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From 5G to 6G Technology: Meets Energy, Internet-of-Things and Machine Learning: A Survey

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Abstract: Due to the rapid development of the fifth-generation (5G) applications, and increased demand for even faster communication networks, we expected to witness the birth of a new 6G technology within the next ten years. Many references suggested that the 6G wireless network standard may arrive around 2030. Therefore, this paper presents a critical analysis of 5G wireless networks', significant technological limitations and reviews the anticipated challenges of the 6G communication networks. In this work, we have considered the applications of three of the highly demanding domains, namely: energy, Internet-of-Things (IoT) and machine learning. To this end, we present our vision on how the 6G communication networks should look like to support the applications of these domains. This work presents a thorough review of 370 papers on the application of energy, IoT and machine learning in 5G and 6G from three major libraries: Web of Science, ACM Digital Library, and IEEE Explore. The main contribution of this work is to provide a more comprehensive perspective, challenges, requirements, and context for potential work in the 6G communication standard.

Keywords: 5G; 6G; energy; deep learning; machine learning; Internet-of-Things; IoT; security

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1. Introduction

Many researchers have anticipated that the year 2030 will bring tremendous changes in technology and business landscapes [1]. The world is moving towards a data-driven, highly digitalised and intelligent environment. The new revolution will introduce new technological challenges and requirements. In order to cope with these technical requirements, the existing communication networks should be improved and enhanced. The sixth-generation (6G) mobile communication network is expected to play a vital role in supporting the required connection speed, reliability, coverage and infrastructure in the future. Based on existing reports, the sixth generation will furnish a full dimensional wireless range and support all industrial functions, including sensing, communication, computation, caching, control, location, radar, navigation, and imaging full-vertical applications. Recent academic articles have been conceptualizing the 6G to be a self-contained ecosystem with intelligence and decision making skills comparable to humans. It is expected that mobile communication will progress from being human-centric to being both human/machine-centric. Moreover, it will brace various communication methods to interact with intelligent end-points; also supporting various biometric-based applications including fingerprints, voice recognition, eye-tracking, and brainwaves. The 6G mobile communication networks are expected to offer up to 100 per cent gain in energy efficiency over their predecessors, the 5G networks, and a highly complex structure due to vast interconnections. Statistical studies show that there will be an increase of mobile data traffic at a rate of 55 per cent annually [2]. By the year 2030, that generated traffic will cross five zettabytes (10^{21}) every month. With this massive volume of data generated, there should be a mechanism to handle and manage the network at various levels. To this end, the application of Artificial Intelligence (AI) will be heavily dependent on the next-generation wireless network. It is interesting to consider how the Internet-of-Things (IoT) enabled devices will communicate [3]. IoT is a crucial technology for attaining the "social information infrastructure" [4], where it can be used to visualise and simplify complicated and mutually related societal problems in the real world. In this study, we present a critical analysis of 5G wireless networks' significant technological limitations with respect to the expected advancement in three major domains: energy, Internet-of-Things, and machine learning. Moreover, the study also presents a review of the anticipated challenges of the 6G communication networks. The overall contribution is presenting a visionary framework on how the 6G should look like to support the applications of these domains.

Contribution: This article aims to draw a complete picture of "how the 5G to 6G Technology: meets Energy, Internet-of-Things and Machine Learning?".

We cover different dimensions and aspects of 5G and 6G focusing on the projected 5G and 6G system architecture, potential technologies, an overview of an existing technique, analysis of ML usage in incorporating energy and IoT in 5G and 6G, applications, and use cases. The taxonomy of the paper is shown in Figure 1, which gives a pictorial view of all sections and subsections presented in this paper. The contributions of this article are summarized as follows.

- We discuss in detail the projected 6G system architecture. Also, the existing research literature reveals that providing full-dimensional advantages of the 6G technology; will 5G application types will be reconsidered by modifying the traditional URLLC, eMBB, and mMTC and providing new services.
- We discuss the primary aims, vision, and trends for 6G network dimensions that include our vision of 6G and IoT and machine learning applications for autonomous networks and revolutionary energy efficiency, which are discussed in detail throughout this paper.
- We highlight all the essential network elements of 6G system architecture and discuss defined issues that current generations of mobile networks are facing; the mobile industry should transition away from traditional strategies and toward some new ones, such as operation in shared spectrum bands, inter-operator spectrum sharing, indoor small cell networks, a large number of local network operators, and on-demand network slice leasing.
- To meet the requirements of the stage where the research results on ML are to be addressed, as well as the methodology used by 5G and 6G for the Internet of Things and energy transmissions. We overview six major categories, including network resource management, security, augmented reality, network scaling, resource allocation, and the smart grid.
- Towards the end, we discuss multiple challenges and research directions applications, issues, research questions, motivation, recommendation criteria, and open challenges of ML usage in incorporating energy and IoT in 5G and 6G,

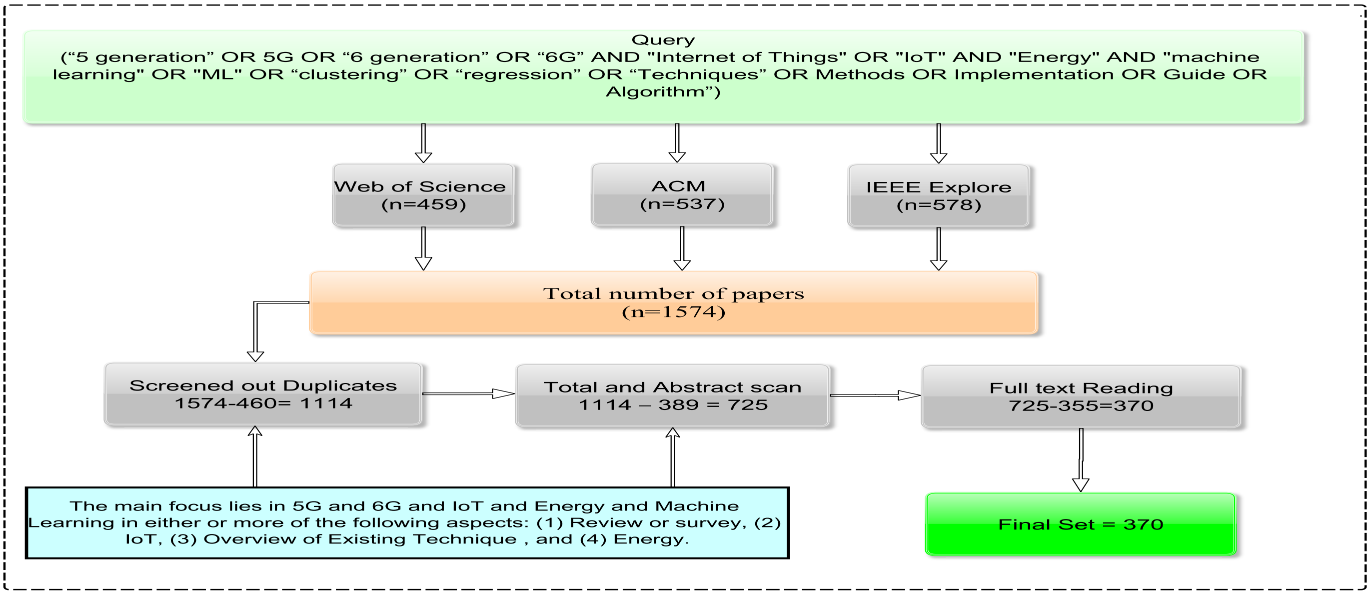

Figure 1. Research Methodology Guideline.

The remaining paper is outlined as follows. Section 2 defines the approach, including the source of material, requirements for eligibility of research, the systematic literature review (SLR) and the effects of search results of publications. The queries of any object from three website papers separated into 4 classes, the literary taxonomy on 5G and 6G Technology. Section 3 We discuss in detail about the projected 6G system architecture. We highlight all the essential network elements of 6G system architecture, application of AI and ML, existing technique, analysis of ML usage in incorporating energy and IoT in 5G and 6G, etc. Section 4 described and summarised in survey and review papers based on the latest state of the art in 5G, 6G, and research documentation. Section 5 investigated in this section, the requirements of the stage where the results of the research on ML are to be addressed, as well as the methodology used by 5G and 6G for the Internet of Things and energy transmissions. Section 6 We've done an explanatory evaluation of the use of the internet of things as the foundation for a transition strategy toward the development of 5G and 6G communications networks and technologies. Section 7 to handle various difficulties in wireless communications in the direction of merging energy and IoT in 5G, 6G, and beyond networks. Section 8 addressed inspiration, difficulties, and recommendations in that research area and a modern approach to the 5G and 6G networks that make use of IoT, energy and machine learning technologies. Finally, Section 9 presents the Conclusion. The reminder of this paper is organized as illustrated in Figure 2.

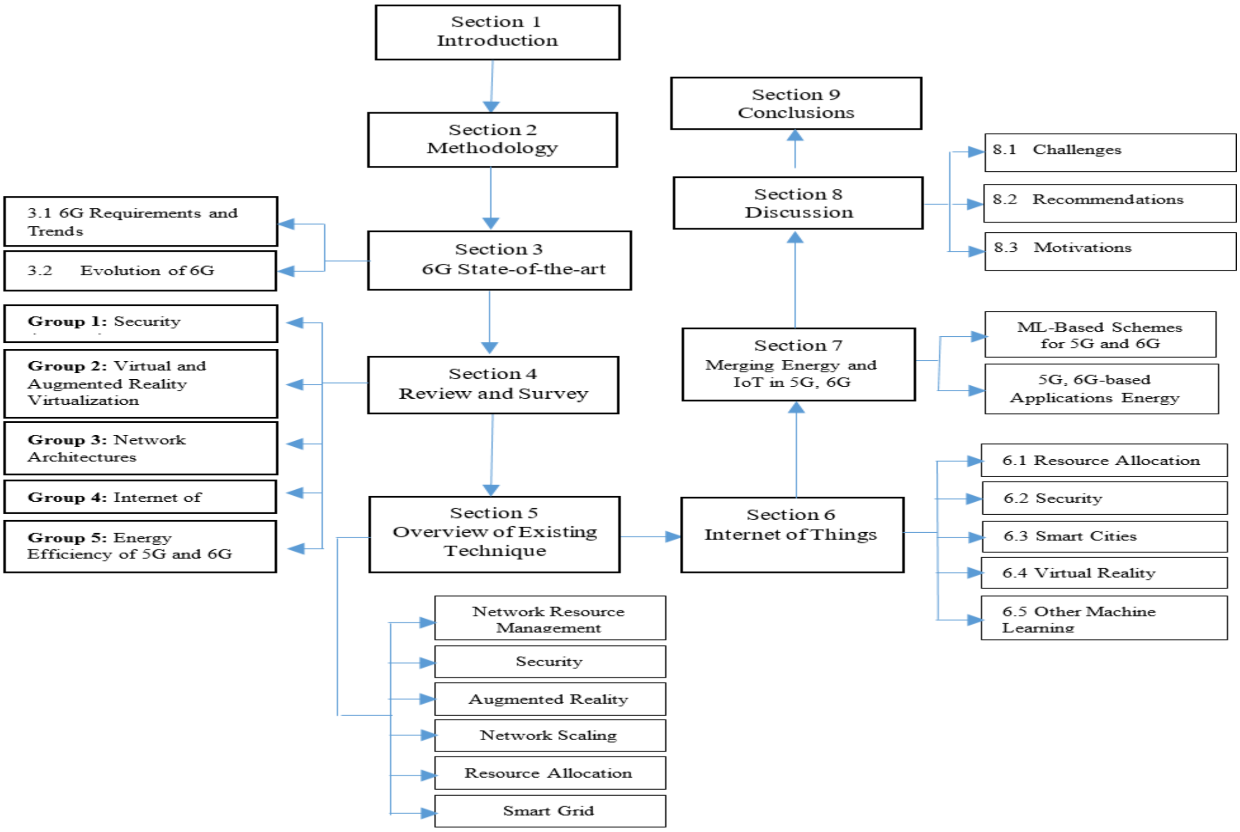

Figure 2. Diagramatic view of the organization of this survey paper.

2. Methodology

We found articles about 5G and 6G by using three keywords: "machine learning", "internet of things", and "energy". The searches were conducted using three digital libraries: (1) Web of Science (WOS), which provides multidisciplinary research articles in the fields of science, arts, and technology; (2) IEEE Explore, which provides articles specialised in the field of electrical and electronics engineering; and (3) ACM digital library, which has a comprehensive database of scientific articles related to computing and technology.

