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FINAL STUDY NOTES

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Optimal MEC Deployment in Smart Cities Using Clustering Algorithms.

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DEDICATION

أُهدي تخرجي إلى من كان سندي في هذه الحياة ومصدر الأمان، إلى من استمددت منه قوتي وساندني طوال مسيرتي الدراسية، وشاء الله أن يُفارقني في آخر المشوار، إلى أبي الغالي، طيب الله ثراه، وجعل الجنة مثواه.

إلى من غرست في قلبي حب العلم والإصرار، إلى من كانت دعوتها رفيقة دربي، وأنارت لي طريق حياتي، إلى أمي الحبيبة، أطال الله في عمرها، وجزاها عني خير الجزاء.

إلى رفاق الخطوات الأولى والأخيرة، إلى من ساندني وكان كتفي في هذه الحياة، إلى إخوتي الأعزاء،

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ملخص

مع تزايد تعقيد التنقل الحضري والنمو السريع في عدد الأجهزة المتصلة، أصبحت هناك حاجة ملحة لتطوير أنظمة نقل ذكية أكثر تكيفًا واستجابة. تهدف هذه الدراسة إلى استكشاف دمج ثلاث تقنيات رئيسية — شبكات الجيل الخامس (5G)، والحوسبة الطرفية المتنقلة (MEC)، والذكاء الاصطناعي (AI) — من أجل تحسين توزيع موارد الحوسبة في المدن الذكية. تم استخدام بيانات حقيقية لحركة المركبات في مدينة سان فرانسيسكو، وتطبيق تقنيات التجميع مثل خوارزمية التجميع التزايدي (Agglomerative Clustering) وأداة التصور الشجري (Dendrogram) لتحديد المواقع المثلى لنشر خوادم (MEC). يهدف هذا النهج إلى تحقيق توزيع فعال للموارد، تقليل زمن الاستجابة، وتحسين تجربة المستخدم في أنظمة النقل الذكية.

الكلمات المفتاحية:

المدن الذكية، شبكات الجيل الخامس (5G)، الحوسبة الطرفية المتنقلة (MEC)، الذكاء الاصطناعي (AI)، التجميع (Clustering)، التجميع التزايدي (AgglomerativeClustering)، الرسم الشجري (Dendrogram).

Résumé

Avec la complexité croissante de la mobilité urbaine et la croissance rapide des dispositifs connectés, il devient essentiel de mettre en place des systèmes de transport plus intelligents et adaptatifs. Cette étude examine l'intégration de trois technologies clés — les réseaux de cinquième génération (5G), le Multi-access Edge Computing (MEC), et l'intelligence artificielle (AI) — afin d'optimiser la répartition des ressources de calcul dans les villes intelligentes. En utilisant des données réelles sur les déplacements de véhicules à San Francisco, des techniques de regroupement telles que l'agglomérative clustering (Agglomerative Clustering) et des outils de visualisation comme le dendrogramme (Dendrogram) sont appliqués pour identifier les emplacements optimaux de déploiement des serveurs MEC. Cette approche vise à améliorer l'allocation des ressources, à réduire la latence et à enrichir l'expérience utilisateur dans les systèmes de transport intelligents.

Mots-clés :

Villes intelligentes, 5G, Multi-access Edge Computing, Intelligence Artificielle, Regroupement, Regroupement Agglomératif, Dendrogramme

Abstract

With the increasing complexity of urban mobility and the rapid growth of connected devices, there is a growing need for more intelligent and adaptive transportation systems. This study explores the integration of three core technologies — Fifth Generation (5G) networks, Multi-access Edge Computing (MEC), and Artificial Intelligence (AI) — to optimize the allocation of computing resources in smart cities. Using real vehicle movement data from San Francisco, clustering techniques such as Agglomerative Clustering and visualization tools like Dendrograms are applied to identify optimal MEC server deployment locations. This approach aims to ensure efficient resource distribution, reduce latency, and enhance user experience within intelligent transportation systems.

Keywords:

Smart Cities, 5G, Multi-access Edge Computing (MEC), Artificial Intelligence (AI), Clustering, Agglomerative Clustering, Dendrogram

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List of Abbreviations

1G	First Generation
2G	Second Generation
3G	Third Generation
4G	Fourth Generation
5G	Fifth Generation
AMPS	Advanced Mobile Phone System
IS-95	Interim Standard 95
GSM	Global System for Mobile Communications
IMT2000	International Mobile Telecommunications 2000
WCDMA	Wideband Code Division Multiple Access
LTE	Long Term Evolution
WiMAX	Worldwide Interoperability for Microwave Access
IP	Internet Protocol
PSTN	Public Switched Telephone Network
WWWW	World Wide Wireless Web
VANETs	Vehicular Ad Hoc Networks
V2V	Vehicle-to-Vehicle
V2I	Vehicle-to-Infrastructure
ITS	Intelligent Transportation Systems
MEC	Multi-access Edge Computing
AI	Artificial Intelligence
V2X	Vehicle-to-Everything
IoT	Internet of Things
URLLC	Ultra-Reliable Low Latency Communication
mMTC	massive Machine-Type Communications
NS	Network Slicing
SDN	Software Defined Networking
QoS	Quality of Service
AR	Augmented Reality
FaaS	Function-as-a-Service
GPU	Graphics Processing Unit

FPGA	Field-Programmable Gate Array
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DBI	Davies-Bouldin Index
CH Index	Calinski-Harabasz Index
RL	Reinforcement Learning
UPF	User Plane Function
AF	Application Function
MA-MEC	Multi-Access Mobile Edge Computing
H-IoT	Heterogeneous Internet of Things
EDGE	Enhanced Data rates for GSM Evolution
FBMC	Filter Bank Multi-Carrier
NOMA	Non-Orthogonal Multiple Access
OFDM	Orthogonal Frequency-Division Multiplexing
MNOs	Mobile Network Operators

General Introduction

General Introduction

The growing complexity of urban mobility, coupled with the rapid rise in connected devices, has created an urgent demand for smarter, more adaptive, and responsive transportation systems. As cities expand and transportation networks become more congested, traditional approaches to traffic management and infrastructure planning are proving insufficient. To address these challenges, innovative technologies are being explored to support real-time communication, low-latency processing, and dynamic decision-making capabilities.

Vehicular Ad Hoc Networks (VANETs) have emerged as a crucial foundation for enabling communication between vehicles (V2V) and between vehicles and infrastructure (V2I). These networks offer significant potential to improve road safety, reduce congestion, and support the implementation of intelligent transportation systems (ITS). However, to fully leverage the power of VANETs, they must be supported by high-performance, scalable, and intelligent communication and processing platforms.

Fifth Generation (5G) mobile networks are designed to meet these requirements, offering ultra-reliable, low-latency communication and the capacity to support massive numbers of connected nodes. The features of 5G, such as network slicing and edge integration, make it an ideal candidate for supporting data-intensive and latency-sensitive vehicular applications. Still, traditional cloud computing models often fall short in delivering the required responsiveness.

To overcome these limitations, Multi-access Edge Computing (MEC) introduces a new paradigm by extending cloud functionalities to the edge of the network. This enables local processing of data closer to the point of generation—improving response times, reducing backhaul load, and enhancing user experience. MEC is particularly valuable in vehicular contexts, where milliseconds can make a difference in safety and efficiency.

Alongside these developments, Artificial Intelligence (AI) brings the capability to analyze large volumes of dynamic data and learn from patterns in real-time. Machine learning algorithms, especially those used in clustering and prediction, play a pivotal role in supporting intelligent decisions such as resource allocation, traffic flow optimization, and network management. AI thus complements both 5G and MEC by adding the layer of intelligence needed for adaptive, data-driven transportation solutions.

This thesis presents a structured study of these three enabling technologies—5G, MEC, and AI—and demonstrates their relevance and interplay in the context of smart urban mobility. The first chapters provide theoretical grounding and technical insights into each component: the architecture and evolution of 5G networks, the principles and deployment models of MEC, and the fundamentals of AI and unsupervised learning methods. These discussions are followed by a practical implementation in which real GPS-based vehicle movement data from San Francisco is used to identify optimal areas for MEC deployment using clustering techniques.

The objective of this research is to explore how the integration of these technologies can be harnessed to enhance the efficiency, scalability, and intelligence of urban transportation systems. The interdisciplinary approach adopted in this work serves as a foundation for future developments in smart cities, where responsive infrastructure and real-time services are essential

Chapter 1

Fifth-Generation Networks (5G)

1.1 Introduction

Fifth-generation (5G) networks represent a major breakthrough in wireless communication technology, offering unprecedented speed, ultra-low latency, and massive device connectivity. This chapter explores the historical evolution from 1G to 5G, highlighting the key technological advances introduced with each generation. Special attention is given to 5G's architecture, performance, and its role as a foundational enabler for emerging applications, particularly in smart cities and mission-critical services.

1.2 Overview of Mobile Network History

Mobile communication has improved significantly over the last several decades, beginning with 1G analog voice systems in the 1980s and advancing to today's powerful 5G networks. Each generation made substantial advances in terms of speed, data capacity, coverage, and service types.[1]

Table 1.1: **Mobile Network Generations**

Generation	Year	Technology	Max Data Rate	Core Network
1G	1980	AMPS	2.4 – 14.4 Kbps	PSTN
2G	1993	IS-95, GSM	14.4 Kbps	PSTN
3G	2001	IMT2000, WCDMA	Up to 3.1 Mbps	Packet Networking
4G	2009	LTE, WiMAX	Up to 100 Mbps	Internet (IP-based)
5G	2020	Unified IP, WWWW	> 1 Gbps	Internet

1.2.1 First Generation (1G)

The first generation of mobile communication appeared in 1979, marking the start of cellular telecommunications. It used analog technology and was designed solely for voice calls. 1G systems employed narrowband frequency channels and supported standards such as the Nordic Mobile Telephone (NMT), Advanced Mobile Phone System (AMPS), and Total Access Communications System (TACS). Despite being groundbreaking at the time, 1G had short battery life, poor voice quality, and inadequate security. The peak data rate was only 2.4 Kbps.

1.2.2 Second Generation (2G)

Introduced in the early 1990s, 2G signaled a significant move from analog to digital communications. The primary goal was to improve the reliability and security of mobile communication. It added services including SMS, call hold, and conference calling. GSM (TDMA/FDD) and

CDMA were used to support numerous users on a single channel. With services like GPRS and EDGE, 2G systems can attain data rates ranging from 50 Kbps to 1 Mbps.

1.2.3 Third Generation (3G)

3G, which was launched in 2001 under the ITU's IMT-2000 framework, marked substantial advances in mobile communications. It allowed users to access emails, browse the web, share multimedia, and have faster internet connections. 3G ushered in the era of smartphones, with improved voice quality and multimedia features. Technologies such as WCDMA and UMTS enabled data rates of up to 2 Mbps in stationary mode and 384 Kbps in mobility. HSPA+ eventually increased theoretical speeds to 21.6 Mbps.

1.2.4 Fourth Generation (4G)

4G was designed to meet IMT-Advanced criteria, providing high-speed, high-capacity, and low-latency connectivity. It planned for speeds of up to 1 Gbps for fixed customers and 100 Mbps for mobile users. OFDM and MIMO were core technologies that enabled efficient spectrum usage and improved service delivery. 4G introduced technologies such as heterogeneous networks (HetNets), tiny cells, carrier aggregation (CA), and Coordinated Multipoint (CoMP), which resulted in a better user experience, less congestion, and increased network dependability.

