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Edge Computing and Distributed Database Systems

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Instructors:
Paraskevas Koukaras
Christos Berberidis

Written By:
Eleftherios Pexomatis
Eleni Vaskantira
Vasileios Kesopoulos
Nikolaos Laoutaris
Georgios Chrysovelidis

Abstract

With the increasing demand for faster computations and seamless communication between operational systems, traditional technologies such as cloud computing are proving insufficient for modern applications like autonomous vehicles and smart cities. Edge computing emerges as a promising solution to address these challenges, enabling real-time processing and efficient resource utilization. This paper examines edge computing to explore its functionality and evaluate its potential in meeting the demands of contemporary technologies. This report was prepared using a comprehensive review of scientific papers, in order to make sure the information presented is reliable and accurate. The analysis helped us understand the core concept of Edge Computing and Distributed Database Systems, and revealed the importance of them in various applications, such as Industrial IoT and Autonomous Vehicles. Design strategies, such as Data Partitioning and Replication Strategies, for Edge Databases were addressed as well, along with security challenges that need to be overcome, and some practices that are implemented to encounter these challenges. What is more, we examine how future advancements in technologies, like 5G Artificial Intelligence and Machine Learning, can affect the potential of the Edge Databases.

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1. **Introduction**

1.1 Background and Context

Nowadays, data is the most crucial component in modern business, providing us with valuable insight and enhancing our decision making. Even though traditional cloud computing has played a huge role in data generation and processing needs, today's ever-increasing volumes of data that need to be processed combined with the emergence of real-time applications is a task that the traditional computing paradigm isn't well suited for handling due to its limitations in bandwidth utilization, latency optimization or network issues(Duan et al., 2020). The edge computing paradigm addresses those limitations by bringing computation and data storage closer to the source.

1.2 Importance of Edge Computing in Modern Applications

The importance of edge computing lies in its ability to reduce latency, save on bandwidth costs and provide enhanced security and privacy. All those qualities are critical for managing the vast amounts of data generated by modern applications and by minimizing the reliance on centralized servers, edge computing can enable faster response times in autonomous vehicles and also improve the reliability of industrial IoT systems(Khan et al., 2020). As the Internet of Things keeps growing and more devices become connected, the importance of edge computing is expected to increase as well.

1.3 Objectives and Scope of the Report

This report focuses on providing an analysis of edge computing and how distributed database systems are integrated into this computing paradigm. It examines the fundamental factors, trends and a comparison analysis between cloud and edge computing. Additionally, it discusses some popular applications, design considerations for edge databases and also, privacy and security challenges that need to be addressed. Finally, it examines the future potential of edge databases and thereby this report attempts to give valuable insights to anyone interested in the topic such as IT professionals, businesses, researchers and so on.

2. Overview of Edge Computing

2.1 Definition and Core Concepts

Edge computing is a distributed computing paradigm in which data storage and computation occurs as much closer to the originating source as possible(Cao et al., 2020) . This type of architecture reduces the latency and leads to quicker responses due to the shorter travel distance of the data, compared to the transmission of data in a centralized way, such as in data centers. Some of the most important core concepts of edge computing are listed below :

- Proximity : Computing resources are located closer to end users, reducing latency and bandwidth costs
- Latency reduction : By Processing data near the source, the time it takes for data to travel to an edge server and return back is crucially reduced

- Scalability : By distributing computation between multiple edge nodes, it can prevent possible overloading of a single central node.
- Resource Efficiency : By reducing the costs that comes from the transmission of large volumes of data over the internet

2.2 Fundamental Factors and Trends

There are many reasons that lead to the adoption and the evolution of edge computing. For example, the ever-increasing number of IoT devices today has led to increased volumes of data that need to be processed for real-time applications and a central server may get overwhelmed (Hassan et al., 2018). However, edge computing faces this issue due to the proximity and scalability concept that was discussed before. Another big factor on why edge computing has become popular is the demand of low latency in autonomous vehicles for example, where milliseconds delays can be life crucial. Hardware advancements also play a role in the evolution of edge computing because it made it more cost-effective and efficient, such as AI accelerators and low-power processors.