The significant articles and literature referred to by the search outputs were selected and categorised based on two criteria: (1) use three iterations in the filtering process, which removes the redundant and duplicated articles, excluding irrelevant articles using the title; and (2) use three iterations in the categorization process, which categorises the significant articles and literature referred by the search outputs. Perform the initial screening, and the selected papers are then subjected to a second selected using the 5G and 6G after carefully reviewing the results of the reduced search.

The three databases mentioned were searched extensively in May 2021, with many different keywords (or phrases) being used, including "5 generations" or "5G" or "6 generations" or "6G" and "machine learning" or ML or "artificial intelligence" or "AI" or "classification" or "clustering" or "regression", and "IoT" or "Internet of Things" and "Energy" or "techniques" or "methods" or "implementation" or "guide".

Figure 2 depicts an example of a query text that might be utilised. Using the advanced features of search engines, we have removed search results that are correspondences, letters, book chapters, and other types of documents. The exclusions are designed to ensure that only the most recent scientific publications are obtained, as well as just those of significant value that improve the 5G and 6G capabilities. The emphasis is on including any articles and scientific submissions that meet all of the requirements for inclusion in this work. Following that, they are separated into two categories, namely, general and coarse-grained classifications. Following the study's findings, the latter is explored in four succeeding sections derived from the results, in which the Google scholar search engine was applied to determine the path of the study.

After the queries were run, 1574 papers were found, with 459 coming from WOS, 578 from IEEE, and 537 from ACM digital libraries. Between 2014 and 2021, all of the articles on this list were published. These articles were then sorted into three groups: (1) 460 redundant articles, (2) 744 irrelevant articles based on titles and abstracts, and 370 articles that met the requirements for 5G, 6G, machine learning, internet of things, and energy.

As previously stated, an article is removed from consideration if it fails to meet the following selection criteria: (1) The paper was not written in an English-speaking environment. (2) The article's emphasis was on techniques and/or procedures. (3) The article's research focus is solely on 5G and 6G, with no mention of the internet of things, energy, or machine learning.

Furthermore, if 5G and 6G were not added in the second iteration, the articles would still be removed. (1) There are no features of machine learning, IoT, or energy considered in the paper's contribution. (2) The paper's discussion is limited to 5G and 6G, with no other topics addressed. Articles are subjected to rigorous machine learning, internet of things, and energy analysis in this study, with the remaining articles being sorted into categories that focus on how to improve 5G and 6G.

Results and Statistical Information of Articles

The review's findings are addressed in the form of responses to the research questions. The taxonomy is shown in Figure 3. There are four basic categories in which the recordings might be classified. (1) Review and Survey (2) Internet of Things (3) Overview of Existing Technique and (4) Energy. The first set of research and survey materials describes the IoT and energy or machine learning methodologies and strategies used in 5G and 6G to achieve their goals and solve challenges. The second section looks at the impacts, triggers, countermeasures, and conditions, as well as technology for better efficacy control. The effects of a methodology used to classify various variables, which can alter different parts of the method or the product as it is generated, are presented in the third category. The fourth category includes a mission's structures, tactics, and low energy usage and operational efficiency.

Figure 3 shows the statistics for the various categories listed above for articles about 5G and 6G. The 370 articles from the three databases are split into four categories in the figure: reviews and surveys (74) [5–78] , Internet of Things (95) [79–139], Overview of Existing Technique (61) [140–234], and publications about Energy studies (140) [235–374]. Figure 3 shows the quick number of publications in 5G and 6G based on the fields and regions where research and studies are conducted. The findings were divided into 74 of the 370 papers, 95 of which are relevant publications on 5G and 6G case analysis 5G and 6G and internet of things strategies, and 61 of the 370 articles, which addressed with the technique used by 5G for IoT and energy. The last categories of scientific contributions and outcomes focused on combining energy and IoT in 5G, 6G, and 140 of 380 papers. Even the mathematical study of several groups is depicted in the illustration.

Figure 4, on the other hand, presents classified scientific publications from 2014 to 2021 and contains papers based on the year of publication. Only two papers were authored in 2014, yet 170 were published between 2015 and 2018. In comparison, 109, 54, and 35 papers have been written for 2019, 2020, and 2021, respectively. Primary sources of analysis were based on 5G and 6G research, and general recommendations were evaluated.

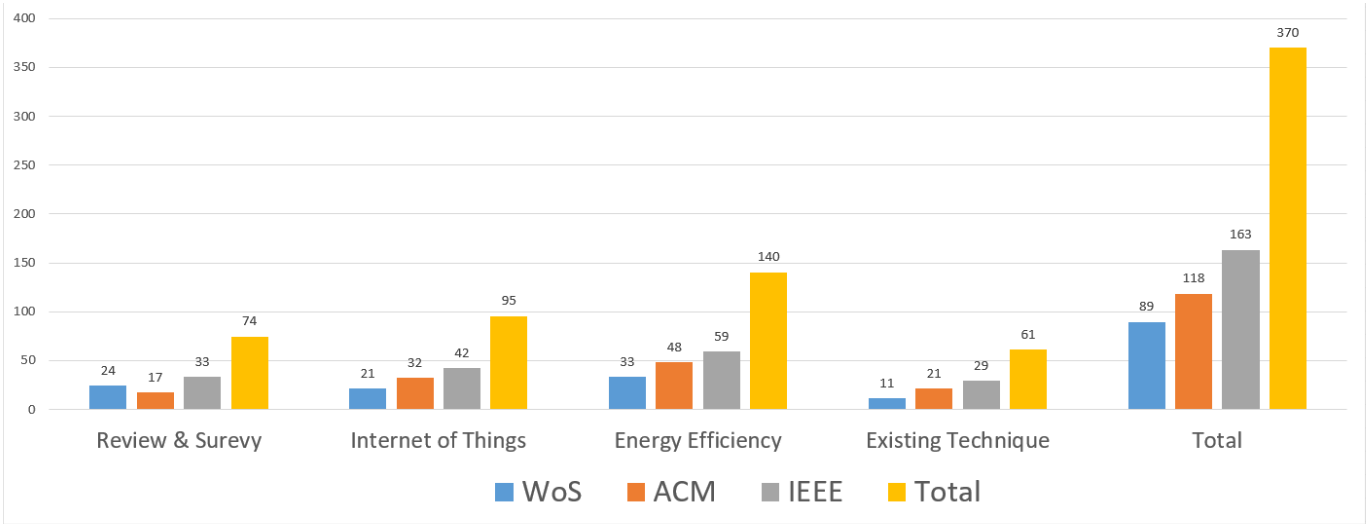

Figure 3. Articles categorized based on their contribution.

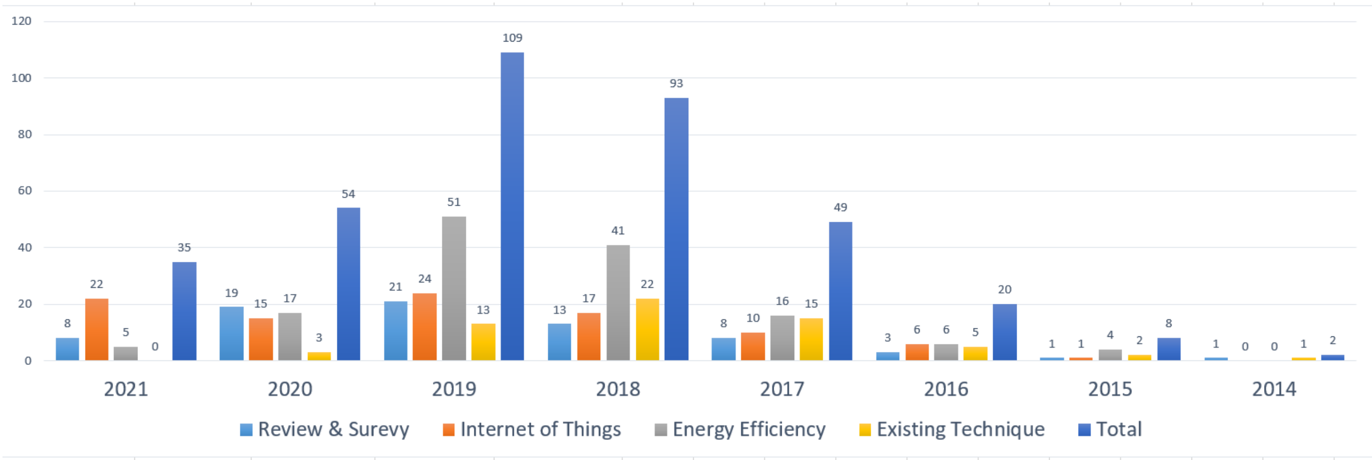

Figure 4. Published articles in between 2014 and 2021.

3. 6G State-of-the-Art

For this vision to become a reality, 6G will be the critical enabler; it will connect everything, provide full-dimensional wireless coverage, and integrate all functions, including sensing and communication, as well as computation, caching, and control [375]. It will also enable full-vertical applications by integrating all functions, including as sensing, communication, computation, caching, and control, as well as location, radar, navigation, and imaging, into a single platform. It is anticipated that 6G would be an autonomous ecosystem with intelligence and consciousness on par with humans. In the coming years, 6G networks will be a significant enabler for the intelligent information society, as they are expected to provide performance superior to 5G networks while also catering to the needs of developing services and applications. Our vision of 6G, as well as IoT and machine learning applications for autonomous networks and revolutionary energy efficiency, are discussed in detail throughout this paper.

Despite the fact that 5G supports URLLC, Zong et al. [376] argue that it has some limitations, such as the weakness of short packet, sensing-based URLLC. This may limit the dependability of low-latency services with high data rates, which are required for AR, MR, and VR. Furthermore, smart devices are expected to exponentially increase data traffic and necessitate high-speed data transfer, both of which are unaccounted for in 5G standards [377]. Similarly, 5G does not support advanced IoT technologies that necessitate the convergence of communication, detection, control, and computing functions. As a result, the need for 6G emerges to support these IoT technologies. In comparison to 5G, 6G will be more reliable, have lower latency, and will be fully integrated with ML, XR, IoT, and blockchain technologies [378]. In addition, 6G wireless networks will: (1) With super-high throughput demands, support SHD and EHD videos. (2) Provide extremely low-latency communications for the industrial Internet (about 10 s). (3) Support the Internet of Nano-Things and the Internet of Bodies by using smart wearable devices and intraday communications enabled by implantable nanodevices and nanosensors that consume very little power. (4) Support underwater and space communications to considerably expand human activity's bounds, such as deep-sea touring and space exploration. (5) In new scenarios, such as HSR, provide consistent service experiences. (6) Boost 5G vertical applications like Massive IoT and completely autonomous vehicles.

3.1. 6G Requirements and Trends

As a result of the clearly defined issues that current generations of mobile networks are facing, the mobile industry should transition away from traditional strategies and toward some new ones, such as operation in shared spectrum bands, inter-operator spectrum sharing, indoor small cell networks, a large number of local network operators, and on-demand network slice leasing. Several of the most essential criteria and trends for the future generation of mobile networks will be discussed in greater detail in the sections to follow.

3.1.1. Self-X Network

The future network must be more adaptive and robust, and it must be capable of managing itself far beyond the capabilities of people. Machine learning approaches that are both intelligent and adaptive are employed to enable 6G networks to be self-sufficient while also capturing insights and comprehension about their surrounding environment. Without the need for human interaction, the future network will be able to perform functions such as learning from its own mistakes, reconfiguring itself to improve its performance, self-healing, organising itself into groups, and protecting itself.

3.1.2. Superior Energy Efficiency

6G devices consume much more energy than prior generations of devices due to their capacity to operate in higher frequency bands than earlier generations. Because of this, energy consumption and efficiency are major issues that must be addressed immediately. Nevertheless, when new techniques are developed, we will witness a rise in energy efficiency as well as the possibility of battery-free internet of things devices, such as energy harvesting in building automation and smart homes.

Interconnectivity in three dimensions: Future networks will extend beyond the confines of two dimensions to include oceans, the atmosphere, and space, allowing for the integration of terrestrial and aerial devices. Various applications, including underwater acoustic ad hoc and sensor networks, weather forecasting, and climate monitoring, will be able to take advantage of such networks.

3.1.3. Satellite Integration

To achieve worldwide coverage, future 6G communications will rely on satellite technologies to be implemented. In the future, 6G will link telecommunications, earth imaging, and navigation satellites to give cellular users with location services, broadcast and Internet connectivity, and forecasting information. One example is the provision of high-speed Internet access aboard fast trains and aeroplanes.

3.1.4. e-Health

The Internet of Things will usher in a new era of healthcare applications by offering real-time haptic input, continuous connection availability, ultra-low-latency data transfer, extremely high reliability, and support for mobility.