1.2.5 Fifth Generation (5G)

5G systems are now being deployed commercially, with the goal of outperforming their predecessor, 4G, in terms of data speeds, latency, connection density, and other improvements. These devices achieved a maximum of 35.46 Gbps by leveraging the millimeter wave (mmWave) spectrum ranging from 30 to 300 GHz.They used small cell technologies to improve coverage and reduce latency.5G systems also used sophisticated access technologies such as beam division multiple access (BDMA), quasi-orthogonal sequences, non-orthogonal multiple access (NOMA), and filter bank multi-carrier (FBMC), among others. In 5G networks, scalable orthogonal frequency-division multiplexing (OFDM) is used extensively to achieve ultra-low latency performance.It also included network slicing (NS), which allows mobile network operators (MNOs) to provide customized services based on service level agreements. The deployment of AI, AR/VR, and XR enabled new use cases, applications, and services.[2]

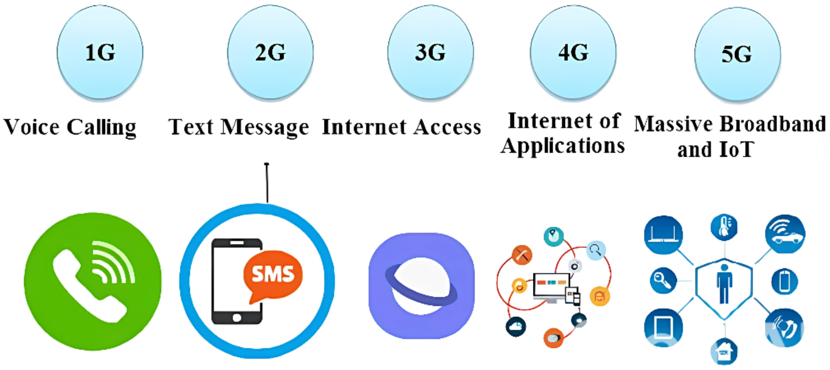


Figure 1.1: The Development of Mobile Communication
[3]

1.3 The Gap from 4G to 5G

As mobile communication evolves, the constraints of 4G networks become increasingly evident, particularly with rising demands for faster speeds, lower latency, and enormous device connectivity. To solve these difficulties, 5G was conceived as a significant advancement—not only in performance, but also in network design and capabilities. This section focuses on the key differences between 4G and 5G technologies, including speed, latency, connectivity, efficiency, and supported use cases.

1.3.1 Data Rate (Speed)

4G networks may deliver data rates ranging from 2 Mbps to 1 Gbps in optimal situations. These speeds enable HD video streaming, online surfing, and video conferencing. However, 5G networks are likely to surpass this, with data rates starting at 1 Gbps and potentially reaching 10 or even 20 Gbps. This significant enhancement enables customers to enjoy nearly rapid downloads and flawless streaming of ultra-HD material. Data rates are increased by using higher frequency bands, greater bandwidth channels, and more complex modulation and antenna techniques. This feature enables novel use cases such as real-time 8K video, holographic communications, and cloud gaming.[4]

1.3.2 Latency

Latency is the time it takes for data to travel from source to destination. Latency in 4G networks typically runs between 30 and 50 milliseconds, which is sufficient for most mobile apps. However, other applications, such as remote surgery, autonomous driving, and industrial robotics, necessitate near-instantaneous communication. 5G addresses this by lowering latency to less than a millisecond. This ultra-low latency offers real-time response, allowing machines or vehicles to be controlled remotely with no visible delay. Latency is reduced through a flatter network topology, edge computing (MEC), and improved signaling protocols.[4]

1.3.3 Device Connectivity (Density)

The number of devices that 4G networks can serve per square kilometer is limited, usually around 100,000 in densely populated areas. This capacity is enough for regular mobile broadband users, but insufficient for future smart settings. 5G is intended to handle up to one million devices per square kilometer, which is essential for enabling the Internet of Things (IoT). This includes sensors, smart meters, connected automobiles, and wearable devices, all of which require consistent communication. The capacity to handle such high device density assures that 5G can support complex systems such as smart cities, smart factories, and intelligent transportation networks without causing congestion or performance deterioration.[4]

1.3.4 Energy and Spectral Efficiency

Spectral efficiency refers to a network's capacity to send more data over a given bandwidth. While 4G made considerable advances over its predecessors, 5G goes much farther by using technology such as Massive MIMO (Multiple Input, Multiple Output), beamforming, and sophisticated modulation methods. These enable 5G to transfer more bits per hertz while using less power, resulting in increased energy efficiency. This is especially crucial for battery-powered IoT devices and minimizing mobile networks' total environmental impact. Furthermore, increased energy efficiency leads to enhanced network performance and cost savings for operators.[4]

1.3.5 Network Architecture and Flexibility

4G networks are built on a hierarchical, all-IP architecture that, while efficient at the time, had limitations in terms of scalability, latency, and adaptability. 5G introduces a flatter, more modular IP-based architecture with virtualized and dynamically reconfigurable components. Network slicing technologies enable 5G networks to establish numerous virtual networks on a shared physical infrastructure, each targeted to certain services or sectors (for example, a low-latency slice for autonomous vehicles and a high-throughput slice for video streaming). Furthermore, 5G incorporates edge computing (MEC), which brings computation closer to the consumer while lowering processing latency.[4]

1.3.6 Technology Components

4G is primarily based on technologies like LTE and LTE-Advanced, which use OFDM, MIMO, and a defined set of frequency channels. In contrast, 5G provides a new radio interface called 5G NR (New Radio) that uses a greater variety of frequency bands, including millimeter wave (mmWave) spectrum above 24 GHz. This allows for significantly enhanced bandwidth availability and capacity. Furthermore, 5G uses Beam Division Multiple Access (BDMA) in addition to classic CDMA, which increases user isolation and interference management. Massive MIMO and beamforming are two key technologies that help focus signals directly on users, improving coverage and performance.[4]

1.3.7 Supported Use Cases

The design and development of 4G was centered on improving mobile broadband—basically, delivering quicker internet access to smartphones and tablets. While this was innovative at the time, 5G was designed with a bigger vision. It is designed to enable a diverse set of vertical applications, such as ultra-reliable low-latency communication (URLLC) for vital missions, massive machine-type communications (mMTC) for IoT, and enhanced mobile broadband (eMBB) for high-data-rate services. 5G's capabilities enable autonomous vehicles, remote surgery, immersive virtual and augmented reality experiences, and highly automated industrial operations. In short, 5G is more than just an advancement of mobile broadband; it's a platform for digital transformation across industries.[4]

1.4 5G Mobile Network Architecture

5G architecture is a significant advancement in mobile networks, aiming to allow fast speeds, low latency, and widespread device connectivity. It presents new technologies and concepts such as network slicing, virtualization, and automation to meet a variety of service requirements. The architecture is divided by important levels and components, as described in the sections below.

1.4.1 Network Slicing

Network slicing is a critical component of 5G architecture, allowing operators to establish distinct logical networks (slices) customized to the needs of different services or customers. For example, one slice can be reserved for ultra-reliable low-latency communications (URLLC), another for enhanced mobile broadband (eMBB), and a third for massive machine-type communications (mMTC). Each slice is managed as a completely autonomous network, with dedicated resources and functions to ensure the requisite Quality of Service (QoS), increasing efficiency and allowing for service delivery innovation.[5]

1.4.2 Softwarization Virtualization

5G is based on technologies such as Network Function Virtualization (NFV) and Software Defined Networking (SDN), which decouple software from hardware. This separation enables network activities like routing, session management, and encryption to run on flexible virtual servers rather than traditional fixed hardware. As a result, the network can swiftly adapt to suit the needs of various users and applications, allowing for easier scaling, upgrading, and maintenance.[5]

1.4.3 Functional Architecture Layers

The 5G architecture is structured into multiple integrated layers, each with a distinct function. These layers work together to improve network efficiency, scalability, and customisation. Each layer works in tandem with the others to guarantee that services are delivered with peak performance and quality.[5]

- **Service Layer**

This layer contains applications and services that are handled by clients or end users. It serves as a gateway for a variety of services, including high-speed internet and mobile services. It also comprises business support systems and regulations that specify how these services will be delivered, monitored, and coordinated. This helps to assure service quality and compliance with market demands.[5]

- **Management and Orchestration Layer (MANO)**

This layer, which manages resources and virtual networks, facilitates coordination between the various network slices, allowing for efficient resource use. VIM (Virtualized Infrastructure Manager) manages the deployment and control of virtual resources such as servers and storage. NFVO (Network Functions Virtualization Orchestrator) organizes and manages virtual network functions based on user requests, resulting in better network performance and responsiveness.[5]

- **Control Layer**

This layer contains controllers such as SDM-C and SDM-X, which manage policy execution and route commands to network functions based on service requirements. It serves as the network's brain, regulating how it is allotted in real time and managing data movement among various components. The control layer optimizes network performance by regulating dynamic network behaviors.[5]

- **Data Layer**

This layer contains the real network functions, either virtual (VNFs) or physical (PNFs). It transfers and processes data between users and services. The data layer guarantees that data is delivered fast and efficiently by lowering latency and boosting network capacity. It specifies how data is routed over the network, ensuring that services are maximized for speed and dependability.[5]

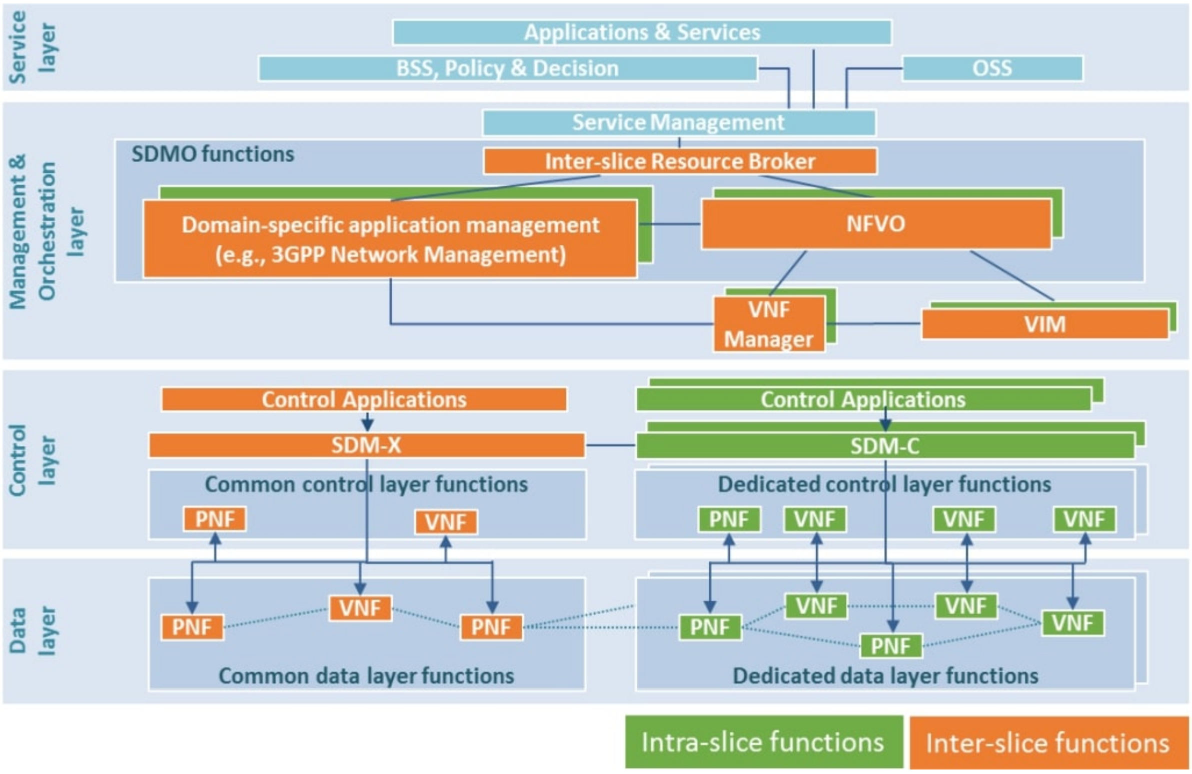


Figure 1.2: Architecture functional layers
[5]

