making. Moon et al. (2024), explored the integration of edge computing with Local Dynamic Map (LDM) platforms to enhance autonomous driving robot systems, emphasizing low-latency processing for real-time decision-making. Experimental results demonstrate significant improvements in efficiency and responsiveness. Carvalho et al. (2021), provided an overview of current trends in edge computing, identifies key research challenges such as security and scalability, and suggests future directions, including the integration of AI and machine learning for enhanced decision-making across various industries.

3.10. Disaster Management

Edge computing plays a pivotal role in disaster management, enabling real-time analytics and rapid decision-making. This is particularly vital during

large-scale disasters when traditional communication networks may be compromised or congested. For instance, mobile edge computing can facilitate smart traffic offloading, improving system throughput and reducing delays for relief workers in disaster areas (Chen et al., 2019). Additionally, the integration of edge computing with cloud and fog computing allows for efficient data management and real-time information dissemination, which is essential for situational awareness during emergencies (Odun-Ayo et al., 2019) (Gaire et al., 2020). By leveraging the Internet of Things (IoT) and cloud technologies, disaster management systems can collect and analyze data from various sources, including sensors and social media, to provide timely and actionable insights (Jangid & Sharma, 2016) (Gaire et al., 2020). This synergy between edge computing and disaster management ultimately leads to more effective responses and reduced loss of life and property during crises.

4. Limitations of Edge Computing

While edge computing presents numerous advantages, it also faces several limitations that can hinder its effectiveness. These limitations include security concerns, interoperability challenges, and scalability issues.

4.1. Secure Concerns

A typical architecture of edge computing consists of numerous distributed devices and nodes. Distributed devices and nodes expose vulnerabilities in architecture security. Edge devices, being closer to the physical environment, become attack-friendly and may result in possible breaches to sensitive data (Caprolu et al., 2019).

i. Attack Surface

The approach of edge computing, being decentralized, increases the number of systems to be secured. Each edge device may be a potential entry point for cybercriminals, hence raising the risk of data breaches (Rapuzzi & Repetto, 2018).

ii. Data Privacy Risks

Sensitive data processed at the edge can be intercepted or manipulated during transmission, posing significant risks to privacy and compliance with regulations such as GDPR (Singh et al., 2022; Ansari et al., 2020).

4.2. Interoperability Challenges

In fact, interoperability between various edge devices and systems constitutes another significant limitation. The absence of standard protocols or interfaces may make it complicated to integrate disparate devices and services.

i. Diverse Ecosystem

Edge computing environments often consist of heterogeneous devices, each with varying capabilities and communication protocols. This diversity can hinder seamless communication and collaboration among devices (Hu et al., 2024; Kundu & Beerel, 2020; Wang et al., 2024).

ii. Vendor Lock-in

Most of the edge solutions are proprietary and, consequently, bring about vendor lock-in situations whereby an organization is not able to implement products from different vendors. This restricts flexibility and scalability potentialities in edges (Bonomi et al., 2014; Satyanarayanan, 2017; Shi et al., 2016; Varghese & Buyya, 2018).

4.3. Scalability Issues

While edge computing is supposed to shoulder additional workloads, the issue of scalability remains a major issue, especially in dynamic environments with varying data-demanding requirements.

i. Resource Management

Scaling edge resources is hard to scale dynamically. Performance deterioration may be induced because the processing power demand is higher than that provided by the edge devices (Li et al., 2020; Bensalem, Ipek, & Jukan, 2023).

ii. Infrastructure Costs

Expanding edge computing infrastructure to accommodate growth can be expensive. Organizations must invest in additional hardware and software, which can become a financial burden (Zhang et al., 2021; Cañete et al., 2022).