3.1.5. Smart Cityh

ITS, IMD, and SRS are examples of smart urban applications that require pervasive sensing as well as intelligent decision-makers and actuators. Smart cities include smart transportation, smart grid, urban infrastructure, resident living environment, transportation management, medical treatment, shopping, and security assurance, among other things.

3.1.6. Smart Home

In the future, intelligent houses will be able to provide consumers with comprehensive services such as energy management, patient support, real-time product labelling, and subscription management, among other features.

3.2. Evolution of 6G

In order to make use of the new technological advantages of 6G technology, 5G application types will be reconsidered by modifying the traditional URLLC, eMBB, and mMTC and providing new services, which are explained below.

3.2.1. Mobile Broadband Reliable Low-Latency

The distinction between eMBB and URLLC will become unsustainable for some applications, such as augmented reality, virtual reality, and wireless brain computing interfaces, because these applications require not just excellent reliability but also data throughput on the order of eMBB. As a result, a new service class called MBRLLC was created to enable 6G technology to achieve any desired performance with great dependability and minimal latency.

3.2.2. mURLLC

6G technology must scale the typical URLLC feature of 5G into a new service called mURLLC, which offers a high-reliability scalability-latency trade-off in comparison to average-based network designs.

3.2.3. HCSs

A new level of physical experience may be delivered with the use of 6G technology, which enables the provision of HCS services that can be tightly tied with human users. As an excellent example of HCS, wireless brain computing interfaces are particularly well-suited since network performance is determined by the physiology and behaviour of human users.

The major needs for 6G systems are high efficiency, smooth integration, innovative technologies, accurate indoor location, high density, advanced connectivity, and healthy communication. 6G systems must also meet the following characteristics. These more advanced requirements necessitate the provision of technical help that is more innovative in nature. Following is a breakdown of the existing techniques in this field into four (4) groups, as seen in the table below.

(1) Offloading energy-conscious tasks the majority of IoT devices are battery-powered and have limited computing and communication capabilities. As a result, these gadgets can only perform a limited number of functions at a slow rate. On the other side, applications are becoming more computationally intensive, necessitating reduced latencies and real-time answers. These apps might quickly consume the devices' power resources, making them unavailable for usage in the network. Extending the lifetime of IoT devices by conserving/boosting device energy to make full use of their finite energy supplies is still a major challenge [379].

(2) Massive IoT: this term refers to the connectivity of a large number of devices, sensors, and equipment on a big scale [380,381]. The Internet of Things is classified according to the number of connected devices and the volume of traffic generated by such devices. The number of devices linked to the Internet has expanded dramatically during the last decade. This number will more than double in the next several years, necessitating the establishment of a robust network to enable their connectivity [382]. The network density in huge IoT is extraordinarily high, reaching roughly 1 million devices per square kilometre [383]. This will result in a significant amount of data being distributed between devices, a large number of tasks being performed, and massive volumes of data being saved and analyzed [384]. As a result, 6G and fog computing will be critical facilitators of huge IoT applications.

(3) High Efficiency: refers to a broad issue that incorporates high data transmission rates, high capacity, large-scale data processing capability, exact research and conclusions, and more.

Dynamic Spectrum Allocation: High flexibility is required for 6G networks to achieve significant efficiency. When it comes to dynamic spectrum allocation, the flexible use of perceptual context information, the rapid allocation of spectrum resources in a matter of seconds, and the intensive use of valuable spectrum resources as a final goal are all possible requirements.

Optimisation of the supply of any service to a varied variety of users, automobiles, equipment, and industries is made possible through the use of dynamic network slicing technologies by network operators.

(4) Energy-Efficient Communication: 6G will meet and exceed a number of requirements, including the delivery of high-energy performance, most notably in the context of widespread IoT use and an eco-system of numerous minute sensors. Additionally, extending the battery life of smartphones is necessary, in accordance with the assumption that their skills and abilities to deal with complex multimedia signal processing improve exponentially as their power consumption increases [385]. Thus, low energy consumption and extended battery charge life length are two study areas in 6G that aim to address the daily recharging challenges faced by the majority of communication equipment and to meet communication objectives. As a result, 6G must elicit a complete plan for energy-efficient wireless communication. A basic goal of 6G communication is to operate battery-free whenever and wherever possible, with a target efficiency of 1 pico-joule per bit [386,387]. Apart from the benefits of high-power THz waves, 6G communication enables directed beam communication via MIMO antenna arrays, allowing devices to deliver power beams in a specific direction. This technology has the ability to provide sufficient energy to devices covered by the network.

6G trends, technologies, and applications state that the services will redefine those provided by the 5G by morphing the classic URLLC, eMBB, and mMTC and providing new services (see Figure 5). The following services will be introduced:

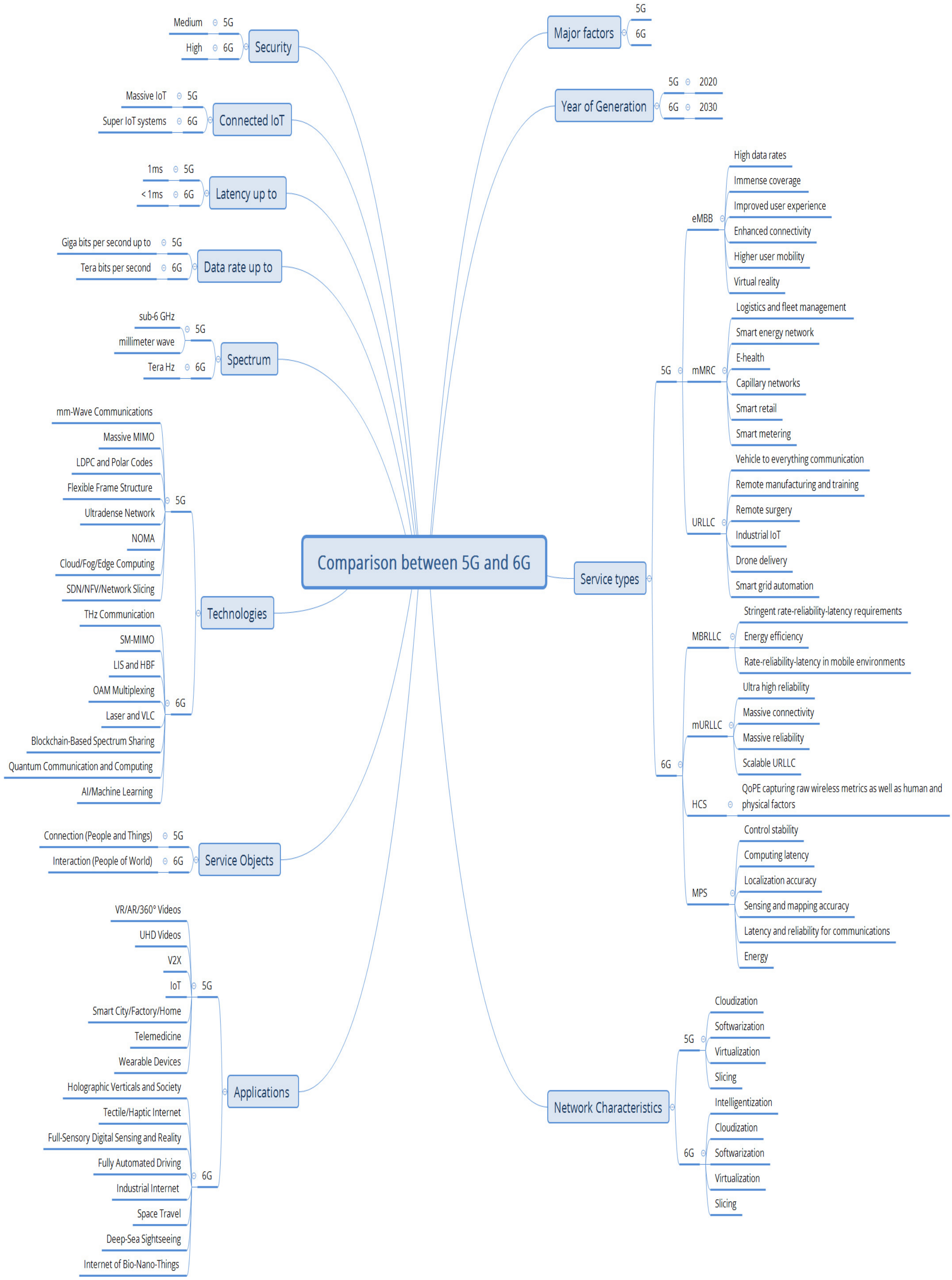

Figure 5. Comparison between 5G and 6G. Service Classes, Their Performance Indicators, And Example Applications.

4. Review and Survey Articles

ML technologies are well described and summarised in survey and review papers based on the latest state of the art in 5G, 6G, and research documentation. The applications that utilise ML technologies are well described and summarised in survey and review articles. In this category, there are seventy-four articles, which have been sorted into five subcategories. In the following sections, we introduce the recent works in IoT, and energy-efficiency in 5G, 6G as highlighted in Table 1 preceding to a discussion on open issues and challenges.

Table 1. Summary of the related review and survey papers.

Ref.	Summary	Machine Leaning		IoT	Security Approaches	VR & AR	Energy	Network Architectures
		Deep Learning	Other ML Methods					
[5]	Made it more robust against various attacks.			✓	✓			
[6]	Workload-based EDoS and Instantiation-based.		✓	✓				
[7]	Threats and sketches to mitigate the security concerns.			✓	✓			✓
[15]	Virtualization explicitly designed for IoT networks.		✓	✓		✓		✓
[16]	5G and Real-Time Communications.		✓	✓		✓		✓
[17]	Various virtual and AR for the world first 5G.		✓			✓		
[18]	Fault management techniques.		✓			✓		✓
[19]	Basic concepts of SON.	✓					✓	✓
[20]	Self-organizing networks solutions.	✓		✓			✓	✓
[21]	Application areas of AI/ML in SDN and NFV based networks.	✓			✓			✓
[22]	Use cases and scenarios of 5G in which ML.		✓		✓		✓	✓
[23]	Challenges from these 5G features and present several technological.		✓	✓				✓
[24]	DRL to address the RA problems.		✓				✓	✓
[25]	DRL based resource management schemes for 5G HetNets.	A					✓	✓
[26]	Big data analytics solution for 5G network.	✓						✓
[27]	ML to assist channel modelling and estimation has been introduced.	✓					✓	✓
[28]	AI and ML for 5G network.		✓				✓	✓
[29]	5G network management, which takes an end-to-end view of the network.		✓		✓	✓	✓	✓
[30]	Improve the efficiency, latency, and reliability of the current and real-time network applications.	✓					✓	✓
[31]	QoS for Users in 5G.	✓					✓	✓
[32]	Capabilities of DL systems to explain to network operators are described below.		✓				✓	✓
[33]	Capabilities of DL systems to explain and justify their suggestions to network operators.	✓		✓			✓	✓
[34]	Slice Network.		✓			✓		✓

Table 1. *Cont.*

Ref.	Summary	Machine Leaning			IoT	Security Approaches	VR & AR	Energy	Network Architectures
		Deep Learning	Other Methods	ML					
[35]	Detection principles that are optimal or near-optimal for huge MIMO systems.	✓					✓	✓	✓
[37]	Outlined the current 5G testbed in Prato.				✓	✓		✓	✓
[38]	Effectively integrating SDN/NFV.		✓						✓
[39]	AI for 5G wireless communication systems.	A			✓	✓		✓	✓
[40]	ML in conjunction with proximity to real-time information technology solutions.	✓			✓			✓	✓
[41]	Investigates the potential features of B5G.	✓			✓	✓	✓	✓	✓
[42]	Mobile and wireless networking research based on DL.	✓			✓	✓	✓	✓	✓
[52]	To enhance the productivity of the system and to avoid the delays.				✓	✓	✓	✓	
[53]	Inductive analysis of the technology required for driverless driving and 5G technology.		✓		✓	✓			
[54]	Explains FL ideas with an emphasis on their implementation in automotive networks.		✓		✓	✓		✓	
[55]	Control may be delegated to clusters of IoT nodes beyond the edge gateway.				✓			✓	
[56]	Offered network is the foundation of the semantics of a technological level of egovernment.		✓		✓	✓		✓	
[57]	IoT systems and services.		✓		✓	✓	✓		
[58]	Financial related issues.				✓			✓	
[59]	View existing wireless IoT connectivity technologies can be effectively used to enable massive connectivity for IoT.		✓		✓	✓	✓		
[60]	ML approaches to UAV-based communications has the potential to improve a variety of design aspects.	✓			✓	✓		✓	
[61]	IoT devices are designed to transmit little data packets with good energy efficiency.				✓	✓	✓	✓	
[62]	ITSs cyber-security, energy-efficient utilization of SGs, effective use of UAVs to assure the best services of 5G.	✓			✓	✓		✓	
[63]	5G technologies are listed and described how these features effect the industries of the future.		✓		✓	✓	✓	✓	
[64]	Investigate the 5G usability in disasters.				✓	✓	✓		
[65]	Construction of a semantic network comprising the most recent concepts in the information.		✓		✓	✓	✓		
[67]	IoT technology is examined from a high-level perspective.	✓			✓	✓	✓	✓	
[68]	Application of a low-complexity Qlearning approach in the mMTC situation.	✓			✓	✓	✓	✓	