1.4.4 Autonomic Management

The 5G architecture enables enhanced autonomic management features like as auto-configuration, adaptive control, and intelligent monitoring, enabling network slices to be managed throughout their lifecycle, from creation to deactivation. This includes aspects such as autonomous adaptability, reconfiguration, scaling, and rapid response to changes in demand or failures.[5]

1.4.5 Business Models and Multi-Tenant Integration

The 5G design allows network operators to deliver services to many tenants using the ”Network-as-a-Service” (NaaS) model. It also allows shared infrastructure, which enables virtual network operators (MVNOs) to resell resources and promotes creativity in new business models. Additionally, any tenant can operate and maintain their own network over the shared infrastructure using standardized APIs.[5]

1.5 Applications for 5G Networks

5G technology ushers in a new era of connectivity that goes far beyond quicker internet on smartphones. Its tremendous speed, ultra-low latency, and capacity to link large numbers of devices pave the way for a variety of creative applications. 5G serves as the foundation for digital transformation in a variety of areas, including smart cities, healthcare, agriculture, and immersive technology.

Key areas include:

- **Internet of Things (IoT):**
  5G enables the simultaneous connectivity of a large number of devices, which is critical for smart surroundings. This comprises smart homes (automatic lighting and appliances), smart factories (interconnected machinery), and smart cities (traffic, pollution, and utility sensors). Its low latency and enormous capacity make real-time data collection and automation more efficient.[6]

- **Agriculture:**
  In modern farming, 5G enables the use of sensors to monitor soil conditions, temperature, humidity, and crop growth. Data-driven decisions enable farmers to optimize irrigation, spot concerns early, and enhance yield.[6]

- **Healthcare:**
  5G improves healthcare by allowing for remote patient monitoring, high-speed medical data transmission, and telehealth services. It also facilitates advanced operations like remote surgery by providing exceptionally low latency and reliable connections.[7]

- **Vehicles and Transportation:**
  5G enables vehicles to communicate with one another and with traffic systems in real time. This improves road safety, aids autonomous driving, and allows for improved traffic management in metropolitan areas.[8]

- **Augmented Reality (AR) and Virtual Reality (VR):**
  5G's high bandwidth and low latency improve AR/VR experiences. This creates new opportunities for gaming, education, medical training, and virtual collaboration.[8]

- **Edge Computing Connectivity:**
  5G enables edge computing by connecting devices to nearby data centers rather than distant cloud servers. This lowers delays and allows speedier decision-making, especially for applications like artificial intelligence, real-time analytics, and critical systems.[9]

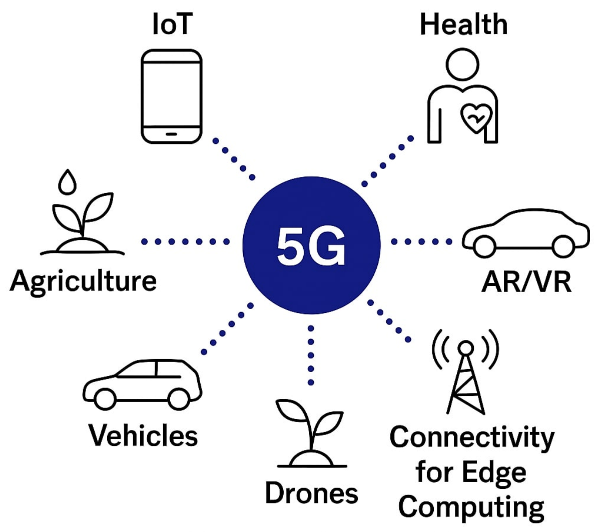


Figure 1.3: 5G Applications
[10]

5G will continue to spread into new areas as it matures, providing transformative possibilities to individuals, industries, and civilizations.

1.6 The Role of 5G Technologies in a Smart City

1.6.1 Smart Connectivity Infrastructure

5G networks are the foundation of smart cities, providing data speeds that are 10 to 100 times faster than 4G and supporting a substantially higher number of connected devices simultaneously. With its ultra-low latency and great dependability, 5G is suited for real-time, mission-critical applications. This includes smart transportation systems, environmental monitoring, remote healthcare services, and intelligent energy grids, all of which require reliable, high-performance connectivity.[11]

1.6.2 Enabling Intelligent Transportation Systems (ITS)

5G enables Intelligent Transportation Systems with sophisticated communication technologies such as Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), Vehicle-to-Pedestrian (V2P), and Vehicle-to-Network (V2N), also known as V2X. These technologies let vehicles to exchange real-time data with one another and with surrounding infrastructure, thereby increasing road safety, minimizing traffic accidents, and optimizing traffic flow throughout urban areas.[11]

1.6.3 Supporting Vertical Industries

5G is a disruptive enabler for a smart city's main businesses, including energy, healthcare, manufacturing, entertainment, and transportation. For example, it improves smart grid management in the energy sector, allows for remote health monitoring and telemedicine, drives industrial automation and robots in manufacturing, and supports autonomous vehicles and real-time traffic systems in transportation. These improvements enable cities to run more effectively and sustainably.[11]

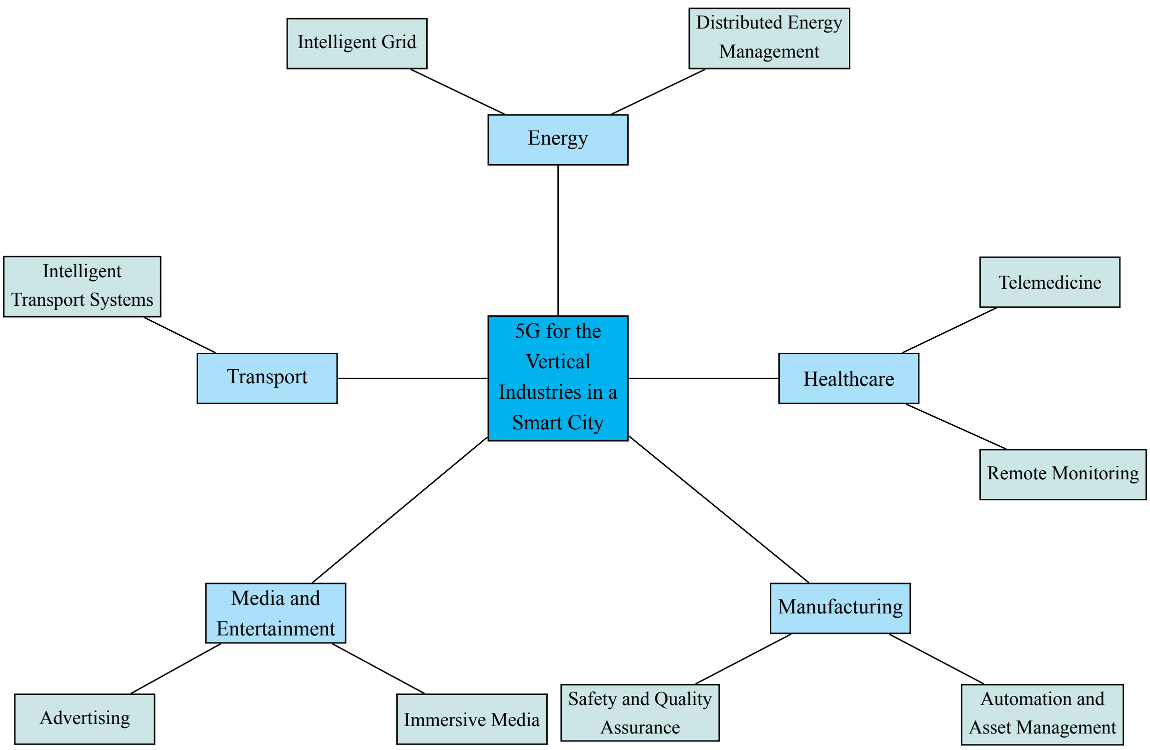


Figure 1.4: 5G Applications in Vertical Industries in a Smart City

1.6.4 Economic Impact

The economic potential for 5G is enormous. By 2035, 5G technologies are estimated to add up to $12.3 trillion to the global economy in a variety of sectors, creating millions of employment along the 5G value chain. In the transportation industry alone, 5G may generate more than $2.4 trillion in economic output, demonstrating its critical role in enabling smart mobility and infrastructure innovation.[11]

1.6.5 Advanced Applications Include

Key applications of 5G in smart cities include:

- **Fully Autonomous Driving**

5G enables real-time communication between vehicles and their surroundings, which is critical for the safe operation of self-driving automobiles with no human intervention.

- **Smart Infrastructure**

5G enables infrastructure such as traffic lights and road sensors to respond dynamically to traffic conditions, reducing congestion and improving safety.

- **Mobility as a Service (MaaS)**

This proposal enables individuals to plan, schedule, and pay for different modes of transportation, including buses, trains, and ride-sharing, using a single digital platform powered by fast and reliable 5G connections.

- **Real-Time Road and Accident Monitoring**

Connected sensors and cameras powered by 5G deliver real-time traffic and accident data, enabling for faster emergency response and improved traffic management.[11]

1.7 Key Technical Features of 5G for Smart Cities & MEC

1.7.1 Ultra-Low Latency

5G allows latencies as low as 1 millisecond, which is critical for real-time data processing at the edge (MEC), particularly in smart city applications such as traffic control, self-driving vehicles, and emergency services.

Latency is an important aspect in enabling URRLC (Ultra-Reliable and Low Latency Communications).[12]

1.7.2 Massive Connectivity

Supports 1 million devices per km², allowing for large-scale IoT deployments (e.g., sensors, smart meters, connected autos) in urban contexts.

This fully fits the concept of massive Machine-Type Communications (mMTC).[13]

1.7.3 Network Slicing

Allows you to create virtual network segments that are suited to specific services or applications (for example, one slice for autonomous vehicles and another for smart healthcare).

This feature improves MEC by assuring the quality of service (QoS) for every type of application.[14]

1.7.4 Edge Computing Integration (MEC Enabler)

5G is intended to natively enable MEC, lowering backhaul traffic and boosting local decision-making capabilities.