5. Edge Computing with Fog Computing

Limitations of edge computing can be compensated by integrating fog computing. In fact, edge computing and fog computing work as two complementary paradigms. The integration of these technologies significantly enhances the flexibility and scalability of various applications across multiple domains, including smart cities, healthcare, and the

Internet of Things (IoT). By distributing data processing both at edge nodes and fog nodes, the latency will considerably decrease. For instance, in smart city scenario, traffic sensors data has to be processed in real time locally at the edge nodes besides being aggregated in fog nodes so for deciding on time, further analysis will take place (Hurbungs et al., 2021). The collaborative framework of edge and fog computing makes scalable resource management possible. Fog nodes can handle various edge devices, distributing the workloads efficiently, and dynamically allocating or deallocating resources as per the demand (Bonomi et al., 2014; Hurbungs et al., 2021; Isaac et al., 2019). It allows the systems to scale up or down depending on dynamic workloads and provides a reliable resource allocation system. For instance, during busy hours, resources can be added to those fog nodes such that increased data at the edge devices can be managed without overloading the central cloud (Balajee et al., 2023; Haseeb et al., 2023). The integration of edge and fog computing facilitates efficient data management, where preliminary data processing occurs at the edge while more complex computations are handled at the fog layer. Edge devices can filter out unnecessary data before it is sent to fog nodes, reducing the volume of data transmitted to the cloud. This is particularly advantageous in IoT applications where vast amounts of data are generated (Wang et al., 2021). It also enhances aspects of security since data is processed locally instead of transferring it to the cloud. By processing, it reduces the risks associated with breaches and enhances the compliance of privacy. However, one of the most important benefits of the integration is in terms of localization of sensitive data. By keeping sensitive data within local networks, organizations can better control data access and comply with regulations, which require stringent data privacy measures.

6. Edge Computing with 5G

5G technology offers significant enhancements to edge computing by delivering advanced features such as network slicing, ultra-reliable low-latency communication (URLLC), massive machine-type communication (mMTC), and multi-access edge computing (MEC). Network slicing, enables multiple

virtual networks to be the same physical infrastructure. This enables the optimization of specific edge computing applications and allows flexibility and scalability (Priyadarshini et al., 2024). Additionally, URLLC reduces latency to 1 millisecond, providing real-time communication that boosts the efficiency of edge computing system. This means that it will be able to support many devices simultaneously by distributing the workload across an extensive network, hence improving the resiliency and scalability of the system (Venkata et al., 2023). The enormous machine-type communication capability further supports the simultaneous connection of a vast number of devices, distributing workloads across a wide network, thereby enhancing system resilience and scalability (Odugu et al., 2022). Lastly, MEC within the 5G ecosystem facilitates data processing closer to the user, reducing the reliance on centralized cloud servers. By minimizing bottlenecks and failures at single-edge nodes, MEC ensures more efficient and reliable edge computing performance (Ganesan et al., 2024).

7. Edge Computing with AI

The integration of Artificial Intelligence (AI) with edge computing brings substantial improvements in addressing key challenges such as resource constraints, dynamic workloads, security threats, and energy inefficiencies. AI-based algorithms enable edge computing systems to predict computational resource needs, reducing the risk of overloading single nodes and optimizing resource allocation. Through AI-driven load balancing, tasks can be distributed across multiple nodes based on real-time network conditions and resource availability, ensuring system efficiency and scalability (Anandakumar & Anandakumar, 2022; Bourechak et al., 2023). Furthermore, AI enhances the autonomy and security of edge computing environments by saving energy without performance loss. By applying AI-based solutions, edge systems can manage energy resources autonomously and hence be more sustainable and responsive to dynamic workloads.

Conclusion

Edge computing has emerged as an indispensable solution to overcome the deficiencies of conventional cloud computing. It addresses some of the most

crucial challenges such as latency, network congestion, and the processing of real-time data by bringing resources closer to data sources with edge computing. Such a paradigm shift is changing several industries, including smart cities and self-driving cars, and making both security, performance, and efficiency better. Despite the benefits of edge computing, there are still issues in using it. Security, interoperability, and scalability are still some of the major issues where edge computing is concerned. The integration of edge computing with emerging technologies such as fog computing, 5G networks, and artificial intelligence, however, presents promising solutions that build the capabilities of edge computing but also pave ways for innovative applications that would take full advantage of the data-driven landscape. As we move forward, research on such integrations, will allow edge computing to be fully realized. This, no doubt, will be a huge factor in terms of shaping the future of technology-towards an efficient and intelligent data ecosystem.

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