Table 1. *Cont.*

Ref.	Summary	Machine Leaning			IoT	Security Approaches	VR & AR	Energy	Network Architectures
		Deep Learning	Other Methods	ML					
[71]	Energy efficiency of radio access, which is at the heart of wireless networks.		✓				✓	✓	
[73]	Big data and the promise of ML for optimization and decision-making in 5G networks.	✓			✓	✓	✓	✓	
[74]	Classified these three pillars, softwarization, energy harvesting, and optimization.	✓					✓	✓	
[8]	AI into 6G and state of the art in ML.		✓		✓	✓		✓	
[9]	ML and privacy in 6G.	✓	✓		✓	✓		✓	
[10]	AI integrated into localization, UAV communication, surveillance, security and privacy preservation.	✓			✓	✓		✓	
[12]	Addressing the shortcomings and limitations of IoT and Blockchain.		✓		✓			✓	✓
[13]	Dimensions of a 6G network, including the air interface.		✓		✓	✓		✓	
[43]	Requirements and challenges of 6G.		✓		✓	✓		✓	
[44]	Added features and key performance indicators of 5G NR.	✓			✓	✓		✓	✓
[45]	Highlighting energy efficiency spectral efficiency security, secrecy, and privacy adorability and customization.	✓			✓	✓		✓	
[46]	THz band antenna, fabrication and measurement are presented.		✓			✓			✓
[47]	Blockchain-Envisioned UAV Communication.		✓		✓	✓		✓	
[66]	6G to IoT technologies and service areas.	A			✓	✓		✓	
[75]	Vision and requirements of 6G.	✓			✓	✓		✓	
[11]	Investigations security and privacy problems associated with 6G technologies.		✓			✓		✓	✓
[48]	Application of learning, prediction, and decision-making to manage the stream of humans.	✓			✓	✓		✓	
[72]	Analyze hardware reuse and multiplexing solution to ease the design of UEs that are both cost-effective and energy-efficient.	✓			✓	✓		✓	✓
[77]	Ability to triple the adaptivity of mmWave and THz.		✓		✓			✓	✓
[76]	Vision for machine type communication in 6G.		✓		✓	✓		✓	
[69]	Vision for machine type communication in 6G.		✓		✓	✓		✓	
[70]	ML, QC, and QML identify their potential benefits, issues in the B5G networks.	✓	✓		✓	✓			✓
[49]	6G challenges, requirements, and trends.		✓		✓	✓			✓
[78]	Applying TL to future 6G communications.		✓		✓			✓	✓
[51]	Evolution of KPIs and technology trends towards 6G.					✓			✓

Table 1. *Cont.*

Ref.	Summary	Machine Leaning			IoT	Security Approaches	VR & AR	Energy	Network Architectures
		Deep Learning	Other Methods	ML					
[14]	Explore the role of blockchain to address formidable challenges in 6G.		✓		✓	✓			✓
[50]	Potential challenge and propose possible technical components in a future 6G system.		✓		✓			✓	✓
[36]	Deals with the answers to those questions for the health vertical of 6G.		✓		✓			✓	✓

The first group—security approaches The review and survey articles look into the framework or platform model that will be developed based on the security approaches. Only one article [5] dissected attacks such as call fraud and data interception in great detail. Several strategies, such as data encryption, mutual authentication, and other approaches can be used to address this issue. A study published in the article [6] examined the EDoS problem in emerging network situations. SON and NFV are the foundations for adaptive approaches. The author provided an overview of how multiple fog devices communicate with one another using Internet of Things paradigms. Describes these dangers and lays out future research on how to minimise the security concerns raised by a modern distributed control infrastructure [7].

Two articles [8,9] comprehensively examine the use of machine learning approaches to significant 6G network concerns such as enhanced radio interface, intelligent traffic control, security protection, administration and orchestration, and network optimization. Furthermore, the latest status of important standardisation initiatives and industry research programmes on applying machine learning to mobile networks transitioning to 6G is examined. Only article [10] provided a full overview of AI-enabled 6G communication technology, which has a wide range of potential uses in the future. Examine how AI can be used in a variety of applications, including object localisation, UAV communication, surveillance, security, and privacy protection, among others.

Finally, a use case was addressed that demonstrates the employment of AI principles in an intelligent transportation system. Only one article [11] was written about the current state of 6G security and privacy. The survey starts with a look back at earlier networking technologies and how they influenced contemporary 6G networking trends. Then, we'll go through four major components of 6G networks: real-time intelligent edge computing, distributed artificial intelligence, intelligent radio, and 3D intercoms, as well as some interesting upcoming technologies in each area, as well as the security and privacy challenges that come with them.

Three papers [12–14] examined the major obstacles in integrating Blockchain and IoT technologies in order to achieve high-level solutions by addressing the weaknesses and limits of both technologies. Many IoT concerns can be addressed with blockchain, however, any merger of two embedded technologies brings additional issues and impediments.

Second group: virtual and augmented reality virtualization Examine 5G and 6G approaches and categorise them into various types of solutions.

Two studies [15,16] reviewed virtualization solutions specifically developed for IoT networks, allowing users and operators to create environments that match their demands while coexisting with other networks in the same physical space.The article [17] looks at the characteristics of the fourth industrial revolution and considers 5G's potential as a GPT. Other researchers offered a new classification of recent fault management research accomplishments in network virtualization environments, as well as a comparison of their primary contributions and flaws [18].

Third group, network architectures Several architectures have been presented by various research units in order to better integrate these services. The first section of this article provides an overview of the connected services managed by the 5G and 6G networks. After that, we'll talk about existing architectures. The essential concepts of self-organizing networks were reviewed and explored in four publications [19–22]. In addition, provide a taxonomy for self-organizing networks use cases and describe their underlying ML techniques, as well as service management by demonstrating how combining ML algorithms with SDN and NFV on a variety of use cases and scenarios can yield insights, detect meaningful events and conditions, and enable the management system to respond appropriately. NMA was discussed in one publication [23] as a way to improve the level of intelligence in network elements. Two papers [24,25] investigated resource allocation in 5G communications utilising RL, as well as a dynamic programming framework for solving RA problems optimally across different network states.

Three publications [26–28] examined big data in the context of 5G and machine learning. The vast data can be divided into two categories: raw data and correct data. If the right data is extracted efficiently from such a large amount of raw data, 5G can be optimised. Big data analytics has evaluated the main taxonomy of machine learning and the fresh trends that could enable this exploitation of data to get network insight a reality. One study [29] examined open data choices as well as alternate ways to obtain data from networks that would otherwise be unavailable to academics. On the IoT side, data storage and synchronisation, cloud storage, the base control system, third-party apps, and the management interface are all available.

Two articles [30,31] introduced the potential of AI in the next-generation wireless networks, ranging from basic learning algorithms such as ML, DL, and others, to help meet the varying requirements of the 5G standards, such as operating in a fully automated manner, meeting increased capacity demand, and providing superior QoE to users.

Only one article [32] looked at the application of machine learning to fault management in cellular networks from an operational standpoint. Based on the building components of a typical fault management system, describe the applicable ML approaches through to DL, and assess the progress that has been made in their implementation. The goal is to combine 5G technology with machine learning to make these technologies more accessible to a wider variety of consumers.

Three articles [33–36] used an empirical analysis of resource management efficiency in network slicing to investigate this trade-off. The results are based on extensive measurement data acquired in a live mobile network and provide insight into the efficiency of network slicing architectures, their dimensioning, and their interaction with resource management algorithms.

By presenting several case examples, discussing the problems, and shedding fresh light on future research paths for using AI. in 5G wireless communications, four articles [37–40] offered an in-depth assessment of AI. and ML for 5G wireless communication systems and networking. One publication [41] looked into the potential features of B5G, as well as future research directions for how machine learning might help realise B5G. Others covered a variety of strategies and platforms that make it easier to install DL on mobile devices. Then, using DL to organise mobile and wireless networking research into different categories, present an encyclopaedic review of the field [42].

Three articles [43–45] presented a systematic overview of 6G that focuses on prospects and development, core techniques, applicable scenarios, and challenges, and proposes a framework for the 6G network, as well as an overview of the first five generations of wireless systems, followed by a survey on the 6G wireless network, as well as a discussion on the possible requirements and challenges.

Specifications for 6G antennas for various applications are highlighted in [46]. A comprehensive review of recent THz band antenna manufacturing and measurement work is provided. The design, construction, and measurement of THz band antennas are discussed. THz band antenna research directions for 6G technology are addressed, as well as THz band antenna design, fabrication, and testing. A description of future research prospects for the integration of blockchain and 6G technologies in UAV communications is offered in another work [47]. Then, show a case study of a blockchain-based UAV communication system that uses 6G networks to secure Industry 4.0 applications.

Another study [48] discusses how integrating AI in URLLC improves multi-level architecture and provides a technique for constructing wireless networks. This is accomplished by using learning, prediction, and decision-making to manage the large number of people who have been trained by big data. The research paper's secondary goal is to improve a multi-level design.

Two publications [49,50] looked into the issues, requirements, and trends around 6G. Also, talk about how AI approaches can help with 6G. Identify some new exciting 6G services and use-cases based on the requirements and solutions that 5G cannot adequately serve.

A study on the evolution of KPIs and technical trends toward 6G was published in one publication [51]. Short-term (2022'ish), medium-term (2025'ish), and long-term (2030'ish) timelines are all considered. Forecasts on developing use cases and their requirements, as well as assumptions on the pace of wireless technology improvements, are used to examine the evolution of these KPIs.

The fourth group 5G, 6G-IoT Information of Things, is discussed as well as in regard to the idea of merging IoT, 5G, and 6G.

Three papers [52–54] reported on the evolving automotive cyber security, which can use 5G to be faster and more efficient. Presented a peer-to-peer IoT infrastructure, built to OpenFog standards, which moves control out to "things" without involving devices or cloud computing. A new article [55] offered a 'Disruptive Networking' strategy, which enables many IoT nodes to take part in autonomous and cooperative decision-making. Other reports [56] explore methods of transitioning the healthcare and renewable energy industries from e-government to smart government.

Three papers [57–59] examined IoT-based strategies for the 5G mobile communications transition. Complex IoT systems necessitate heterogeneous computing and high-speed communication networks like 5G. Several real-world IoT systems infrastructures utilising heterogeneous computing are also introduced. Classify and review different wireless IoT connectivity solutions, starting with the connectivity range.

Four papers [60–63] presented practical approaches for the smooth integration of smart city applications in 5G networks. In-depth use of ITSs, cyber-security, energy-efficient use of SGs, effective use of UAVs for the provision of the best 5G and B5G services, and a smart health care system in a smart city.

Three [64–66] studies evaluated how 5G technology could help with the management of disasters. The way to managing government, corporate, and personal disaster responses is to use Big Data, IoT, social media, and cloud computing.

Two different publications [67,68] summarise the main enabling technologies as well as a whole slew of new developing uses of 5G-IoT, each tied to advancements in artificial intelligence, ML, and digital edge computing. This post outlined the essential enablers for mMTC in cellular networks.

One article [69] article investigated different issues associated with fog computing in 6G-enabled large IoT. Categorize several energy-efficient fog computing options for IoT and summarise the current progress. Future projects and open potential to build energy-efficient fog computing solutions are discussed at last. One study [70] provides a full analysis of ML, QC, and QML, highlighting their possible benefits, challenges, and use cases for the B5G networks. A QC-assisted and QML-based framework for 6G communication networks was proposed, where it outlined the infrastructure, edge, air interface, and user end.

Final Group Energy Efficiency of 5G and 6G 5G and 6G analyses the most recent works that address energy efficiency. We offer an overview of 5G, 6G, enormous IoT, and it concentrates on recent works.

Two articles summarise current work on the radio access and core of wireless networks and identify ongoing difficulties and opportunities. The following are paths for power optimization: using game theory and machine learning, as well as different energy-saving measures [71,72].