This is critical for smart transportation systems, especially in a place like San Francisco, where you use Cabspotting data.[14][12]

1.8 Conclusion

In conclusion, 5G is not merely a technological upgrade, but rather a transformative infrastructure that enables a hyper-connected digital ecosystem. Its advanced capabilities, such as network slicing and seamless integration with Multi-access Edge Computing (MEC), pave the way for revolutionary applications in healthcare, transportation, and industrial automation. As the backbone of future smart environments, 5G will play a central role in reshaping digital communication and urban innovation.

Chapter 2

Multi-access Edge Computing (MEC)

2.1 Introduction

As network demands grow increasingly complex, Multi-access Edge Computing (MEC) emerges as a promising solution to address the limitations of traditional cloud computing. This chapter introduces the concept of MEC, explaining how it brings computing resources closer to end users and devices. The discussion includes comparisons with cloud computing, the benefits of MEC such as reduced latency and improved security, and its significance in supporting real-time applications in the context of 5G-enabled smart cities.

2.2 Cloud computing

Cloud computing is a technology that allows computing services to be delivered via the Internet (the cloud), including servers, storage, databases, networking, software, and analytics. It enables users and businesses to remotely access, manage, and store data, dynamically scale resources in response to demand, and reduce the expense and complexity of owning and managing physical infrastructure.[15]

2.3 Cloud vs. Edge Computing

2.3.1 Cloud

The cloud is described as a ”model that allows on-demand access to computing resources (such as networks, servers, storage, applications, and services) over the internet with minimal interaction with service providers”.[16]

2.3.2 Edge

Edge computing is defined as a ”decentralized computing model that moves processing and data closer to the end-user or data source rather than relying on a central data center.” The idea is to reduce latency and increase efficiency by processing data at the edge”.[16]

Table 2.1: **Main differences between cloud and edge computing.** [17]

	Applicable situation	**Network bandwidth pressure**	**Real-time**	**Calculation mode**
Cloud computing	Global	More	High	Large scale centralized processing
Edge computing	Local	Less	Low	Small scale intelligent analysis

2.4 Multi-acce Edge Computing (MEC)

Mobile Edge Computing (MEC), also known as Multi-access Edge Computing, is a network design paradigm that puts cloud computing capabilities and IT service environments closer to mobile network edges, where end users and data sources are located.[18]
It allows for low-latency, location-aware, and real-time applications by putting computation and storage resources to base stations, radio access nodes (gNB/eNB), and aggregation points. MEC enables service delivery without the need to route data through a centralized cloud or core network, which is crucial for 5G performance objectives such as ultra-reliable low latency communications (URLLC) and huge IoT.[19]

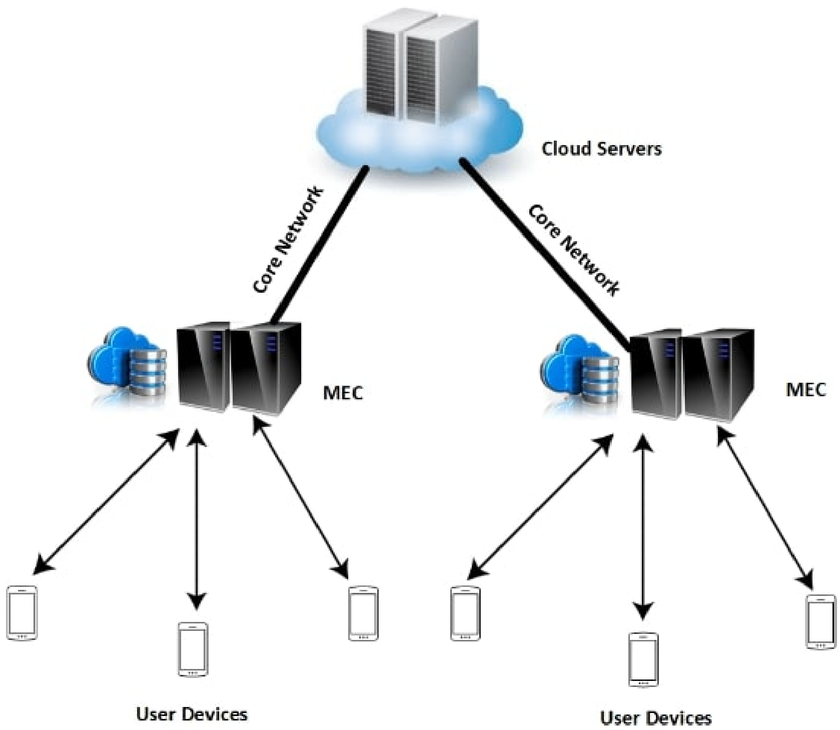


Figure 2.1: MEC Architecture
[20]

2.5 Mobile and Multi-access edge computing

Mobile Edge Computing (MEC) is a potential technology for meeting the needs of heterogeneous Internet of Things (H-IoT) applications by bringing computing and storage resources closer to smart devices.However, it faces the challenge of limited communication capacity between devices and the cloud terminal, particularly given the growing demand for low latency and dependable connections. To solve these restrictions, multi-access edge computing (MA-MEC) has arisen, combining different wireless access protocols such as 5 G, LTE, and Wi-Fi. This integration improves the devices' ability to connect to the edge and provides advantages such as faster reaction time, more privacy, and big data analysis at the point of generation.MA-MEC is thus a natural and necessary development to meet the demands of today's IoT applications.

2.6 The growth of edge computing

Peripheral computing evolved as a result of the growth of technologies such as the Internet of Things, artificial intelligence, and 5G, all of which create data that need immediate processing. Traditional cloud computing is no longer adequate to meet the needs of sensitive applications, resulting in the emergence of multi-access edge computing (MEC), which processes data close to its source, reducing response time and supporting real-time applications while improving the performance of smart cities. MEC is an addition to the cloud, not a replacement for it.[21]

2.7 MEC Servers Work

MEC servers are located in areas close to end users, such as base stations or local data centers within the 5G network, enabling for local processing and storage operations. These servers run applications directly, eliminating the need to transfer data to external data centers, resulting in faster reaction times and improved performance, particularly in sensitive applications like augmented reality and autonomous driving. MEC servers also integrate with the underlying network, utilizing technologies such as NFV and SDN to create a flexible and scalable environment, as well as software interfaces that enable developers to exploit real-time network and context information.[18]

2.8 MEC characteristics

2.8.1 Dense Geographical Distribution

MEC is distinguished by the vast geographical distribution of computer infrastructure near end users. This dense distribution enables services to be delivered with minimal delay, without the need for centralized cloud data centers. This type of deployment enables real-time and accurate big data analytics, as well as applications such as environmental monitoring and pipeline inspection that use distributed sensor networks.[22]

2.8.2 Mobility Support

Mobility is a major element of MEC, allowing users to maintain uninterrupted access to computing services while moving across network zones. Protocols like the Locator ID Separation Protocol (LISP) are used to separate location and identification, allowing devices to relocate without affecting existing services. This is especially crucial for mobile users, such as those who use smartphones or drive in vehicles that demand persistent connectivity and low latency replies. [22]

2.8.3 Location Awareness

MEC systems provide location awareness by detecting the user's physical location via technologies such as GPS, cellular networks, or Wi-Fi access points. This feature allows services to be delivered from the closest edge server, lowering latency and improving the user experience. Location awareness is useful for applications such as vehicle safety systems, smart city services, and disaster response systems. [22]

2.8.4 Proximity to Users

A distinguishing feature of MEC is the availability of processing and storage resources close to end users. This closeness improves service quality by lowering the time required to process and respond to user requests. Contextual information, such as device status and user activity, can also help service providers optimize resource allocation and application performance. [22]

2.8.5 Low Latency

MEC dramatically reduces service latency by moving computing closer to the data source. This low-latency environment is critical for applications that are sensitive to delays, such as augmented reality, real-time video streaming, and interactive games. MEC improves computing responsiveness and efficiency by reducing round-trip time between the user and the server.[22]

2.8.6 Context Awareness

Context awareness in MEC refers to making intelligent judgments about job offloading and service delivery based on real-time information like as network conditions, user location, and device status. This adaptive feature enables MEC to provide individualized and optimized services, hence increasing customer happiness and overall quality of experience.[22]

2.8.7 Heterogeneity

MEC settings are naturally heterogeneous, incorporating a wide range of devices, platforms, and network technologies. This heterogeneity includes end devices, edge servers, and communication protocols. While diversity brings flexibility, it also creates obstacles in terms of interoperability and integration. Addressing these disparities is critical to the successful deployment and operation of MEC systems. [22]

2.9 Importance of MEC

2.9.1 Low Latency

MEC dramatically reduces latency in automotive networks by putting data processing closer to the user, removing the need to transport data to remote centralized data centers. This proximity allows for substantially faster response times, which is crucial in applications that require real-time interactions, such as autonomous driving and vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) communications. According to studies, MEC may reduce network delays from 70ms to as low as 10ms, making it perfect for safety-critical applications.[23]

2.9.2 Fast Hand-Off During Mobility

As cars travel quickly between access points or base stations, ensuring continuous and seamless connectivity becomes a huge concern. MEC facilitates rapid and smooth hand-off by prepping new communication channels prior to the actual transition. This provides continuous data transport while avoiding packet loss or service degradation, which is critical in dynamic, high-speed environments like highways.[23]

2.9.3 Offloading the Core Network

MEC alleviates the load on the centralized core network and data centers by completing computing operations at the periphery. Offloading reduces data traffic over the backbone network and relieves congestion, improving overall resource use efficiency. It also improves the network's scalability and responsiveness, especially during peak traffic periods or in congested metropolitan regions.[23]

2.9.4 Support for Real-Time Applications

MEC allows for the deployment of time-sensitive applications that require immediate data processing, such as collision avoidance systems, intelligent traffic lights, and real-time road monitoring. Processing such data locally allows for fast decision-making without the delays incurred by sending information through centralized systems. This is critical for vehicle safety and traffic efficiency.[23]

2.9.5 Improved Quality of Service and User Experience

MEC improves QoS and user experience by decreasing data pathways and lowering transmission delays. Applications function more smoothly, and consumers benefit from faster reaction times and more consistent connectivity. This is especially useful in connected car scenarios where service reliability and performance are crucial.[23]

2.9.6 Flexibility in Application and Service Deployment

MEC enables the deployment and management of services locally at edge nodes, resulting in faster updates, easier scalability, and personalized service delivery based on geography or traffic conditions. This adaptability enables a smarter and more adaptive infrastructure that responds to the changing demands of next-generation networks like 5G.[23]

2.10 Applications of MEC

2.10.1 Augmented Reality (AR)

MEC allows real-time augmented reality services by processing data close to the user. This is especially beneficial in places like museums or tourist attractions where users can quickly acquire contextual information. MEC provides reduced latency and seamless interactions.[24]

2.10.2 Intelligent Video Acceleration

By assessing real-time radio network circumstances, MEC enables video servers to dynamically adjust stream quality. This lowers buffering, speeds up loading times, and improves the mobile video streaming experience.[24]

2.10.3 Connected Cars (V2X Communication)

MEC facilitates vehicle-to-everything connection by enabling fast data processing near road infrastructure. It enables vehicles to share real-time information on road conditions or hazards, improving safety with ultra-low latency.[24]

2.10.4 IoT Gateway

MEC functions as a local aggregator for IoT devices, processing and analysing data locally. This decreases transmission delays, increases response time, improves security, and reduces the demand on central cloud resources, making it ideal for industrial and smart city applications.[24]