There are numerous trends that exist in edge computing today. The growth of 5G networks is a popular example. 5G networks offer high download speeds and low latency and they can be connected with edge networks and provide the necessary bandwidth and responsiveness for real-time data transmission between edge servers and devices(Gosain et al., 2023). One other popular trend is focused on the enhancement of data privacy. By processing data locally with the use of edge computing solutions, data leakage during transmissions is remarkably reduced.

2.3 Comparison with Cloud Computing

Edge computing and cloud computing are both distributed computing technologies that work together but they differ in the location where the data processing occurs and the approaches they take in latency or scalability. In cloud computing, the data processing is done at a central location such as a data center whereas in cloud computing, it is done at the edge of the network and specifically near the device that generates the data and, in this approach, the need for communication with a central server is reduced. As has been previously discussed, edge computing reduces latency, which makes this technology ideal for real-time applications such as autonomous vehicles and IoT devices. On the other hand, cloud computing is preferred for applications such as file storage or web applications. Another important distinct difference among them is scalability. Cloud computing makes scalability easier where users are allowed to scale up or down their computing resources according to necessity. As far as data security, cloud computing faces more challenges because data needs to be transmitted over the internet whereas in edge computing, since data is processed near the source, so the risk of sensitive information being accessed is minimized. However, it introduces some new security challenges that should be addressed(Zeyu et al., 2020).

3. Distributed Database Systems in Edge Computing

Distributed databases are integral to edge computing, enabling efficient data management, scalability, and real-time processing across decentralized systems. They support diverse applications, ensuring high availability, performance, and consistency in dynamic environments.

3.1 Role and Importance of Distributed Databases

Distributed database systems are crucial in edge computing for scalability, availability, efficiency, and data consistency. They enable horizontal scalability, managing increasing data from IoT devices across multiple servers. High Availability (HA) systems ensure continuous operation, even during hardware failures, ensuring real-time processing for applications like autonomous vehicles. These systems support different consistency models, including ACID and Eventual Consistency, to balance data availability and consistency under latency constraints. By distributing data across multiple locations, they enable parallel processing, reduce latency, and optimize performance. Distributed databases also offer flexibility across edge, fog, and cloud environments, ensuring efficient resource management and optimized network performance.(Priya Rajagopal, 2023)

3.2 Architectural Models for Edge Databases

There are 5 architectures centered around edge computing. First, the **Cloud to Edge** model integrates cloud infrastructure with edge nodes, providing a consistent experience and enabling containerized applications at the edge, where databases are often distributed to reduce latency. Then the **Data Center to Edge** model brings computing closer to the edge by monitoring for potential issues with gas pipeline (edge).There is also the **Edge Manufacturing** experience that boosts manufacturing efficiency and product quality with AI and ML out to the edge.

Moreover, the **Edge Medical Diagnosis** accelerates medical diagnosis using condition detection in medical imagery with AI/ML at medical facilities. Last but not least, **SCADA Interface Modernisation** provides interfaces with SCADA systems that are compliant with NERC regulations creating different layers of API (Application Programming Interface) getaways to protect business service depending on the network zones.(Eric D. Schabell, 2022)