This paper proposed that future cellular networks will have different system requirements, which include utilising energy-harvesting technologies and optimising tool sets [73].

Another article discusses the opportunities and problems given by 5G networks. This review discusses the latest progress on standardisation, possible architecture candidates, and the energy considerations in 5G networks [74]. The authors [75,76] presented a panoramic perspective of the supporting technologies for 6G and 6G-capable applications, such as multi-sensory–extended reality, digital replica, and more. There are over ten new applications of the 6G technology that are only just starting to be implemented. Furthermore, explore the multi-faceted communication possibilities of 6G, which will bring about a drastic transformation in the corporate arena.

In next-generation applications of mmWave and THz solutions, space-air-ground integrated networks, full-duplex techniques, and other sophisticated channel coding assisted system designs, where powerful machine learning algorithms are expected to make autonomous decisions about the best mode of operation with minimal human intervention, this intelligent Tripple-fold adaptivity offers significant benefits [77].

One article [78] described, as mentioned above, requirements were contradictory, such as high efficiency and high density. This combination eventually led to reduced energy efficiency. TL can alleviate practically every problem caused by 6G needs.

5. Overview of Existing Technique

A scheme, structure type, or technique model is investigated in this second section, which contains 61 papers, to meet the requirements of the stage where the results of the research on ML are to be addressed, as well as the methodology used by 5G and 6G for the Internet of Things and energy transmissions. The following Table 2 preceding to a discussion subsections provide an overview of six major categories, including network resource management, security, augmented reality, network scaling, resource allocation, and the smart grid.

Table 3 summarises the possible services, core idea, and solutions uses of Existing Technique related to machine learning in 5G and 6G-based energy technologies.

Table 2. Overview of Existing Technique.

Ref.	Technique	Core Term	Core Idea	Solution	Drawbacks
1-	Network	Resource	Management		
[79]	URLLC.	Functions needed for defining and automating 5G experiments.	E2E configuration of 5G testbeds is supervised throughout.	Framework deployment, control, management, monitoring, analytics, and security in 5G testbeds.	Vertical should select a test case from a list of test cases for a separate KPI.
[80]	OpenAirInterface.	Performance.	OAI is essential to the development of the key 5G technologies.	3GPP-compliant LTE systems for real-time indoor/outdoor testing and demonstration.	Demands adaptable and realistic experimentation platforms that support a wide range of experimentation modalities.
[81]	STRAIGHT.	Mobility state estimation.	UE mobility which complies with UE historical information standards.	Compensate for varying mobility classes, both low and high.	Complex networks with overlapping cells of varied sizes.
[82]	D2D mode.	SINR proximity distance and battery consumption.	Dynamic network's mode selection method.	Delivered a better outcome than conventional mode selection up to 30%.	Mode selection applied at the BS, and device-centric principles should be employed to accomplish 5G network goals.

Table 2. *Cont.*

Ref.	Technique	Core Term	Core Idea	Solution	Drawbacks
[83]	CMAC.	Cooperative caching.	CMAC method to lower the average delay of providing material.	Attentively monitor QoE and content-access latency.	Various trace-driven simulations show that CMAC offers up to 13% less average content-access latency.
[84]	DICE.	Network protocol design.	The DICE ICN forwarding strategy.	Delivered up to 2X more successful delivery and incurs just a tenth of the network overhead.	To optimise the energy consumption of different wireless technologies.
[85]	Tactile Internet.	Network components.	Internet system using SDN in the core of the cellular network and MEC in multi-levels.	Even though 1ms round-trip latency can be a challenge, Tactile Internet has proven to be a success.	To reduce the round-trip latency is to limit the number of network nodes engaged in the communication process.
[86]	Mobility Management.	Transport protocols.	Performance evaluation of TCP on mmWave cellular systems with mobility management.	Increasing network density can greatly enhance the performance of TCP with respect to both throughput and latency in mobile environments with blocking.	Expand the simulation and put it in the real world. Both create network topologies that lower the end-to-end latency of a connection and implement a performance-boosting proxy.
[87]	eTOM.	QoS.	Build a virtualized architecture for dynamic delivery of services, QoS, and increased resource performance.	All of these functionalities were implemented using modules within the OpenStack cloud manager.	To complete the OSR end-to-end process grouping and the automation and support for FAB framework functional blocks implementation.
[88]	Wireless Spectrum Management.	Network algorithms.	Cognitive cellular network-oriented wireless spectrum management technique, based on cognitive radio technology.	Before allocating resources, design a double pricing model that charges cognitive users lower fees.	A convenient mechanism, better suited to day-to-day scenarios.
[89]	Cyber-Physical Systems.	Network services.	OSM, a popular 5G management and orchestration platform was used to deploy virtual network functionalities.	Scenarios showing how 5G technologies might help the CPS sector.	Virtual services plus networking will be created by PNFs that can be made to the device quickly.
[90]	NR access technology.	QoS.	Numerology FDM Simulate FDM numerology in the ns-3 network simulator.	Followed the 3GPP specifications to configure the time/frequency resource units automatically.	Puncturing the resources already committed for eMBB and designating processes to identify so would be essential.
[91]	Integration of Carrier Aggregation.	Network simulations.	Implementation for the mmWave ns-3 multi-connectivity techniques for 3GPP New Radio.	DC-implementation illustrated, along with details on the integration with CA.	To research additional CC management policies, which could benefit from a PHY-MAC cross-layer with additional channel information used in resource allocation.
[92]	Mobile core.	Network Architecture	Distributed core network architecture for future cellular networks.	Architecture mitigates latency and performance issues in essential network control and data gateways.	Experimental results on orbit radio testbed latency and mobility.
[93]	NFV MANO.	NFV MANO.	Proposing a 5G platform-oriented solution amid alternative authentication and authorisation techniques.	Integrate procedures for authentication and authorisation to build a scalable and secure solution in a 5G platform.	Integrate well-known procedures for authentication and authorisation to build a scalable and secure solution in a 5G platform.
[94]	Multi Administrative Domain Networking.	Networking components.	Prototype based on various open source components showcasing blockchain DApp abilities.	Open-source software ecosystem promotes concepts while sparking conversation on difficult practical elements of multi-administrative.	Open conversations about speculative technology and ongoing research and development.
[95]	SoftH.	Network mobility.	SoftH: an SDN-based handover decision criterion model.	Mechanism seeks to let the cell transfer decisions assert their position at the SDN controller	Decisions are made dynamic according to the changing conditions of the network.

Table 2. *Cont.*

Ref.	Technique	Core Term	Core Idea	Solution	Drawbacks
[96]	DIY model	Mobile networks.	Constructing mobile networks in places where prior community cellular networks were focused on low end service provisioning.	5G to spread to more rural and non-urban areas by empowering small-scale local operators and communities to create and run contemporary networks.	Subscriber base can have recurring costs under $1 USD per month.
[97]	C-RAN.	Network resources allocation.	Energy-efficient joint workload scheduling and BBU allocation algorithm, utilising queueing theory.	C-RAN controller distributes workload allocation among BBU servers in a time slot basis.	For restricted power and cost budgets, the scheduling strategy is suitable.
[98]	AirSea.	Robotics.	Clever manufacturing facility in the sea.	Sea-based, land-based, air-based, and space-based linkages are incorporated into the design of an air and sea manta ray robot.	Seaplane, WIG effect, and manta ray robots will significantly benefit ocean engineering and resource and energy development.
[99]	Throughput 5G.	Wireless access networks.	Offered a 5G multi-cell ns-3 simulation framework.	5G trace dataset, and a large-scale multi-cell 5G/mmwave simulation framework.	Incorporate mmwave and sub-6GHz as shown in actual-world next-generation 5G networks.
[100]	Augmenting QoS.	QoS.	V3I Cloud SDK toolchains support creating complex automated cloud.	Executed an experimental system in which automobiles formed a cloud resource unit.	Under investigation and outcomes.
[101]	MEC in the Cloud-RAN.	Core Network.	Situation where disaggregated base stations capable of provisioning MEC capabilities in per-packet.	Developed a signalling for communication between DUs and a MEC agent, which has access to container-based services.	Test how service replication via edge nodes serves different base stations' technology mix.
[102]	OpenAirInterface	Cloud-RAN.	Modular SDN/NFV-based SON testbed for future 5G mobile networks.	A CDSA-based testbed is required to enable examination of the NG-SON capabilities for practical implementations.	
[103]	Network function virtualization.	Intent–based networking.	Pondered an Intent-based approach to mobile backhauling for 5G networks.	Backhaul interface based on intent. Wireless controllers should have little contact with the wired backhaul controller.	Incorporate VNF migration, path restoration, and telemetry support for the Intent interface.
[104]	Network simulations.	Network performance analysis.	Investigated 5G mobile communication system performance, MAS with polarized antenna based BS system is applied.	Simulation results reveal that the misaligned polarisation causes more power loss for the polarised antenna structure.	As a result, system capacity increases when the polarised antenna arrangement is implemented.
[105]	DES.	Maintenance performance.	These principles were used to give real-world industrial 5G pilot deployment assessments.	Inputs will be used in the requirement definition for 5G networks, such as mission-critical clouds and analytics services, as well as other network services.	It is vital to use DES in tandem with establishing business justifications for investments.
[106]	FiWi.	FiWi access networks	Focus on very low latency and ultra-high reliability of 5G and study how they can be obtained in FiWi upgraded LTE-A HetNets.	DOFR's proposed routing technique helped increase the aggregate FiWi enhanced LTE-A throughput substantially.	
[107]	5G infrastructure emulator.	Service Deployment.	5G infrastructure emulator capable of emulating a realistic 5G network on a small number of commercial-off-the-shelf servers via virtualization.	Proposed approach provides an emulator of 5G infrastructures, which can accurately replicate 5G infrastructure.	Emulation platform and empirical data reported in terms of 5G service rollout times on bare metals.

Table 2. *Cont.*

Ref.	Technique	Core Term	Core Idea	Solution	Drawbacks
2-	Security	Approaches			
[108]	Mobility management system design.	Virtualized network.	Virtual to physical address encapsulation empowers mobility capabilities, and mobility is implemented through a flow table entry.	User and mobile node independence rendered changes in network availability undetectable to the user.	Better control of heterogeneity and service scalability are provided by service decoupling.
[109]	Data privacy.	Communication system security.	Discussed the reasons why IMSI catcher protection is not given in 3G or 4G networks.	These might become adversaries against identity and location privacy.	In both situations, it is the same security, but since it is for different networks, there are different reasons for offering the protection.
[110]	5GReasoner.	Security models.	Control-plane protocol protocols spanning across various layers of the 5G protocol stack.	Behaviour-specific abstraction enables an automated analysis of 5G Reasoner.	To integrate additional critical control-layer protocols.
[111]	Bootstrapping in Cellular Networks.	Security and privacy.	Precomputation-based digital signature creation techniques and three-dimensional optimizations DPKI technique, protocol, and cryptographic scheme.	Examine cryptography-backed authentication mechanisms to prevent adversaries from enticing unsuspecting cellular devices to connect to malicious base stations.	To create a tailored cellular IoT scheme with 5G URLLC protocol.
[112]	Software-Defined Security.	Software-Defined Security.	Proposed to integrate security into the slice life cycle, effecting the administration and orchestration of the virtualization/softwarization architecture.	Security architecture is made up of built-in security features based on the ability to combine enforcement and monitoring operations within the software-defined network infrastructure.	The problem is in properly connecting network and computing resource control with network control.
[113]	Data Origin Authentication.	Trust.	Studied the security provided for group communication in 5G networks.	Two attack scenarios were created to highlight an opponent that gains illegitimate data access via a stated source of authenticity.	Deferred signing class might be used to conserve computing resources but increasing communication costs.
[114]	Security Event Management.	Security and privacy.	To deliver security monitoring and correlation capabilities to mobile network operators, infrastructure service providers, and tenants, verticals, and horizontal applications.	Ensured automatic security operations and security services management using 5G network automated SLA.	Find strategies to control security in network slices. concentrate on metrics to estimate deployment and configuration impact on performance needs.
[115]	Privacy	Network, architecture.	Presented a detailed analysis comparing the security of 5G wireless network systems to 4G cellular networks.	Proposing a study on a security sharing method for 5G	Security is not required, so saying that it is a disadvantage would not hinder the system in checking for it.
[116]	AKA protocol.	Security and privacy.	Models in the AKA family: 5G AKA. Extract 5G requirements from the 3GPP standards and discover missing security targets.	Utilize Tamarin to perform a complete security audit of the model with respect to the 5G security goals.	To see if AKA protocol versions such as 3G and 4G can deliver security benefits as compared to 5G AKA
[117]	5G HetNets.	Security and privacy.	Designing a new handover authentication method for SDN aided 5G HetNets.	Proposed a mutual physical layer handover authentication system for 5G HetNets.	Weighing parameters differ in simulations. Additionally, an evaluation is conducted using different SNRs and weighting parameters to examine proposed authentication technique.