2.10.5 Context-Aware Services

MEC allows applications to react to real-time contexts such as user location and network circumstances. For example, it enables targeted advertising and dynamic content distribution, hence increasing user experience through smarter, more localized services.[24]

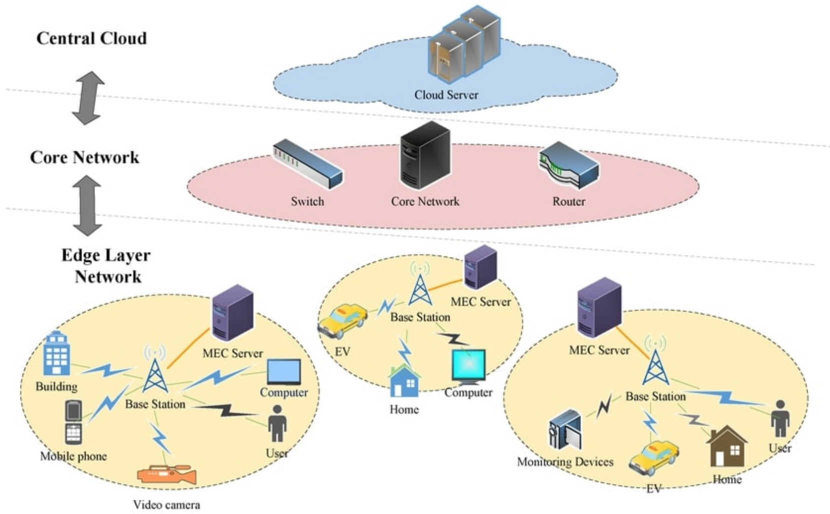


Figure 2.2: Applications of edge computing in the smart city.
[25]

2.11 Synergy Between 5G and MEC

Multi-access edge computing (MEC) is a critical enabler for maximizing the promise of 5G networks. By bringing computing and storage resources closer to end users and linked devices, MEC drastically reduces latency and improves bandwidth economy. Rather than offloading all data to distant centralized cloud servers, MEC processes and stores data locally at the network edge, allowing for ultra-responsive applications like driverless vehicles, augmented reality, and the Internet of Things. MEC is smoothly integrated into 5G's service-based architecture via important components such as the User Plane Function (UPF) and Application Function (AF), which handle traffic routing and network interactions. This partnership improves the user experience, reduces core network congestion, and enables mission-critical, low-latency, high-quality services.[26]

2.12 Enabling AI with 5G and Edge

5G and edge computing are critical technologies for enabling Artificial Intelligence (AI).5G networks provide extremely fast speed and low latency, making them perfect for time-sensitive AI applications such as smart healthcare and self-driving cars.At the same time, edge computing analyzes data near to the source, lowering latency while improving privacy and security.In this context, the AI@EDGE project is an integrated framework that integrates serverless computing (FaaS), hardware acceleration with GPUs and FPGAs, and AI approaches to deploy distributed "AI Functions" across edge and cloud infrastructure.This collaboration allows for effective and secure training and deployment of GenAI models, particularly in multi-stakeholder situations.Furthermore, this technical convergence is predicted to result in a 100-fold improvement in industrial output by 2025, with accuracy exceeding 99.99%, considerably enhancing the dependability and performance of distributed AI systems.[27]

2.13 Conclusion

This chapter demonstrates that MEC is not simply a technological extension, but a fundamental shift in the way computing services are delivered. By decentralizing data processing, MEC enables faster response times, improved quality of service, and better support for latency-sensitive applications. Its tight integration with 5G networks forms the cornerstone for deploying intelligent systems and services in dynamic urban environments, thus accelerating the realization of smart cities.

Chapter 3

Artificial Intelligence (AI)

3.1 Introduction

Artificial Intelligence (AI) is rapidly reshaping modern computing through its ability to emulate human reasoning, learning, and decision-making. This chapter provides a comprehensive overview of AI and its core branches, with a particular focus on Machine Learning (ML), including supervised, unsupervised, and reinforcement learning paradigms. It also introduces clustering techniques such as Agglomerative Clustering and evaluation metrics, offering a foundation for their later application in real-world scenarios.

3.2 Artificial Intelligence Overview

Artificial intelligence (AI) is a branch of computer science that focuses on creating systems that can mimic human intellect in tasks like thinking, learning, and problem solving. It is described as allowing machines to execute functions that normally need human cognition. AI systems are intended to learn from experience and improve performance over time. The discipline divides AI systems into four categories: systems that think like people, systems that think logically, systems that act like humans, and systems that act rationally. These approaches lead the creation of intelligent agents that employ technologies such as machine learning, neural networks, and natural language processing. AI seeks to not just replicate human talents, but also to function well in complex and dynamic contexts.[28]

3.3 Machine Learning

Machine learning is a branch of artificial intelligence that focuses on creating computer systems that can learn and improve automatically based on experience and data, rather than being manually coded for each task. T. O. Ayodele defines machine learning as the process of creating models that extract meaningful information and patterns from data via inference, fitting, or learning from examples, allowing the system to improve its performance on its own. The goal of machine learning is to construct simple, interpretable categorization models that imitate human thinking and can function without direct human interaction once taught. This field seeks to overcome the limits of traditional manual programming and is frequently used to handle massive, complicated datasets across multiple domains.[29]

3.4 Types of Machine Learning

In this section, we will go into the types of machine learning in detail, as shown in the diagram.

1. Supervised Learning

2. Unsupervised Learning

3. Reinforcement Learning

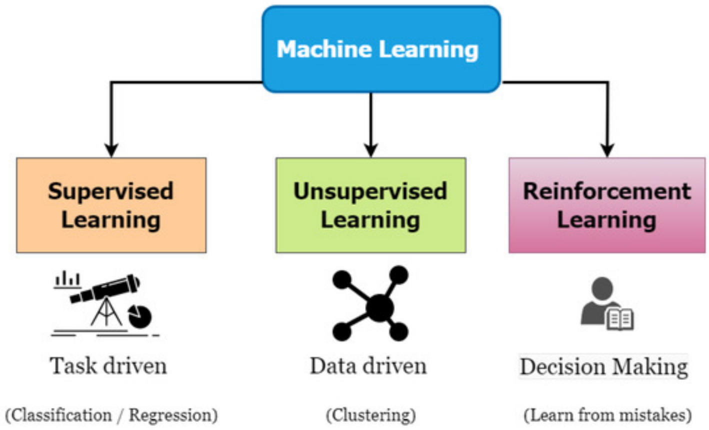


Figure 3.1: Machine learning classification techniques
[30]

3.4.1 Supervised Learning

Supervised learning is a sort of machine learning in which a model is trained on data containing both input features and known output labels.Each training example is assigned a specific goal value (label).The purpose of this method is to develop a mathematical function or predictive model that generalizes the link between inputs and outputs, allowing it to accurately anticipate outcomes for previously unseen data.This is accomplished by an iterative process that involves comparing the model's predictions to the actual outputs and adjusting its parameters to decrease error, frequently employing optimization techniques such as gradient descent. Supervised learning is one of the most common types of machine learning, and it is utilized in a variety of real-world applications, including text classification, financial forecasting, and data-driven medical diagnosis.[29]

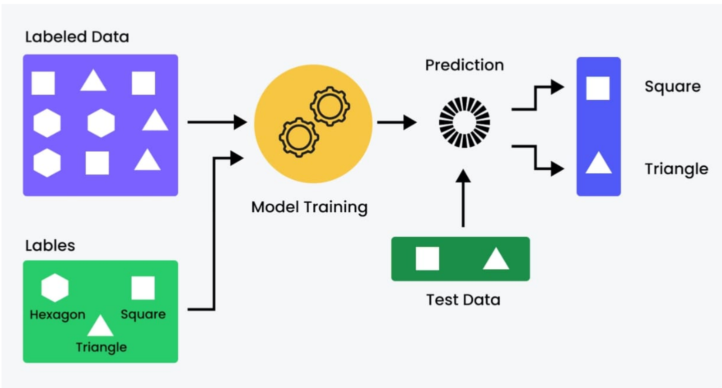


Figure 3.2: Supervised learning
[31]

3.4.1.1 Types of Supervised learning

- **Classification:**

In this scenario, the purpose is to group incoming data into preset categories or classes. For example, emails can be classified as ”spam” or ”not spam.” Classification is a fundamental job in supervised learning that is widely applied in a variety of fields, including medical diagnosis, facial recognition, and text sentiment analysis. Decision trees, support vector machines (SVM), and logistic regression are some of the most common categorization algorithms.[29]

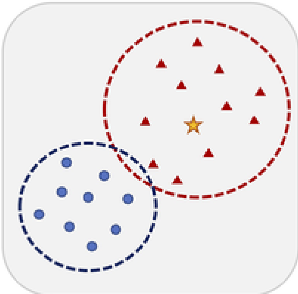


Figure 3.3: Graph of Classification
[32]

- **Regression:**

The goal is to anticipate a continuous numerical value based on input data. For example, forecasting the price of a home based on factors such as size and location. Regression is employed when the result is a real number that can vary over a large range. It is necessary for financial forecasting, trend analysis, and quantitative modeling. Linear regression, nonlinear regression, and neural networks are three often used regression algorithms.[29]

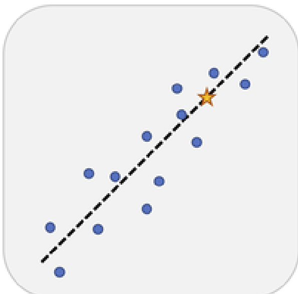


Figure 3.4: Graph of Regression
[32]

3.4.2 Unsupervised Learning

Unsupervised learning is a sort of machine learning that uses data without known outputs or labels. In this case, the model is not given explicit instructions on what to learn; rather, it is tasked with independently detecting the underlying structure or patterns in the data. This learning approach's major purpose is to organize or simplify data samples by analyzing their linkages and distributions. This strategy is based on the model's ability to extract information from data without supervision, which allows it to find hidden groupings or structures that a human observer may not notice right away. This is especially useful in cases where labeled data is difficult or expensive to collect.[29]

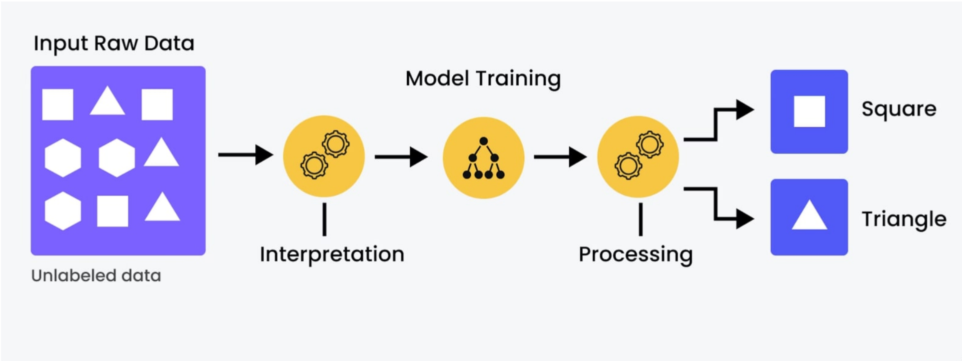


Figure 3.5: Unsupervised learning
[31]