3.3 Examples of Edge Database Systems

The rapid advancement of IoT and big data technologies has underscored the importance of edge computing, enabling seamless high-frequency data collection and localized processing to meet the demands of modern applications. Therefore, some dedicated time-series databases have been developed to provide adequate performance for these applications, such as Gorilla, Apache HBase, c-treeEDGE, OpenTSDB, and InfluxDB. **Gorilla** is an in-memory TSDB (Time Series Database) that functions as a writethrough cache for monitoring data written to an HBase data store. The monitoring data stored in Gorilla is a simple 3-tuple of a string key, a 64 bit time stamp integer and a double precision floating point value. **Apache HBase** is an open-source non-relational distributed database modeled after Google's Bigtable and written in Java. HBase is a column-oriented, non-relational database. This means that data is stored in individual columns, and indexed by a unique row key. This architecture allows for rapid retrieval of individual rows and columns and efficient scans over individual columns within a table(Wang et al., 2023) . FairCom's **c-treeEDGE** IoT Database is a high-performance solution with a robust architecture that empowers organizations to reliably manage their data on the edge, opening the door for mission-critical, real-time decision making at or near the collection point. C-treeEDGE is designed to run on gateways and on the smallest edge IoT devices, yet powerful enough to host data from thousands of sensors in real time OpenTSDB (Time Series Database), which operates based on HBase, is a distributed and scalable time series database. **OpenTSDB** is created for processing tasks such as saving, indexing, and delivering metric information collected from servers, networks, and applications(Q. Liu et al., 2023) . **InfluxDB** is a new open-source time series database, with an even richer data model than OpenTSDB. Each event in a time series can have a full set of meta data. While this flexibility does allow for rich data, it necessarily results in larger disk usage than schemes that only store time series within the database. (Pelkonen et al., 2015)

4. Applications of Edge Databases

There are some applications which are very popular nowadays such as smart cities and industrial applications utilizing internet of things, autonomous vehicles, healthcare and telemedicine and so much more where fast computations are crucial for their performance. In such cases, edge computing is way better than the "traditional" cloud computing, where data is processed in remote servers, because it reduces latency, enhances performance and improves the efficiency of the calculations that must be performed.

4.1 Smart Cities

Analyzing data from various sources like sensors, life in cities can be optimized in many ways. To begin with, traffic jams can be reduced to a great level by studying sensor data in real time and using traffic lights accordingly. Also, edge computing can be used to reduce energy consumption in cities by changing the lighting, heating, and cooling in real time based on occupancy and the weather by processing data from IoT devices and smart meters at the edge. Up to 30% less energy has been used in places that are taking part in experiments like this. Finally, public safety can also be improved by IoT sensors that can provide immediate alerts for hazards like crimes, floods, wildfires or floods.

4.2 Industrial IoT

Edge computing can also be used nicely in industrial environments in various ways.
First of all, real time sensors can check the quality of the produced product, to check for any necessary corrections or for any faulty products, lowering the number of products that must be thrown away significantly which makes a production line more time efficient. By analyzing equipment performance in real time, edge computing enables predictive maintenance(Qiu et al., 2020). This approach prevents unexpected breakdowns, enhances equipment availability, and optimizes production processes. Finally, industrial robots and robotic vehicles can also use edge computing in industrial environments to communicate efficiently and in real time, improving coordination and efficiency.

4.3 Autonomous Vehicles

Using a network of autonomous vehicles in an urban environment is a very challenging task for us humans to do, because time efficiency in calculations that need to be done by the vehicles, and their communication is crucial for our own safety. Every milli-second matter and edge computing might be the answer or at least a part of the answer to some of these problems. Autonomous vehicles (AVs), also known as self-driving cars, signify a profound shift in the automotive industry.

Equipped with advanced sensors, cameras, and artificial intelligence (AI) systems, these vehicles navigate without human intervention, heralding a new era in transportation.(Yan, 2024) The successful deployment of AVs depends on the ability to process vast amounts of data in real-time, ensuring swift decision-making and robust system performance. Edge computing has emerged as a critical technology in addressing these requirements by bringing computational resources closer to the data source, reducing latency and enhancing data processing capabilities. Edge computing plays a crucial role in supporting Internet of Things (IoT) devices and 5G networks by handling the large volumes of data these devices generate.(Chirlawar, 2024)

4.4 Healthcare and Telemedicine

It is common nowadays for many people to have wearables like smart watches or smart rings that help them monitor their vital signs like heart rate, blood pressure, their sleeping schedule and much more.(Ramanathan et al., 2024) Devices like this, can detect or prevent various health conditions by analyzing this data in real time, suggesting a visit or even sending the data to a healthcare expert to further analyze the situation and provide a deeper understanding, solving any health issues if there are any. This can be extremely helpful for doctors and patients. Additionally, monitoring devices like this can be used in hospitals to analyze doses of medication that someone must take, regarding their real time condition, monitoring patients in real time. Finally, continuous analysis of health data through edge devices allows early detection of medical conditions, enabling preventative care and reducing the burden on healthcare systems.