Table 2. *Cont.*

Ref.	Technique	Core Term	Core Idea	Solution	Drawbacks
[118]	WireGuard.	Security and privacy.	Alternative to IPsec, WireGuard is proposed. Based on the analysis, the influence of security mechanisms on latency is insignificant.	Tested the eCPRI transportation in-depth. Even though overhead from security protocols has minor impact on latency, it is important to keep reduced latency in mind.	Interesting to use hardware to minimise the latency of 5G fronthaul. 5G can be maintained without compromising security by using a Quantum-secure version of MACsec, IPsec, and WireGuard.
3-	Augmented	Reality			
[119]	Mobility management system design.	Virtualized network.	Virtual to physical address encapsulation empowers mobility capabilities, and mobility is implemented through a flow table entry.	User and mobile node independence rendered changes in network availability undetectable to the user.	Better control of heterogeneity and service scalability are provided by service decoupling.
[120]	5G VR/AR.	Human-centered computing.	An effective representation method for constructing the 360 films is needed in order to avoid sending a huge 360.	Ascertaining huge operational efficiency improvements over state-of-the-art caching and 360○ video representation techniques is extraordinarily promising.	
[121]	AR application.	Network architectures.	Investigate both dynamic and hybrid profiling, as well as adaptive partitioning, to address a demanding augmented reality scenario.	The key role of edge computing in the effective deployment of AR apps.	
[122]	VR and AR.	Mobile networks.	The usage of multi-path, multi-tier 360° video streaming solutions are created to deal with both bandwidth and viewer motion.	Multimodal 360° video streaming solutions for 5G wireless networks. Use a 5G network to its full capacity and deal with bandwidth volatility.	Real-world traces of the 5G wireless network and user FoV analysis can be utilised to direct the design of future 360° video streaming systems in 5G networks.
[123]	AR and VR.	Network services.	5G virtualized architecture focused on a network function which might relieve bandwidth constraints of immersive application scenarios.	Potential feature that might be used to relieve network resource utilisation.	The datasets were actual, with tag information focused on the needs of users.
4-	Network	Scaling			
[124]	Orion.	RAN slicing.	a RAN slicing technology that enables the dynamic on-the-fly virtualization of base stations, as well as the customisation of slices to match their particular service needs, was unveiled.	A low-powered yet flexible RAN virtualization tool for LTE was built as a proof of concept.	Orion is built for single-RAT setups but might be expanded to handle multi-RAT situations.
[125]	Slice Allocation.	Network resource Allocation.	Solves an actual problem by combining several infrastructure providers.	A slice allocation mechanism proposed based on matching game theory.	Dynamic pricing and power levels on a slice.
[126]	SuperFlex.	Network architectures.	SuperFlex, a network slicing architecture that delivers tailor-made treatment for subscribers without increasing capital and operating expenses.	A pluggable multidomain, dual-layered slicing based efficient, scalable, and extensible 5G wireless network architecture providing universal connectivity in a sliced environment.	Concentrate on efficient chaining across multiple slices while enforcing rigorous latency constraints.

Table 2. *Cont.*

Ref.	Technique	Core Term	Core Idea	Solution	Drawbacks
[127]	Multi-service 5G Network.	Network management.	Described implementation experiences when deploying a small-scale multi-service network prototype, used to demonstrate some selected advanced features of 5G Networking.	Two heterogeneous services over two independent slices, namely, video streaming and AR, showcasing key features such as multi-slice orchestration RAN slicing and support for local breakout.	Software is based on open source components, and most of it is also released as open-source on public repositories.
[128]	NSRA.	Heterogeneous Network.	A cache-enabled content delivery system for the 5G heterogeneous network uses base stations and the macro cell as connected servers to host caches.	5G heterogeneous system model method minimise the absolute gap between the data rate necessary and the rate obtained for all users in the system.	Future studies will incorporate densely-populated urban network simulations with higher-order MIMO.
[129]	IMAKE-GA.	Security and privacy.	Proposed an implicit mutual authentication and key exchange with group anonymity via proxy re-encryption on elliptic curve.	IMAKE-GA protocol secures distributed, the secure association between network slice NSC pairs. It employs proxy re-encryption utilising bilinear pairing on an elliptic curve.	
[130]	SLAs.	KPIs.	A solution that introduces a preemption mechanism to cut low-latency traffic while addressing the issue of flexible traffic that necessitates a higher throughput is provided.	The suggested solution's primary acting element is PASS, an inter-slice scheduler that supplies services to each traffic type based on SLA demands.	The next step is to integrate this method with grant-less uplink transmission schemes, as the scheduler has outdated views of the UE uplink.
[131]	URRLC.	Architecting RAN Slicing.	This study outlines certain crucial architecture design parameters, system components, and interactions that enable RAN slicing for URLLC.	High-level architecture to tackle the URLLC and network slicing problems via a MEC system, focusing on design criteria, system components, and basic interactions.	These crucial outstanding issues set the path for future research initiatives in this direction.
[132]	Agile and flexible service platforms.	Mobile networks.	TPresented Mosaic5G, a community-led consortium for sharing platforms, featuring the software components FlexRAN, LL-MEC, and JOX on top of OpenAirInterface platform.	Mosaic5G, a community-led partnership for platform sharing. It offers the software components FlexRAN, LL-MEC, JOX, and Store, all of which are designed to help produce an open-source 5G research environment.	
[133]	End-to-end NFV.	Noisy Neighbor.	Proposed an approach that reduces noise by applying dynamic CPU pinning coupled with load balancing dependent on dynamic network slicing.	TDemonstrated an end-to-end framework for noisy neighbour situations, regardless of NFV deployment model.	Must employ tools that imitate the actual world infrastructure to gauge the framework's effect.
5-	Resource	Allocation			
[134]	System Throughput Maximization.	Resource allocation.	Study the topic of underutilised 5G heterogeneous network spectrum resources.	Perform offloading in a multichannel context. So, in order to optimise total system throughput, a solution is devised that incorporates power regulation and interference.	
[135]	Network resources allocation.	SLAs.	Aimed to reduce energy consumption in the network by simultaneously solving the user association and backhaul routing problems.	A possible solution is point-to-point networks with enormous bandwidth available in the mmWave frequency spectrum.	Work on a case when both base stations and backhaul lines are disabled to obtain even more energy savings.

Table 2. *Cont.*

Ref.	Technique	Core Term	Core Idea	Solution	Drawbacks
[136]	QoS.	Network resources allocation.	To assign resources to the uplink transmitters will result in increased spectral efficiency and maximum data rate for all users.	Modeled heterogeneous multi-tier networks with the concept of stable matching.	The proposed technique can be expanded to the forthcoming 5G cellular networks.
[137]	SOGMS.	Network performance analysis.	Applications have an impact on the exponential growth of multimedia services in mobile networks.	SOGMS approach is offered for multimedia services, focusing on efficient utilisation, system capacity, and sustainability requirements.	Future 5G networks should look to put in place proactive edging caching with video popularity to help with the users' QoE during video delivery.
6-	Smart	Grid			
[138]	Future Smart Grid.	Smart grid.	Loss of ARPU in emerging countries in the context of 4G LTE and 5G networks are analysed.	More equipment and software applications will be required on the grid, including as sensors, faster processors, and stronger algorithms, in order to achieve greater efficiency and dependability in the distribution system.	Issues around standardisation, interoperability, security, and of course, cost are among the growing 5G's priorities, but the long-term rewards are enticing.
[139]	SimCT.	Computing methodologies.	Designed a tool to test the spatial resiliency of 5G networks.	Demonstrated how urban growth impacts 5G network coverage and quality of service.	Need to simulate seasonal effects like vegetation, rain, and snow. It incorporates data on travel patterns and simulations of city expansion.

An overview of the security and privacy issues associated with key 6G technologies is presented in Table 4.

Table 3. The possible services, core idea, and solutions uses of the existing Techniques.

	Core Idea	Limitations	Ref.
1-	Network Resource Management		
Framework	Dynamic network's mode selection method. Also Distributed core network architecture for future cellular networks.	Framework deployment,control,management,monitoring, analytics, and security in 5G test beds. Also provides an emulator of 5G infrastructures,which can accurately replicate5G infrastructure.	[79,82,92,95,96,99,103,106,107]
Performance	Build a virtualized architecture for dynamic delivery of services, QoS, and increased resource performance. Also, Proposing a 5G platform-oriented solution amid alternative authentication and authorisation techniques.	All of these functionalities were implemented using modules within the OpenStack cloud manager.	[80,81,83,87,89,90,93,97,98,100,104]
Network components	Internet system using SDN in the core of the cellular network and MEC in multilevels. Cognitive cellular network-oriented wireless spectrum management technique, based on cognitive radio technology.	Delivered up to 2X more successful delivery and incurs just a tenth of the network overhead. Open-source software ecosystem promotes concepts while sparking conversation on difficult practical elements of multi-administrative.	[84–86,88,91,94,101,102,105]
2-	Security Approaches		
Framework	To integrate security into the slice life cycle, effecting the administration and orchestration of the virtualization/softwarization architecture.	Security architecture is made up of built-in security features based on the ability to combine enforcement and monitoring operations within the software-defined network infrastructure.	[110,112,114,115]
Performance	Precomputation-based digital signature creation techniques and three-dimensional optimizations DPKI technique, protocol, and cryptographic scheme.	Examine cryptography-backed authentication mechanisms to prevent adversaries from enticing unsuspecting cellular devices to connect to malicious base stations.	[111,118]
Network components	Virtual to physical address encapsulation empowers mobility capabilities, and mobility is implemented through a flow table entry.	User and mobile node independence rendered changes in network availability undetectable to the user.	[108,109,113,116,117]
3-	Augmented Reality		
Framework	5G virtualized architecture focused on a network function which might relieve bandwidth constraints of immersive application scenarios.	Potential feature that might be used to relieve network resource utilisation.	[119,121,123]
Performance	The usage of multi-path, multi-tier 360° video streaming solutions are created to deal with both bandwidth and viewer motion.	Multimodal 360° video streaming solutions for 5G wireless networks. Use a 5G network to its full capacity and deal with bandwidth volatility.	[122]
Network components	An effective representation method for constructing the 360 films is needed in order to avoid sending a huge 360.	Ascertaining huge operational efficiency improvements over state-of-the-art caching and 360◦ video representation techniques is extraordinarily promising.	[120]

Table 3. *Cont.*

	Core Idea	Limitations	Ref.
4-	Network Scaling		
Framework	5G Solves an actual problem by combining several infrastructure providers.	A slice allocation mechanism proposed based on matching game theory.	[125,126,128,132,133]
Performance	RAN slicing technology that enables the dynamic on-the-fly virtualization of base stations, as well as the customisation of slices to match their particular service needs, was unveiled.	A low-powered yet flexible RAN virtualization tool for LTE was built as a proof of concept.	[124,129]
Network components	Described implementation experiences when deploying a small-scale multi-service network prototype, used to demonstrate some selected advanced features of 5G Networking.	Two heterogeneous services over two independent slices, namely, video streaming and AR, showcasing key features such as multi-slice orchestration RAN slicing and support for local breakout.	[127,130,131]
5-	Resource Allocation		
Framework	Study the topic of underutilised 5G heterogeneous network spectrum resources.	Perform offloading in a multi-channel context. So, in order to optimise total system throughput, a solution is devised that incorporates power regulation and interference.	[134]
Performance	To assign resources to the uplink transmitters will result in increased spectral efficiency and maximum data rate for all users. Modeled heterogeneous multi-tier networks with the concept of stable matching.	The proposed technique can be expanded to the forthcoming 5G cellular networks.	[136,137]
Network components	Applications have an impact on the exponential growth of multimedia services in mobile networks.	SOGMS approach is offered for multimedia services, focusing on efficient utilisation, system capacity, and sustainability requirements.	[135]
6-	Smart Grid		
Framework	Loss of ARPU in emerging countries in the context of 4G LTE and 5G networks are analysed.	More equipment and software applications will be required on the grid, including as sensors, faster processors, and stronger algorithms, in order to achieve greater efficiency and dependability in the distribution system.	[138]
Performance	Designed a tool to test the spatial resiliency of 5G networks.	Demonstrated how urban growth impacts 5G network coverage and quality of service.	[139]

Table 4. Overview of the main security and privacy issues in key 6G technologies.