3.4.2.1 Types of Unsupervised learning

- **Clustering**

Clustering is the process of dividing data into clusters based on similarity, with data points within the same group being more similar to one another than those in other groups. This technique is used to find natural groupings in a dataset. Customer segmentation is a widespread practice in which consumers are divided into distinct categories depending on their purchasing behavior, allowing firms to adjust marketing techniques to each category. K-Means and Hierarchical Clustering are two often used clustering algorithms.[29]

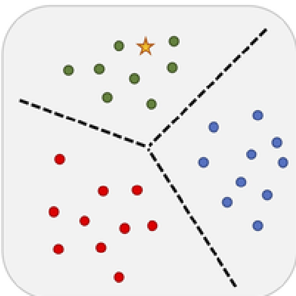


Figure 3.6: Graph of Clustering
[32]

- **Association Rule Learning:**

Association rule learning seeks to uncover meaningful links or patterns between things in massive datasets. It is commonly employed in market basket analysis, in which the system learns that customers who buy one product (e.g., bread) are more likely to buy another (e.g., butter). These found criteria are frequently utilized to enhance recommendation systems and product placement tactics. Popular algorithms in this subject include Apriori and FP-Growth.[29]

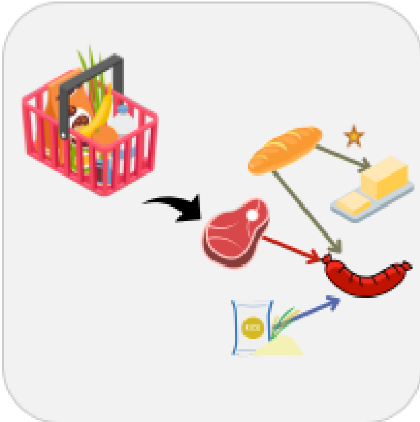


Figure 3.7: Example of Association Rule Learning

3.4.3 Reinforcement Learning

Reinforcement Learning (RL) is a type of machine learning that trains an agent to interact with its environment in order to make decisions that maximize long-term rewards. At each time step, the agent observes the current state of the environment, chooses an action, and receives a reward based on the outcome, as well as a transition to the next state. Through repeated interactions, the agent develops a policy—a technique for selecting actions—with the goal of achieving the maximum potential cumulative reward. RL is particularly well-suited for activities that require sequential decision-making, such as robotics, gaming, and autonomous systems.[33]

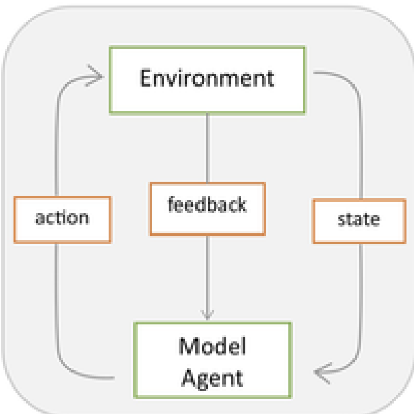


Figure 3.8: Architecture of Reinforcement
[32]

3.5 Agglomerative Clustering

Agglomerative Clustering is a widely used hierarchical clustering technique that takes a bottom-up approach. It begins by treating each data point as a separate cluster, then repeatedly merges the two closest clusters using a distance measure such as single linkage, complete linkage, or average linkage. This process continues until all points are combined into a single cluster or a predetermined number of clusters is attained. The ultimate result is a dendrogram, which visually depicts the merging process and aids in determining the ideal number of clusters. This method is straightforward, does not require prior knowledge of the number of clusters, and has applications in geographic analysis, biology, and document organizing.[34]

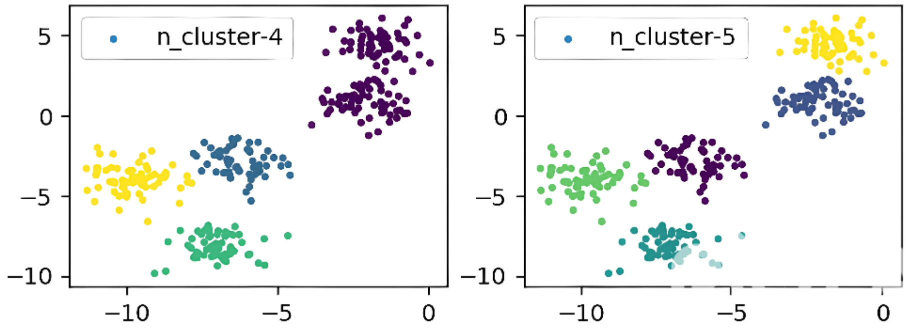


Figure 3.9: Graph of Agglomerative Clustering
[35]

3.5.1 How Agglomerative Clustering work

3.5.1.1 Initialization

Agglomerative clustering starts by treating each data point as a separate cluster. So if there are N data points, the algorithm will begin with N clusters. The goal is to gradually merge these clusters until only one final cluster exists, containing all points.[36]

3.5.1.2 Compute Pairwise Distances

In this stage, the algorithm determines the distance or dissimilarity between each pair of clusters. Typically, the Euclidean distance is used to determine how similar or dissimilar two points (or clusters) are.[36]

3.5.1.3 Linkage Criteria

Various linking methods are utilized to determine the distance between large clusters, rather than simply individual locations. This includes:

- **Single Linkage:** utilizes the shortest route between any two sites from separate clusters.

- **Complete Linkage:** takes the longest distance between any two places in separate clusters.
- **Average Linkage:** calculates the average of all pairwise distances between points in two clusters.
- **Centroid Linkage:** Calculates the distance between the two clusters' centroids (mean points).
- **Median Linkage:** computes the new cluster centroid by averaging the centroids being combined.
- **Ward's Method:** combines the two clusters that cause the least increase in within-cluster variation.[36]

3.5.1.4 Merge Clusters

The algorithm merges the two clusters that are closest to one other, depending on the linkage method used. Each merge updates the list of clusters and recalculates the distances between the new cluster and all others.[36]

3.5.1.5 Repeat

The merging procedure is iterative, with distances adjusted after each merge, until all data points are aggregated into a single cluster. The ultimate result is a hierarchical tree structure known as a dendrogram, which shows the merging order and distances between groups.[36]

3.5.2 Dendrogram in Hierarchical Clustering

A dendrogram is a tree-like diagram that depicts the hierarchical relationships among data points in hierarchical clustering. It graphically depicts how individual data points or clusters are merged one by one based on their similarity. Each branch is a set of data points that combine at a specific similarity degree. By "cutting" the dendrogram at a given height, one can calculate the ideal number of clusters. Dendrograms are strong visualization tools that assist in understanding the internal structure of data and selecting a suitable number of clusters in a flexible and data-driven manner.[37]

3.5.3 Example of how it works

- Consider the following set of 6 one dimensional data points: 18, 22, 25, 42, 27, 43
- Apply the Agglomerative hierarchical clustering algorithm to build the hierarchical clustering dendrogram
- Merge the clusters using Min distance and update the proximity matrix accordingly

- Clearly shows the proximity matrix corresponding to each iteration of the algorithm

Step 1

Table 3.1: Complete Distance Matrix

	18	22	25	27	42	43
18	0	4	7	9	24	25
22	4	0	3	5	20	21
25	7	3	0	2	17	18
27	9	5	2	0	15	16
42	24	20	17	15	0	1
43	25	21	18	16	1	0

Table 3.2: Closest Pair Highlighted

	18	22	25	27	42	43
18	0	4	7	9	24	25
22	4	0	3	5	20	21
25	7	3	0	2	17	18
27	9	5	2	0	15	16
42	24	20	17	15	0	1
43	25	21	18	16	1	0

At this stage of the Agglomerative Hierarchical Clustering algorithm, the distances between all pairs of data points have been calculated, as shown in the first table. It can be observed that the shortest distance in the matrix is between points 42 and 43, with a value of only 1. Based on this, the algorithm merges these two points into a single cluster in the first step of the clustering process. The second table displays the same distance matrix, but with the rows and columns corresponding to points 42 and 43 highlighted to emphasize their position and relationship to the other points. This visual aid helps to better understand how the algorithm identifies and merges the closest pairs of data points in each successive step.

Step 2

Table 3.3: Distance Matrix

	18	22	25	27	42,43
18	0	4	7	9	24
22	4	0	3	5	20
25	7	3	0	2	17
27	9	5	2	0	15
42,43	24	20	17	15	0

Table 3.4: Highlighting (25 and 27)

	18	22	25	27	42,43
18	0	4	7	9	24
22	4	0	3	5	20
25	7	3	0	2	17
27	9	5	2	0	15
42,43	24	20	17	15	0

The smallest distance in the distance matrix was found between elements 25 and 27. Therefore, these two elements were merged into a single cluster. The corresponding table highlights these elements prior to merging.

Step 3

Table 3.5: Distance Matrix

	18	22	25,27	42,43
18	0	4	7	24
22	4	0	3	20
25,27	7	3	0	15
42,43	24	20	15	0

Table 3.6: Highlighting (22 and 25,27)

	18	22	25,27	42,43
18	0	4	7	24
22	4	0	3	20
25,27	7	3	0	15
42,43	24	20	15	0

After forming the cluster (25, 27), the distance matrix was updated. The closest element to this new cluster was 22, which was then merged with it to form the new cluster (22, 25, 27).

Step 4

Table 3.7: Distance Matrix

	18	22,25,27	42,43
18	0	4	24
22,25,27	4	0	15
42,43	24	15	0

Table 3.8: Highlighting (18 and 22,25,27)

	18	22,25,27	42,43
18	0	4	24
22,25,27	4	0	15
42,43	24	15	0

In this step, the distance matrix was updated again. It was found that element 18 had the smallest distance to the cluster (22, 25, 27), and was therefore merged into it, resulting in a larger cluster containing four elements.

Last Step

Table 3.9: Distance Matrix

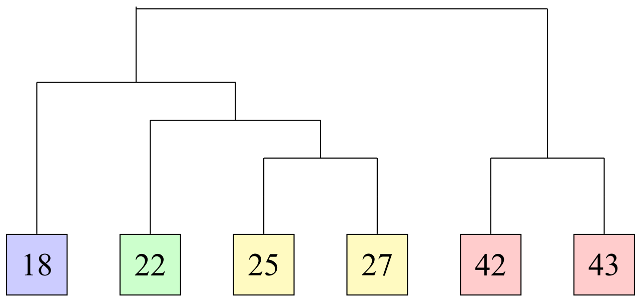
	18,22,25,27	42,43
18,22,25,27	0	15
42,43	15	0

Table 3.10: Final Matrix

	18,22,25,27,42,43
18,22,25,27,42,43	0

In the final step, the remaining two clusters—(18, 22, 25, 27) and (42, 43)—were merged. This resulted in a single final cluster containing all the elements, completing the hierarchical clustering process.

Dendrogram



Dendrogram of Hierarchical Clustering
((42,43),(((25,27),22),18))

The dendrogram above illustrates the process of hierarchical clustering. Each leaf node represents a data point (18, 22, 25, 27, 42, 43), and the horizontal lines indicate the levels at which these points or clusters are merged. The height of each merge corresponds to the distance or dissimilarity between the joined clusters. This visualization helps in identifying the natural groupings and the ideal number of clusters within the dataset.