5. Design Considerations for Edge Databases

Now that we have explored the aspects, importance and applications of edge databases, let us delve into some design strategies to tackle the most frequent challenges. In this chapter we address four key considerations.

5.1 Data Partitioning and Replication Strategies

To design an edge database, we must naturally address the issue of distributing and managing data across distant nodes.

Data partitioning is the act of dividing datasets into smaller subsets, to ensure they are more easily manageable. **Range partitioning** divides data based on a range of values to simplify range queries, while risking creating uneven data distributions. **Hash partitioning** spreads data evenly across nodes using a hash function to determine the storage location, achieving load balancing but complicating range queries. **Geographic partitioning** allocates data to nodes based on geographic proximity and is especially relevant for IoT applications.

Data replication is the practice of maintaining copies of data across multiple nodes to ensure instant availability and fault tolerance. **Synchronous replication** propagates updates to all replicas *before* each transaction, sacrificing latency for data accuracy and consistency. **Asynchronous replication** does the same but *after* transactions, reducing latency but introducing eventual consistency. **Selective replication** replicates data selectively based on frequency of access or importance, achieving more balanced performance.

It should already be apparent that partitioning and replication conflict. The CAP theorem states that a distributed database system can achieve at most two out of the three properties - **C**onsistency, **A**vailability, and **P**artition Tolerance - simultaneously. Researchers have proposed various strategies to optimize data placement costs, access latency, migration costs, and load balancing constraints (Venkatesh et al., 2023).

5.2 Latency Optimization

Latency optimization is crucial for real time edge computing applications. Even a small delay can disrupt the smooth decision-making processes of time-sensitive applications. Reducing latency can lead to a more seamless user experience and ensure stability for vital operations.

One key strategy for latency optimization is edge caching, where frequently accessed data is stored at edge nodes, close to users. P**roximity-based query routing** is another approach, where data requests are redirected to the nearest edge node.

Network technologies obviously play a crucial role here. The integration of 5G networks improves latency, ensuring faster communication between edge devices and central servers (S. Liu et al., 2019).

5.3 Scalability and Resource Management

When it comes to distributing dynamic workloads, **scalability** and **resource management** are a crucial topic. Edge systems are expected to handle fluctuating traffic with stability, a task that becomes increasingly difficult as the number of devices and users increases.

C**ontainerization** technologies, like the widespread tool **Kubernetes**, enable automated management and scaling by employing containers and allocating resources dynamically based on demand. Another emerging technology is **predictive resource allocation**, that further boosts performance by integrating powerful AI and ML techniques to accurately estimate future request arrivals and pre-allocate resources accordingly (Ouyang et al., 2023).

5.4 Fault Tolerance and Disaster Recovery

When it comes to **fault tolerance**, edge databases often rely on **redundant nodes** and **self-healing mechanisms**, through transferring workloads to healthy nodes dynamically in case of failure. Should disaster occur, however, the predominant **disaster recovery** strategy is **checkpointing**, a process where the state of critical systems is periodically “saved”, enabling post-failure restoration with minimal loss.

Once again, a natural trade-off exists between system resilience and cost-efficiency; with maintaining redundant nodes and frequent checkpoints, operational costs add up. Recent advancements, such as fault-tolerant consensus mechanisms tailored for edge environments, have enhanced reliability in distributed edge databases without significant cost increase (Jing et al., 2023).

6. Data Privacy and Security Challenges

Even though edge computing has many implementations, and can speed up and optimize different processes, it does not come with no cost. Concerns regarding privacy may arise, along with some security challenges that need to be overcome.

6.1 Privacy Concerns in Edge Computing

The migration of services between local and global scales is required for IoT functionality, making the network more vulnerable to malicious activities. The three main processes in Edge Computing servers are a) communication b) computation c) storage, and malicious attacks can be encountered in all three of them.