Security and Privacy Issues	Key Technology Contribution	Ref.
1-	THz	
Authentication	attacks that can exist in the 5G.then the security requirements in the 5G	[5,46,48,116,201,207,208]
Privacy	Describes these threats and sketches future research on how to mitigate the security concerns that a modern distributed control infrastructure poses.	[7,53,109,111,115]
Malicious behavior	Privacy and confidentiality issues.	[29,68,75,114]
2-	AI	
Communication	vision of AI-enabled 6G system, the driving forces of introducing AI into 6G and the state of the art in machine learning.	[8,10,22,62,112,113,203,204]
Privacy	Secure ML structure, or the correct application of ML, can protect privacy in 6G.	[9,11,21,37,61]
Access control	Identify fascinating services and use-cases of 6G, which can not be supported by 5G appropriately..	[49,60]
3-	Quantum communication	
Communication	Highlight the use cases and applications of the proposed 6G networks in various dimensions.	[13,65,118,209]
4-	Blockchain	
Communication	Challenges and canvassed the key role of blockchain.	[14,44,47,66]
5-	Molecular communication	
Privacy	Preserving the privacy of the users is the primary concern of mobile and service providers.	[39,41,42,52,54,56,57,67,202]
Encryption	Several challenges pertaining to resource allocation, task offloading, energy efficiency, latency reduction, fairness and security based 6G enabled massive IoT.	[69,70]

Table 4. *Cont.*

Security and Privacy Issues	Key Technology Contribution	Ref.
Authentication	Securing 5G hetNets using mutual physical layer authentication	[117,200]
6-	VLC	
Communication	Overview of the first five generations of wireless systems.	[43,45,63,64,198]
Malicious behavior	how to ensure seamless operability (including, but not limited to, authorization, security, service provisioning, accounting, etc.).	[76,108,206]

6. Internet of Things (IoT)

The IoT is a network concept that allows different objects to connect with one another. These gadgets are integrated with embedded technology, which allows them to communicate with both internal systems and the outer environment at the same time. We've done an explanatory evaluation of the use of the internet of things as the foundation for a transition strategy toward the development of 5G and 6G communications networks and technologies. The ninety-five articles in this category were separated into five subcategories, each of which had a single article.

6.1. Resource Allocation

IoT networks may be setup with a control centre to give centralised control to be compatible with existing cellular mobile networks such as the 3GPP LTE/LTE-A. IoT networks, on the other hand, can be structured in a dispersed form for greater flexibility and scalability. As a result, the frameworks of both centralised and distributed IoT networks will be addressed in this section. Some publications [140–144] proposed a service slicing technique that may divide network resources between distinct service slices with greater flexibility. It provides an ultra-reliable low-latency service for uRLLC applications, as well as low to medium latency services for xMBB and mIoT applications in future 5G networks.

Implement a set of parallelism-aware compile tools for swift to take use of parallelism while developing apps. The performance of the multi-protocol strategy and the characterization of bottlenecks in the evaluated protocols are among the contributions. Other papers [145,146] offered a cross-layer MAC and physical layer solution for low-power, low-bitrate devices with a long communication range and short access delay. By modifying the edge network, primarily eNodeB, the proposed protocol will combine IoT traffic with traditional systems. Other articles [147,148] discussed the existing proposed spectrum for 5G and the internet of things, as well as licenced, unlicensed, and licenced shared access schemes for future generations, as well as deployment scenarios for countries and effective ranges to achieve better results for harmonised spectrum. Also, investigate and illustrate how to compensate for the uncertain and time-varying latency introduced by a 5G mobile network when controlling a latency-sensitive plant.

For the baseband units pool in CRAN, three studies [149–151] developed efficient cache management strategies. It uses an exponential decay approach to hold recently frequently requested records in cache and AHP to allow different degrees of mobility and QoS. To make the marriage between mobile business processes and NFV MANO more fruitful, we'll use our understanding of how QoS limitations change in specific sets of operations.

Several papers [152–154] proposed a distributed latency-aware data processing model in which fog computing enabled GWs dynamically exchange processing and storage capability information and probabilistically forward data to neighbouring GWs or the Cloud only when local processing or storage capacity is limited. The suggested technique reduces overall response time and lowers the total cost significantly. Cache management strategies are designed and evaluated in few publications [155–158]. A probability-based scoring method, a hierarchical or tiered, approach, and improvements to previously existing approaches are among the algorithms. The control plane functions are self-contained in the sense that they can be run independently. By handling this signalling locally, the control functions can use the distributed cloud to manage the massive amount of control signalling.

Many articles [159–162] advocated integrating a message broker and Publish/Subscribe messaging transport using lightweight Internet protocols. To reduce the need for microcontroller in IoT devices, the design was validated using firmware. Demonstrate that the proposed technique improves the system's energy efficiency as compared to an IP-based implementation. The suggested technique also provides a framework for implementing application-level access control and QoS support. In the context of the 5G environment, three studies [163–165] suggested revolutionary centralised energy balancing uneven concentric chain clustering technique for the IoT system. To lessen the stress on the cluster head, it incorporates a probability-based suboptimal multi-hop path selection algorithm that adjusts the cluster head diameter based on the energy level and distance to the base station.

Three publications [166–168] focused on the resource allocation challenge in FiWi access networks supporting IoT services presented a one-of-a-kind system running at 4.8 GHz frequency for measuring the WCI of post-surgical falls and other human activities. The total system makes use of low-cost wireless hardware such as a network interface card, an RF signal generator, an omnidirectional antenna, and a desktop PC. ML algorithms such as SVM, NB, and DT are used to classify falls and other human behaviours. The accuracy rises at a rate of 4% to 5% per year.

Two papers [169,170] presented a collaborative distributed Q-learning approach for resource-constrained MTC devices to enable them to locate unique RA slots for their transmissions, hence reducing the number of possible collisions.

Two papers [171,172] proposed a resource allocation for Industry 4.0 based on software-defined networking and network function virtualization technologies, machine learning tools, and the slicing paradigm, in which each slice of the network is dedicated to a category of services with similar QoS requirements.

Another paper [173] described a unique MTC architecture that provides NFC as a service rather than collecting raw large-volume MTC data. Different modules of the communication infrastructure are orchestrated into a directed network topology for a given application demand, and each module is assigned an appropriately defined atomic function over the input data, allowing the desired global network function to be evaluated over MTC data and a requested MTC-NFC service to be delivered. One paper [174] proposed a network architecture that combines green IoT and 5G networks. To analyse massive data in 5G networks, we presented a human-enabled green IoT system. Green IoT is achieved by grouping together various mobile devices.

Two articles [175,176] in 6G-based edge computing, SSPS was proposed for MCS. In addition to task acceptance rate and weighted schedulability, QoS is taken into account in SSPS to improve the system's service quality. Jobs are assigned to each processor via the SSPS, and some tasks can be moved to other processors as quickly as possible.

Three papers [177–179] proposed a low-cost sensor array design technique based on irregular subarrays, which divides the practical application challenge into two subproblems based on scene scale. To address these issues, other articles [180] offer practical recommendations such as deep Q-learning and federated learning-based transceivers, blockchain-based secure business models, homomorphic encryption, and distributed-ledger-based authentication systems.

Three publications [181–183] provide a process-oriented optimization methodology for simultaneously assigning sub-channels, transmit power, and hovering durations that takes into account the entire flight process of UAVs and only needs slowly-varying large-scale channel state information (CSI).

Another article [184] describes a two-tier matching method that combines the Gale-Shapley-based matching algorithm for users and HAPs with the random path to a pairwise-stable matching technique for HAPs and satellites. The proposed algorithms' effectiveness is demonstrated by numerical results.

A solution based on an integrated DL algorithm was offered in several articles [185–188]. The positive samples are extended to balance the number of positive and negative samples, and CT images are pre-processed using image clipping, normalisation, and segmentation.

An ACO strategy is described in two studies [189,190], prompted by the requirement to secure 6G IoT networks by adopting various objectives and employing transaction deletion to secure secret and sensitive information.

Many articles [191–194] in big data-driven and nonparametric model supported by 6G is suggested to extract comparable traffic patterns over time for accurate and efficient short-term traffic flow prediction in enormous IoT, which is mostly based on time-aware LSH, which is mainly based on time-aware LSH.

To characterise the spatiotemporal relationships among heterogeneous data, the authors of [195] proposed approach employs a multidimensional data relationship diagram. Then, to reduce the impacts of noise on sensor data and aid in the detection of anomalies, an autoregressive exogenous model is used. Finally, the method generates a CCoV, which can be used to detect high-value sensing devices and enable huge IoT with 6G using the data's unique patterns.

The logistics mode is optimised and improved, and the agricultural e-commerce common delivery method is presented in two publications [196,197] based on an examination of the distribution efficiency of the current mainstream agricultural goods logistics distribution mode. RoF is one of the most promising enablers for 6G IoT systems due to its excellent flexibility and efficiency.

6.2. Security

This section details the research that looked into the security of IoT design properties, architecture, and protocols, as well as their practicality in terms of security.

Four authentication techniques were evaluated in two papers [198,199], and the discussion of the results led to the conclusion that each protocol had advantages and disadvantages and that these analyses should be followed. The security elements of this research team's new 5G-IoT architecture, which was just designed. At each tier of the 5G-IoT architecture, classify potential security attacks in the context of smart city applications, a security taxonomy for 5G-IoT architecture. This taxonomy is made up of five layers that are used to defend against the attacks that have been examined as well as to secure the privacy of customers.

The importance of device capabilities information supplied for 5G devices in creating security associations between the device and the network was investigated in two studies [200,201]. Introduce three new types of attacks against cellular devices that take advantage of unsecured device capabilities information in 4G and forthcoming 5G networks: identity attacks, bidding down attacks, and battery drain attacks.

Three articles [202–204] provide a solution that relieves the IoT provider's burden of device identity management while also lowering operational costs. Open-source software for LTE, identity management, and IoT is used to implement the solution. Integrate adaptive wormholes with CRKE, a lightweight security solution for IoT devices that may be even more crucial for the 5G tactile Internet and its embedded low-end devices.

A framework for a road-side infrastructure-independent traffic event detection system based on 5G communications, big data analytics, and augmented reality was proposed in another article [205]. The preliminary results of a traffic detection algorithm have been provided, as well as a direction for future research. An efficient physical layer identifies spoofing attack detection mechanism for IoT was proposed in another article [206]. A two-step detection approach exploits the sparsity of the virtual channel in Mm-Wave and Massive MIMO 5G communication. The technique finds anomalies in the first stage by angles of arrival (AoA) and path gains of all IoT devices in the VCS at the same time.

Another article [207] the EKF approach, is used initially to forecast future harvesting power. Then, in each energy-aware cycle, create a mathematical model to compute the necessary energy of various security measures and select the maximum level of protection that can match service requirements while avoiding energy exhaustion.

The goal of this effort, according to one publication [208], is to build a safe and secure CDS in a wireless network that runs over an SB, which will provide users with a safer and more efficient environment for browsing the Internet, sharing, and handling enormous amounts of data in the fog. There were two sorts of servers in this CDS: one cloud server and one edge server.

One article [209] explored the security and privacy issues that the available 6G specifications and possible 6G applications may provide. Give the reader an overview of the standardisation activities and research programmes related to 6G security. Security concerns with 6G enabling technologies such as DLT, physical layer security, distributed AI/ML, VLC, THz, and quantum computing were examined in particular.

6.3. Smart Cities

This section details the research that was done to examine smart home IoT design features, architecture, and feasibility in terms of 5G and 6G.

Two publications [210,211] proposed upgrading current infrastructure to host cloudlets on a city-wide scale, allowing smart cities to provide new services to inhabitants. The findings suggest that updating a small number of access points can result in city-wide cloudlet coverage.

Three articles [212–214] look at the latest cooperative MIMO antenna technologies, which are the bridging technologies to 5G, by first looking at the benefits of cooperative MIMO in smart city applications like smart transportation, home automation, and security, and then evaluating the impact of cooperative MIMO technologies on achieving higher spectral efficiency.

Some articles [215–220] point to unsolved issues and emphasise the necessity for piloting with 5G apps in order to better understand the setup of 5G networks and the use of applications in a variety of vertical industries. In a typical smart house, you can see numerous topologies and configurations employing ZigBee communication. Dedicated to smart homes and, in particular, ZigBee as a smart data collection element. In addition, the IoT SoftRadio tool is introduced, and NB-IoT UEs sharing scenarios are summarised.