3.6 Determining the ideal number of clusters

3.6.1 What is Davies-Bouldin Index (DBI)?

The **Davies-Bouldin Index (DBI)** is an internal evaluation metric for clustering algorithms. It quantifies the average similarity between each cluster and its most similar one, based on the ratio of within-cluster distances to between-cluster distances. A lower DBI indicates better clustering quality.[38]

3.6.2 How is it calculated?

For each cluster C_i in the clustering result:[38]

- S_i: The average distance between each point in cluster C_i and the centroid of C_i (a measure of intra-cluster dispersion).
- $M_{i,j}$: The distance between the centroids of clusters C_i and C_j (inter-cluster separation).
- $R_{i,j} = \frac{S_i+S_j}{M_{i,j}}$: The similarity measure between clusters C_i and C_j.

The Davies-Bouldin Index is computed as:

$$\text{DBI} = \frac{1}{k}\sum_{i=1}^{k}\max_{j\neq i} R_{i,j}$$

Where k is the total number of clusters.

Table 3.11: Davies-Bouldin Index Ranges and Their Clustering Interpretations

DBI Range	Description
0.0 to 0.5	Excellent clustering: Clusters are compact and well-separated.
0.5 to 1.0	Good clustering: Some overlap between clusters, but still acceptable.
1.0 to 2.0	Weak clustering: Clusters are not well separated; quality is low.
> 2.0	Poor clustering: Clusters are highly overlapping or not meaningful.

3.6.3 What is Calinski-Harabasz Index (CH Index)?

The **Calinski-Harabasz Index (CH Index)**, also known as the Variance Ratio Criterion, is an internal evaluation metric used in clustering analysis to assess the compactness and separation of the resulting clusters. It measures the ratio of the between-cluster dispersion and the within-cluster dispersion.[39]

3.6.4 How is it calculated?

Let:

- N: Total number of data points.
- C: Number of clusters.
- u_i: Centroid of cluster i.
- U: Overall centroid of the dataset.
- CL_i: Set of points in cluster i.
- $d(\cdot, \cdot)$: Distance function (typically Euclidean distance).

The Calinski-Harabasz Index is calculated as:

$$\text{CH} = \frac{N - C}{C - 1} \cdot \frac{\sum_{i=1}^{C} d(u_i, U)}{\sum_{i=1}^{C} \sum_{x_j \in CL_i} d(x_j, u_i)}$$

Where:

- The numerator measures the between-cluster dispersion.
- The denominator measures the within-cluster dispersion.

Table 3.12: Interpretation of Calinski-Harabasz Index Values

CH Index Value	Interpretation
High	Good clustering: clusters are compact and well separated.
Low	Poor clustering: clusters may be overlapping or not well defined.

3.7 Conclusion

The chapter concludes by emphasizing the pivotal role of AI in unlocking new levels of automation and efficiency across various domains. When combined with MEC and 5G, AI facilitates the development of highly responsive, context-aware applications that are essential for next-generation smart infrastructures. As intelligent agents increasingly drive decision-making, AI becomes indispensable for building adaptive and resilient digital ecosystems.

Chapter 4

Experimental Analysis

4.1 Introduction

This chapter presents the experimental framework for applying AI and MEC principles using real-world mobility data from the Cabspotting project in San Francisco. It details the data preprocessing steps, the selection and implementation of clustering algorithms, and the evaluation of their performance using established metrics. The objective is to identify optimal MEC deployment zones based on vehicle movement patterns and density.

4.2 Architecture System

4.3 Setup

The dataset used in this study was obtained from the Cabspotting project, which provides real GPS traces of taxi movements in San Francisco. It was uploaded to Google Drive and accessed through Google Colab, which offered a cloud-based environment with a free T4 GPU to accelerate computations. The implementation was carried out using Python, relying on libraries such as Pandas, NumPy, Scikit-learn, and Matplotlib for data processing, clustering analysis, and visualization. This setup enabled effective exploration of urban mobility patterns and simulation of optimal MEC deployment using AI-based clustering techniques.

4.4 Tools and Programming Languages

4.4.1 Python:

Python is a high-level, open-source programming language created by Guido van Rossum in 1991. It is noted for its simplicity and readability, making it suitable for both new and experienced developers. Python is widely utilized in many industries, including web development, data analysis, artificial intelligence, and task automation. It supports a variety of programming paradigms, including object-oriented and functional programming, and provides a large library of libraries for rapid and efficient development across numerous applications.[40]
Python serves as the primary programming language for our model development, while several libraries augment its functionality:

- **Scikit-learn:**

is an open-source Python framework for implementing machine learning techniques including classification, regression, and clustering. It is well-known for its simplicity and speed of execution, making it a popular choice in research, education, and real-world data science and AI applications.[41]

- **Pandas:**

is a Python toolkit for data analysis that includes strong data structures such as Series and DataFrame. It simplifies the handling of structured data, such as filtering, grouping, managing missing values, and doing statistical analysis. Pandas is a fundamental tool for rapid and intuitive data manipulation, widely used in domains such as statistics, finance, and data science.[42]

- **NumPy:**

is a Python package that allows for efficient numerical and data processing. It enables the ndarray object to conduct mathematical operations on multidimensional data in a swift and effective manner, making it an essential tool in domains such as data science, artificial intelligence, and scientific computing.[43]

- **Matplotlib:**

is a Python library that allows you to create production-quality 2D plots. It allows both interactive and non-interactive charting and may output in a variety of formats, including PNG, PDF, and SVG. It supports a variety of chart formats, including lines, bars, pie charts, histograms, and more, and may be integrated into desktop applications or online pages. Its architecture is modeled after MATLAB, making it recognizable to many scientists and engineers.[44]

4.4.2 Google Colab

Google Colab is a free service supplied by Google that allows users to build interactive notebooks similar to the Jupyter Notebook environment straight from a web browser, without the need for any prior setup or expensive hardware. It supports the Python programming language and offers free code execution on cloud-based servers equipped with GPUs. Google Colab is an excellent platform for interactive teaching and learning, particularly in remote classrooms. It also promotes collaboration among students by allowing them to share and collaborate on the same notebook in real time.[45]

Propossed Approach

4.5 Data utilized

4.5.1 CabSpotting in San Francisco

The cabspotting.org project gathered information about each of San Francisco's Yellow Cabs, such as their location, timestamp, and whether or not they were carrying a paying customer.

4.5.2 The Data

We used the Cabspotting dataset. The dataset consists of 537 text files with a total of 11220490 records. Each text file corresponds to a taxi. Here is an example of one of the files.

```
37.78806 -122.40009 0 1213033316
37.78802 -122.4003 0 1213033254
37.78837 -122.39999 0 1213033238
37.7883 -122.40009 1 1213033231
37.78743 -122.40083 1 1213033196
```

Figure 4.1: CabSpotting Dataset

Columns are, respectively:

- latitude
- longitude
- occupancy (1 for passengers, 0 for empty)
- time (number of seconds since the Unix epoch: 00:00:00 UTC on 1 January 1970)

4.5.3 Data Preprocessing

- **Merge Data:**

○ merged all 536 separate text files in a single CSV file

- **Data Cleaning:**

○ Create a "CarID" column with unique IDs (from 2 to 537) to identify each cab.
○ Removed "Occupancy" column.
○ Converted the "Timestamp" column from UNIX Epoch to standard time format.

1	CarID,Latitude,Longitude,Timestamp
2	2,37.75134,-122.39488,2008-06-10 07:58:07
3	2,37.75136,-122.39527,2008-06-10 07:57:39
4	2,37.75199,-122.3946,2008-06-10 07:55:40
5	2,37.7508,-122.39346,2008-06-10 07:54:49
6	2,37.75015,-122.39256,2008-06-10 07:50:37

Figure 4.2: Dataset Head

The Data after :

- Assigning a Unique CarID to Each Cab: A unique numeric CarID was assigned to each file to identify and associate each data point with its corresponding cab.
- Cleaning Invalid Entries: Only lines containing exactly four values were retained. Any lines with missing or invalid values, including malformed timestamps, were discarded to ensure data consistency.
- Timestamp Conversion to Human-Readable Format: Unix timestamps were converted into a human-readable format (YYYY-MM-DD HH:MM:SS) to facilitate further temporal analysis and visualization.
- Structuring Cleaned Data: Valid data points were collected in a structured format with fields: CarID, Latitude, Longitude, and Timestamp.
- Exporting to CSV Format: The cleaned and structured data was saved to a CSV file, enabling easier access and use in downstream tasks like machine learning or visualization.

4.6 Clustering Algorithm Selection

Agglomerative Clustering and DBSCAN were tested for determining vehicle concentration zones to enable MEC deployment.[46]

4.6.1 Agglomerative Clustering

Agglomerative Clustering generated well-defined and consistent clusters, indicating its suitability for detecting stable vehicle groupings. It demonstrated stronger clustering quality, making it a reliable choice for planning fixed MEC unit locations.

4.6.2 DBSCAN

DBSCAN, on the other hand, was effective in identifying irregular patterns and isolating noise points, which is valuable for detecting temporary or dynamic hotspots. However, the overall structure of its clusters was less distinct compared to Agglomerative Clustering, suggesting its better use in flexible or mobile MEC deployment scenarios.

Table 4.1: Comparison Between Agglomerative Clustering and DBSCAN

Criterion	**Agglomerative Clustering**	**DBSCAN**
Algorithm Type	Hierarchical, builds nested clusters	Density-based, clusters based on point density
Cluster Definition	Merges clusters based on linkage	Finds dense areas separated by sparse regions

Criterion	Agglomerative Clustering	DBSCAN
Predefined Clusters	Not required (uses distance threshold)	Not required (uses `epsilon` and `min_samples`)
Cluster Shapes	Prefers spherical/regular shapes	Can handle arbitrary shapes
Noise Handling	No explicit outlier detection	Explicitly detects and labels noise
Stability	High stability across runs	Sensitive to parameter changes
Interpretability	Easy to visualize using dendrograms	Less intuitive without domain knowledge
Best Use Case	Clear structure, consistent density	Variable density, anomaly detection
Suitability Here	**Recommended for MEC placement**	**Less precise in this context**

4.7 Evaluation Metrics

At this stage, the Agglomerative Clustering algorithm was applied without specifying a predefined number of clusters by setting n_clusters=None and defining a distance_threshold. Different threshold values were tested to observe their effect on the number of resulting clusters. When the distance threshold was set to 0.005, the algorithm produced 66 clusters, while a threshold of 0.01 resulted in 32 clusters. After comparison and analysis, the value 0.02 was selected as it automatically generated 19 clusters, which was considered ideal. This value provided a good balance between the number of clusters and the practical deployment of MEC units, ensuring efficient coverage while avoiding excessive fragmentation.

Although there are several clustering evaluation metrics, the Davies-Bouldin and Calinski-Harabasz indices were specifically chosen for their ability to provide a balanced assessment of cluster compactness and separation. The results showed that using k = 19 achieved a well-structured clustering, making it suitable for efficient MEC deployment in smart city environments.

4.7.1 Davies-Bouldin Index

This index is preferred to be low, as lower values indicate that the clusters are more compact and less overlapping. We observe that the value at k = 19 is among the lowest on the chart, suggesting that the clusters at this point have strong internal cohesion and are well-separated from each other. This reflects good model performance in organizing the data into distinct and well-formed groups. Therefore, this index supports the selection of k = 19 as an optimal number of clusters.