With moving data processing to edge devices, the user's privacy can be compromised, as their data, for instance location or behavior, can be stolen, leaked or misused by service providers or edge data centers (Alwarafy et al., 2021). This can happen because (Parikli et al., 2019):

a) The credentials used for protection are weak, making it easier for malicious users to infiltrate the system.
b) The communication between devices is often insecure, making them vulnerable to eavesdropping and data tampering.
c) During an outage, the recovery and backup may be inadequate.
d) Delays in delivering and/or applying updates, like software patches, to edge systems or devices.
e) There are challenges in monitoring and understanding the state and activity of the network.
f) Users cannot select which data is collected by edge devices or systems.

6.2 Security Threats and Attack Surfaces

Below you can find some types of security and privacy threats (Alwarafy et al., 2021):

Malicious Hardware/Software Injection: Hacking processes are performed by attackers, such as stealing data, exposing the integrity of a database, bypassing authentication and more. This is done by adding unauthorized software/hardware components to EC node levels, leading to malicious input into the EC servers.

Jamming Attacks: Counterfeit messages are thrown into the network to disrupt communication or other processes in EC networks.

Distributed Denial-of-Service Attacks: The most famous DDoS attacks are Outage attacks, sleep deprivation and battery draining. In the first case EC nodes are exposed to unauthorized access, stopping their performance. In the second case EC nodes are overwhelmed with an undesired set of requests. In the last case, attackers aim at node failure, by depleting the battery of EC nodes or devices.

Physical Attacks or Tampering: Only happens when attackers can physically access EC nodes or devices. Attackers extract cryptographic information, or modify the software or operating systems.

Eavesdropping: Network traffic is monitored by malicious users, who are hidden, and steal user data.

6.3 Best Practices and Emerging Solutions

In order to ensure data privacy there are some common practices that can be implemented.

Data encryption and secure storage: Secure Data Aggregation and Secure Data Deduplication are two techniques that can be used to achieve that. In Data Aggregation, homomorphic encryption schemes are used by devices to encrypt their own data, which are then sent to EC nodes, where all data is aggregated and finally sent to the central cloud servers. In Data Deduplication, replicated copies of data in EC nodes are removed, with intermediaries having access to them but without gaining any knowledge on it.

Authorization - Authentication: Entities are required to authenticate one another in different trust domains, including both single/cross-domain and handover authentication.

Trust Modeling: IoT devices are more vulnerable to internal threats. Trust Modeling is targeted to prevent these internal attacks by implementing not only traditional security mechanisms, but trust modeling techniques. Most of the times, attackers initially employ IoT devices in the network. A trust evaluation mechanism identifies the source of the internal attack to eliminate or reduce the threat.

While solid solutions are still under development, there are some promising approaches from related fields, that can address the aforementioned threats. (Roman et al., 2018)

Identity and Authentication: There are no comprehensive solutions at the moment, however there are approaches from related fields that can be adopted. Techniques like Single Sign-On, pairing cryptosystems, location-based authentication and hybrid encryption look promising.

Access Control Systems: Potential solutions may be offered by models like RBAC with inter-domain mapping and privacy-preserving techniques.

Protocol and network security: Solutions like SDN and NFV, may enhance network security and management, but still need more development.

Trust management: There are emerging trust solutions that adapt systems from related fields. Such are decentralized self-managed trust, community-based trust models and Bayesian approaches for hybrid clouds.

Intrusion detection systems: Distributed architectures, SDN-based systems, federated security frameworks and GPU-accelerated monitoring show promise for adaptation but still need further research.

Privacy: Data encryption, privacy helpers and pseudonym systems help with identity protection.

7. Future Potential of Edge Databases

The future of edge and cloud computing will be shaped by innovations such as federated learning, distributed AI, quantum computing, edge data centers, serverless computing, and autonomous devices. These advancements, along with blockchain and advanced networking, will enhance performance, security, and scalability, enabling new use cases and driving digital transformation.

7.1 Innovations in Edge Database Technology

Modern data management solutions prioritize scalability, simplicity, and flexibility, often at the expense of consistency. Known as NoSQL, these alternatives to traditional relational DBMS (SQL) have introduced new data structures (e.g., lists, arrays) and user-defined functions, resulting in more complex data models and languages(Ahmad Ferdaws Ahmadi et al., 2024).