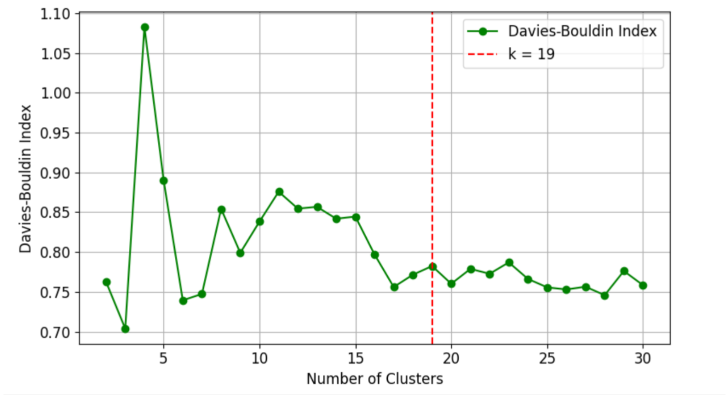


Figure 4.3: Graph of Davies-Bouldin

The Davies-Bouldin Index is relatively low, which is desirable, as it suggests that the clusters are well-separated and not highly overlapping.

Table 4.2: Davies-Bouldin Index

Metric	**Agglomerative Clustering**	**DBSCAN**	**Interpretation**
Davies-Bouldin Index	0.782	1.745	Lower is better → **Agglomerative wins**

4.7.2 Calinski-Harabasz Index

In this chart, higher values indicate better clustering performance, reflecting the model's ability to form compact and well-separated clusters. We observe that at k = 19, there is a noticeable improvement in the index compared to the surrounding values, indicating a clear and meaningful structure in the data at this cluster count. This strengthens the reliability of the model and serves as a strong indicator of clustering quality. Therefore, k = 19 is considered a suitable and effective choice for dividing the data in a logical and organized way.

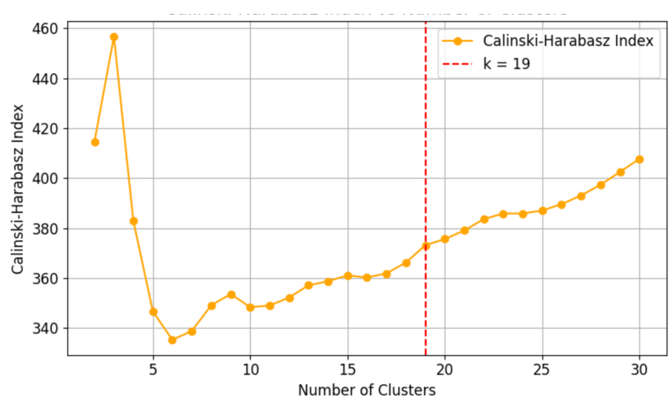


Figure 4.4: Graph of Calinski-Harabasz

The Calinski-Harabasz Index displays an upward trend, meaning the clusters are becoming more distinct, which is a positive sign of improved clustering quality.

Table 4.3: Calinski-Harabasz Index

Metric	Agglomerative Clustering	DBSCAN	Interpretation
Calinski-Harabasz Index	373.166	14.217	Higher is better → **Agglomerative wins**

4.7.3 Dendrogram

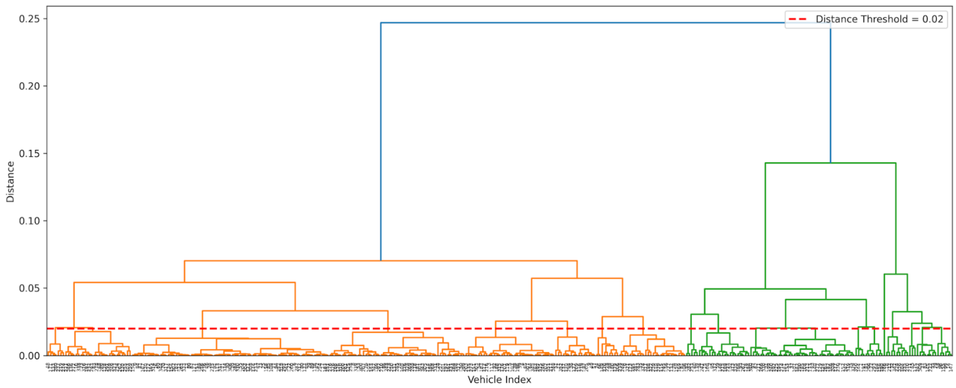


Figure 4.5: Agglomerative Clustering Dendrogram

The dendrogram visualizes how data points were gradually merged using agglomerative clustering. A distance threshold of 0.02 was applied, resulting in 19 automatically identified clusters. This hierarchical representation helps understand the structure of the data and supports efficient MEC placement based on vehicle distribution.

Comparison With existing work

The following two figures present the results of applying two different clustering algorithms to the predicted positions. The first figure shows the outcome of the K-Means algorithm with 22 clusters, where the number of clusters was predetermined based on previous analysis. The second figure displays the result of the Agglomerative Clustering algorithm, which automatically identified 19 clusters based on a distance threshold of 0.02. The comparison highlights the differences in cluster distribution between the two methods, offering insight into the effectiveness of each algorithm in capturing spatial patterns and cluster separability.

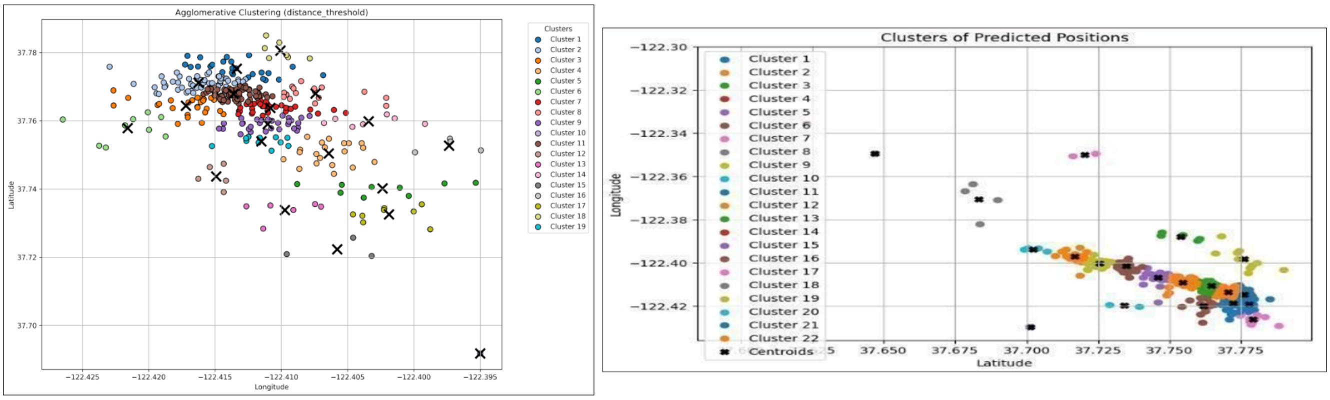


Figure 4.6: Agglomerative Vs K-means
[10]

Table 4.4: Comparison Between Agglomerative and K-means

Aspect	Previous Work	Our Work	Advantage
Clustering Algorithm	K-Means	Agglomerative Clustering	Better for non-uniform, complex data
Number of Clusters	22	19	More optimal, avoids over-segmentation
Cluster Distribution	Dense and overlapping	Balanced and widespread	Improved spatial coverage
Centroid Placement	Some centroids are too close	Well distributed	More efficient MEC resource allocation
QoS Impact	Not clearly optimized	Clearly enhanced	Reduced latency, better network performance

As seen in Table 4.4, our method demonstrates a more efficient clustering strategy. The reduced number of clusters, balanced distribution, and improved centroid placement contribute to enhanced MEC deployment and better Quality of Service (QoS).

4.8 MEC Placement Based on Vehicle Clusters

This map illustrates the deployment of MEC (Multi-access Edge Computing) nodes across San Francisco, with each marker representing the central location of a vehicle cluster identified using Agglomerative Clustering. These cluster centers were computed from vehicle GPS data and serve as optimal positions for placing MEC units to ensure low-latency communication and efficient service delivery. The strategy aims to enhance the performance of edge-enabled applications by placing computing resources closer to areas with high vehicle density.

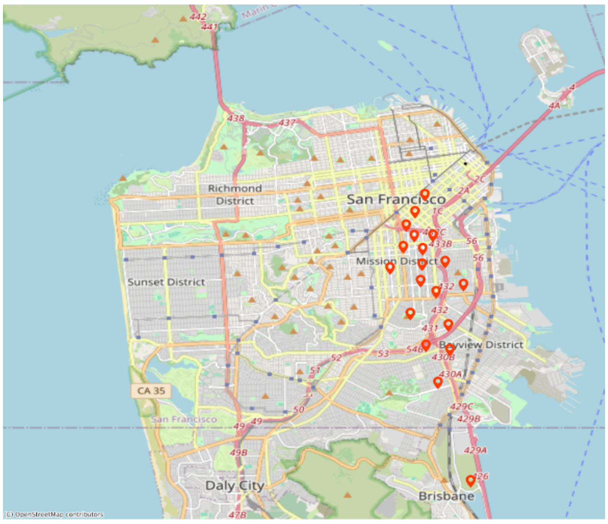


Figure 4.7: Map of San Francisco with positions of MEC

4.9 Conclusion

The experimental findings validate the effectiveness of using clustering algorithms—particularly Agglomerative Clustering—for planning the strategic placement of MEC units. By analyzing real-time urban mobility data, the study demonstrates how AI-driven techniques can inform network optimization and service provisioning. This practical approach highlights the power of integrating AI, MEC, and 5G to support data-driven decision-making in smart city environments.

General Conclusion

General Conclusion

This thesis has presented an integrated exploration of three key technologies—Fifth Generation (5G) networks, Multi-access Edge Computing (MEC), and Artificial Intelligence (AI)—and their role in supporting the evolution of intelligent, data-driven transportation systems. Each of these technologies contributes uniquely to the development of next-generation mobility: 5G offers the high-speed, low-latency communication backbone; MEC brings computing resources closer to data sources, enabling real-time processing; and AI enhances decision-making through learning from complex data patterns.

Through the detailed discussions in the early chapters, the theoretical foundations and architectural aspects of these technologies were examined, emphasizing their synergies and interdependencies. The practical section of the thesis then provided a real-world application of these concepts. By analyzing vehicle movement data from San Francisco, clustering techniques were employed to determine optimal areas for MEC deployment, simulating a strategic framework for intelligent service provisioning in smart urban environments.

The experimental results confirmed the potential of combining AI-driven analytics with edge-enabled communication networks to improve system efficiency, responsiveness, and scalability. Clustering algorithms, particularly Agglomerative Clustering, proved effective in identifying high-density regions that could benefit from localized edge computing services. These findings underscore the importance of data-centric approaches in the planning and optimization of future urban infrastructure.

Ultimately, this thesis demonstrates that the integration of 5G, MEC, and AI is not only technically feasible but also highly beneficial for building responsive, adaptive, and intelligent transportation networks. As cities continue to digitize and expand, such an integrated framework can support a wide range of applications—from traffic management and autonomous mobility to public safety and environmental monitoring.

Future work could expand on this foundation by incorporating real-time streaming data, enhancing model adaptability, and applying the proposed framework to other cities or larger-scale scenarios. The continued evolution of smart cities will depend heavily on such interdisciplinary approaches that unite communication, computing, and intelligence to create truly connected urban ecosystems.

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