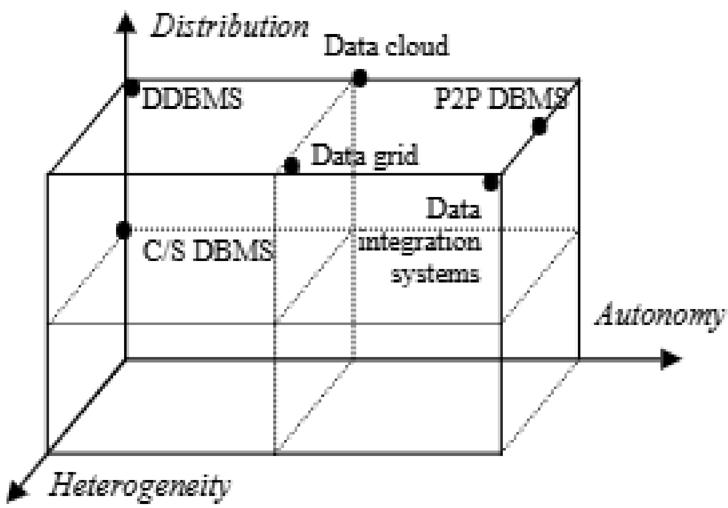

Image. Architecture of Contemporary DBMS

Emerging solutions adopt specific data models tailored to application needs. For instance, Bigtable leverages the Google File System (GFS) to store structured data with fault tolerance for distributed systems. Social networks utilize graph-based models, while scientific applications, like SciDB, rely on array-based models with operators for specialized processing. Frameworks like MapReduce,(Dean & Ghemawat, n.d.), enable parallel processing with simple key-value data models, while tools like Pig Latin offer algebraic query languages. Specialized algebras increasingly drive abstraction and optimization in vast data workflows.(Valduriez, n.d.)

7.2 Impact of 5G and Beyond

Nowadays, Edge computing in 5G has several key objectives. It improves data management by processing large, delay-sensitive data locally, reducing reliance on the cloud and enabling real-time applications like remote surgery. It enhances Quality of Service (QoS) to meet diverse requirements for applications such as OTT services, ensuring low latency and high bandwidth. Additionally, it predicts network demand to allocate resources efficiently, deciding whether tasks should be processed locally or in the cloud. Edge computing also enables location awareness by allowing edge servers to track device locations and support location-based services, such as emergency response. Furthermore, it optimizes resource management to enhance network performance, addressing the limited resources of edge clouds while meeting user demands. (Hassan et al., 2019),(Parcu et al., 2023)

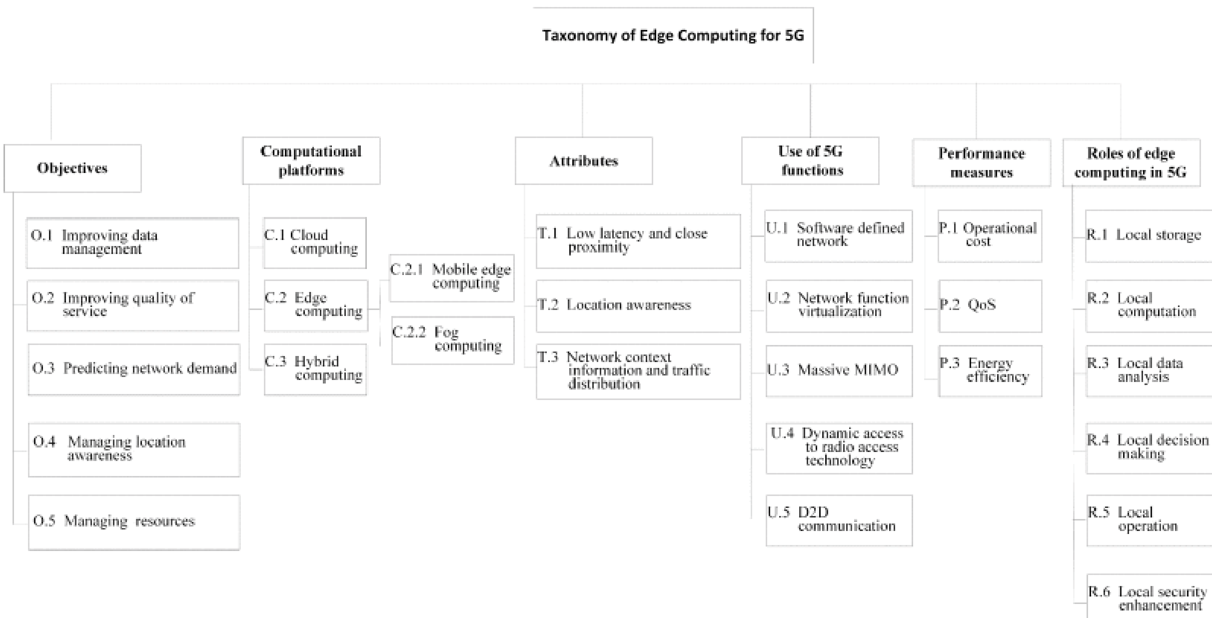

Image Taxonomy of Edge Computing for 5G.

7.3 Integration with Artificial Intelligence (AI) and Machine Learning (ML)

Edge computing (EC) enhances AI & ML applications by addressing challenges in the big data era, where AI's widespread use is inevitable. However, AI's need for significant computing power and energy often exceeds the capabilities of terminal devices. Traditionally, cloud computing has handled these tasks, but it faces issues like bandwidth limitations and high latency when managing numerous AI models. Edge Computing resolves this by bringing AI closer to users and devices, offering low latency and high network stability. It introduces three approaches to AI integration(Chang et al., 2021):

1. preprocessing massive data for cloud-based training, which doesn't meet latency demands for certain applications
2. performing AI reasoning on the edge while cloud handles training; and

3. delegating training and reasoning tasks entirely to the edge, improving location awareness and reducing latency but increasing energy and computing power demands.

Each approach has pros and cons, so the optimal choice depends on specific needs.(Hua et al., 2023)

7.4 Environmental and Sustainability Considerations

Edge computing presents significant environmental and sustainability benefits by reducing the energy consumption associated with data transmission and processing. By processing data closer to its source, edge computing minimizes the need for large-scale data centers, thereby lowering carbon emissions linked to centralized cloud services. This localized approach not only enhances efficiency but also decreases latency, contributing to more sustainable operations in industries like IoT and smart devices. Moreover, as organizations seek to lower their carbon footprints, integrating edge computing into their infrastructure can facilitate better resource management and promote greener technologies. Ultimately, edge computing supports a transition towards more sustainable digital ecosystems while addressing pressing environmental challenges(Santos et al., 2024).

8. Conclusion

8.1 Key Takeaways

Edge computing appears to have the potential to transform the way we tackle modern data processing challenges. Bringing computations closer to the data source reduces latency, promotes scalability and improves efficiency. Distributed Database Systems are designed to be a perfect fit for edge environments and ensure fast and safe data management through partitioning, replication and fault-tolerance mechanisms. Already we feel the effect and benefits of these technologies through applications in IoT, smart cities, autonomous vehicles and telemedicine. Furthermore, design strategies like latency optimization, containerization and predictive resource management allow us to achieve balance between performance, resilience and cost.

8.2 Challenges and Opportunities

Challenges can still be found in spite of all this rapid growth. Data privacy and security are, as always, primary concerns, even more so if we consider that edge nodes are inherently more vulnerable against the ever-growing cyber threat sophistication. Moreover, innovative solutions continue to be needed when it comes to trade-offs between cost and performance as well as scaling dynamic workloads.

However, much opportunity awaits as well. Equipping edge databases with 5G and incorporating AI-powered processes is only just beginning to unlock the full potential of edge environments. Future innovative trends include quantum computing, federated learning and sustainable edge architectures, which pave the way for the edge ecosystem of the future.

The next chapter of edge computing and distributed database systems is still being written. Addressing these challenges while looking over the horizon to new opportunities will define the way we think about databases and perhaps the data ecosystem as a whole.

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