Finally, using the current NB-IoT radio performance management framework. Discuss the state of the art in the topic of call admission control in 5G networks. Which study will be carried out in order to propose and create an algorithm for admission control modelling in the situation of New Radio access, namely NR 5G? An RNN-based arrival angle predictor was proposed in two studies [221,222] to predict the particular communication location of UAVs in 5G IoT networks. To make the training process easier and more effective, a grid-based coordinate system is used during data preparation.

One article [223] aimed to chart the major directions and scope emerging dimensions inherent to 6G technology, including digital twins and immersive realities that, development and application of 6G, noting its numerous potential benefits in tackling a variety of urban challenges, including environmental dimensions, needs to be accompanied by political policy agendas supporting sustainability transnationally.

The authors of [224] designed a system based on 6G network communication standards for the next IoT level. Water flow management, wind shield control, security concerns, and carbon dioxide limitation via adaptive ventilation are all effective with the proposed control approach. The infrastructure has been developed to support the new 6G communication standard, which will improve efficiency and data flow at the end-user device and local area level.

A framework for DAIaaS provisioning for IoE and 6G contexts was proposed in one study [225]. Because the actual training and inference computations are divided into smaller, concurrent computations tailored to the degree and capacity of resources accessible with cloud, fog, and edge layers, the AI service is called “distributed”. To study the design choices and performance bottlenecks of DAIaaS, multiple DAIaaS provisioning settings for distributed training and inference are provided.

Another article [226] offered a conceptual design for job off-loading and resource allocation dubbed the typical model. Second, expand on the traditional paradigm to include intelligence for work off-loading and resource allocation, produce particular research questions in order to build and evaluate the performance of various units within the above-mentioned models in order to accommodate technological improvements such as the employment of AI in the 6G wireless communication era.

6.4. Virtual Reality

One of the most critical high-throughput application-level requirements of 6G is AR/VR. When AR/VR can be utilised more efficiently, conveniently, and without regard to location, it will encourage the rapid creation of AR/VR services and applications, which will, in turn, encourage the quick development and maturity of AR/VR devices.

One publication [227] described a case study in an oilfield that looked at the MAS paradigm and the possibilities for new development with 5G. Production management and related tasks, such as production monitoring, cost analysis, maintenance scheduling, inventory control, and supply chain management, are the emphasis of the proposed MAS model. The ultimate VR 360 that satisfies human eye fidelity is the subject of another article [228]. The ultimate VR 360 requires a 1.5 Gbps downlink and a 6.6 Gbps uplink for live streaming, with a round-trip time of less than 8.3 milliseconds. Examine whether the most cutting-edge wireless communication technologies are capable of supporting the ultimate VR 360 experience.

In one publication [229], the authors listed key enabling technologies for an intelligent and open 6G network, all of which included 3C convergence. 3C-based spectrum management, radio channel design, delay-aware transmission, wireless distributed computing, and network self-evolution are among the subjects covered by these technologies.

Other unique VLC concepts, such as interactive VLC, light-based IoT, living surfaces, and optical communications through bio-tissues, are given and discussed in another paper [230]. These extremely interesting technologies can be applied to the selected 6G verticals, hence expanding 6G research into new sectors.

6.5. Other Machine Learning

ML-based intelligent application scenarios will enable rich, heterogeneous connections, as well as large data storage and processing.

A concept for such a traffic control system was proposed in three publications [231–233]. Its components are described as well, including 5G networking, RFID-based parking space monitoring, and cloud services for supervisory control and ML. For the social sustainability of smart cities, joint verification of smart user profiles is necessary. The collaborative architecture delegated the detection of potential identity theft to other smart users who are the potential victim's social platform contacts.

Another paper [234] presented an uncoordinated access protocol for huge connectivity that takes advantage of a large number of antennas at the base station and is likely to be widely used in cellular networks. A large number of IoT devices can transmit data without any prior scheduling procedure using the proposed approach, which consists of a sparse frame structure and receiver processing based on sparse dictionary learning.

7. Merging Energy and IoT in 5G, 6G

There have been several recent attempts in implementing strategies to handle various difficulties in wireless communications in the direction of merging energy and IoT in 5G, 6G, and beyond networks. This category's 104 articles were broken into two subcategories.

(1) Table 5 Analysis of ML Usage in Incorporating Energy and IoT in 5G and 6G.

(2) Table 6 Summary of Machine Learning-Based schemes for 5G and 6G mobile and wireless communications technology [235–238].

The primary objective of this article is to discuss the advantages and disadvantages of various ways of learning in the context of future 5G and 6G communications. The article discusses detection and learning approaches in the context of energy-efficient 5G and 6G networks. It was demonstrated that the volume of examined context-awareness information is huge. Table 5 summarises the possible services, core idea, and limitations uses of machine learning in 5G and 6G-based energy technologies.

Table 5. Analysis of ML Usage in Incorporating Energy and IoT in 5G and 6G.

ML	5G, 6G-Based Applications Energy and IoT
ANN	Their primary advantages have been identified, and the feasibility of their implementation in tackling the problem of accurate attack detection in m2m adhoc self-organizing networks has been assessed [239].
DL	looked into the challenges involved in trying to blend MEC with C-RAN, specifically regarding cloud resources. energy-reduction [240,241].
DL	Implemented a modern vehicle-internet infrastructure-aware ML architecture. It has made managing network slicing difficult in the context of 5G-enabled networks [242].
DL	Has provided an APP-SON system which optimises 4G/5G network performance and user QoE. App-son offers a scalable big data platform for targeted optimization by evaluating cell application features in temporal space [243,244].
DL	proposed to apply DL algorithm based on 5G-V2X for AI-based 5G base station allocation for platooning cars [245,246].
RL	Found an E2E network slicing system that uses deep reinforcement learning to manage many resources to efficiently generate network slices [247–249].
Bayesian	Bayesian learning was used to identify the broadcast signals for LA-CDMA uplink access. Using the sparse signals, this proposed strategy leverages our ignorance about user activities. Furthermore, introduce Gaussian mixture model approach to calculate the transmitted signals [250].
ML	Proposed an online learning detection approach for the NOMA uplink. Build an online adaptive filter in the sum space of linear and Gaussian reproducing kernel Hilbert spaces. So, this approach is robust to dynamic wireless networks that can degrade the efficacy of a nonlinear adaptive filter [251].
ML	Proposed the first online learning method designed to aid beam selection in mmWave vehicular systems. in particular, see this as a multi-armed bandit problem. Next, developed a lightweight context-aware online learning algorithm, known as FML, with proven performance and assured convergence [252,253].
ML	Investigated healthcare scenarios where communication is conducted at THz frequencies. Combined with an ML mechanism, THz communications protocols result in fewer signal route losses in the system [254–256].
ML	The new algorithm that incorporated a change in the hidden layer of the RNN is known as GRUs. The RNN-GRU model is used for determining whether or not to enable the VC mode. Received signal strength measurements were utilised to train the RNN-GRU model [257,258].
ML	Most notable similarities between the cloud-fog node architecture and the human brain-spinal cord-nerve network model involve the presence of fog nodes [259–261].
RL	The user association problem is tackled with a reinforcement learning method that considers content placement profiles and frontal constraints [262–264].
ML	Detected the mood of patients by implementing an intelligent real-sense camera system prototype. ML, an SVM, and the RealSense facial detection system can be utilised to track patient demeanour for pain monitoring [265].
ML	Developed a lightweight context-aware online learning method called FML with performance and convergence guaranteed. Using coarse location information and aggregating the data, FML learns from and adapts to its environment. Furthermore, propose a standard-compliant protocol that utilises the existing cellular network architecture and the future 5G characteristics [266–268].
ML	Focused on designing and detecting RA preamble for 6G IoT satellite-assisted 6G an energy-conscious course for big IoT devices [269]. The drone follows the shortest path across a connected graph. This path decides the visiting order of devices. According to system identification theory, and with the use of neural networks, the model is constructed based on the results [270,271].
NN	FA neural network combined with system identification theory is used, and the model is created based on the gathered data [272].
ML	Enriched standard HetNets with a user-centric ML dimension [273].

Table 6. Summary of Machine Learning-Based Schemes for 5G and 6G Mobile.

ML	Core Idea	Limitations	Ref.
1-	Networks Architectures		
ANN	Ensure the accuracy and simplify channel estimate.	How to increase the algorithm's accuracy, and hence its estimating performance.	[274]
ANN	Use SMDP for the decision-making.	N3AC scales to huge scenarios and is useful in real applications.	[275,276]
BL	Used for the forecast of throughput. Parameter estimation forecasts future test results.	Converts probability distributions into images and applies assumptions of conditional independence to decrease the computational load of probabilistic reasoning.	[277,278]
DL	Proposed a DNN-based AS/STSK MIMO system.	Only the simulation shows that NN.	[279]

Table 6. *Cont.*

ML	Core Idea	Limitations	Ref.
DL	5G-oriented architecture in which to analyse network traffic.	Only TensorFlow was tested, and an in-depth comparison of deep learning frameworks would be essential.	[280]
DL	Using ML methods to minimise link failure at handover.	It might enable cellular systems to escape threshold-based handover decisions and follow ML-based methods.	[281–283]
DL	Reduce network load and availability.	Need to include mimicking the created model in a real production environment once the 5G ecosystem is accessible for customers.	[284,285]
DL	Create realistic synthetic data by exploiting the GAN's capacity to generate and separate data.	Proactive SON algorithms run by GAN generated synthetic CDRs.	[286,287]
DL	Semantic edge cache optimization for multimedia services in 5G, which online improves caching settings depending on user playing behaviour.	Sharing the cache resource across many BSs is essential for heterogeneous networks.	[288,289]
ML	Verification of quality of experience.	Add more diverse and difficult scenarios, like deployment, client movement, and dynamic video and client attributes.	[290,291]
ML	Distributing resources to high mobility users while utilising only their position estimates.	Training the ML unit of the proposed approach will help alleviate inaccurately position information availability-related performance loss.	[292]
ML	Consider the case of 5G network slicing, and elaborate on the design, construction, deployment, operation, control, and management of slices.	Extend this inquiry to examine representative ML strategies for autonomic allocation and adjustment of computing and network resources on the basis of service requirements.	[293,294]
ML	5G challenges and the importance of a changed management paradigm for 5G.	Next steps include actions such as checking the proposed algorithms at scale on commercial networks to validate the idea of adaptive SDN route planning in context.	[295–299]
ML	MIMO mmWave-assisted downlink for multiple users and Massive MIMO beamforming.	Compared ML-based with CVX-based optimal RRM.	[300–302]
ML	It is possible to learn basic state representations, minimising the complexity of the fundamental network design requirements.	Comparative simulation results demonstrated the suggested decision framework in multi-agent settings.	[303,304]
ML	Used ML to construct a framework for 5G network orchestration.	ML approaches use Decision Maker building blocks using neural networks for optimization.	[305,306]
ML	Allocation of the slice is explored and solved using ML approaches.	Solve for scalability.	[307]
ML	Found features that alter NFP resiliency. Many of these features are design and engineering features, therefore are difficult to measure.	ML and blockchain can improve the resilience of aerial networks.	[308]
ML	Presented a comprehensive self-healing mechanism as an enabler for a truly holistic and resilient solution.	TL strategies will be researched in regards to self-healing, which focuses on applying corrective measures.	[309]
ML	Flow of thinking led to this assumption, which is then used to define the journey towards CAN and a functional design of a typical CAN system.	Concurrently design and assemble a comprehensive CAN-based architecture.	[310–312]
ML	Research approaches for SON functions for anomaly detection, load balancing, and capacity optimization.	Next-generation SON networks should be built using ML-based user-centric techniques in order to achieve a linked eco-system with enhanced user experience.	[313,314]
ML	Plotted the locations of the drone-BSs and calculated the frequency reuse factor based on an octahedron-shaped structure.	Proposed approach drastically lowers the latency of drone-user UEs.	[315,316]
RL	Feature-learning was applied to mine and understand the complex correlation between multi-RMIs and link quality.	To anticipate the movement, apply strategy learning, and regard the location as the input.	[325,326]
RL	Methodology is shown using a network simulation in ns-3 and the ML implementation in Python.	In autonomous and user-centric networks where the system can provide the most effective path for end-users when going from a given source to a destination, there is the potential to implement OCSP.	[327]
RL	Provided insight into the learning challenge of cognitive radio networks and highlights methodologies such as RL used in cognitive radio networks.	5G network slicing-based design that integrates with the ML-based CRN to maximise the use of the restricted spectrum.	[328,329]
RL	Research towards a ML-based remote local (D2D) communication network focused on effective connectivity and minimum latency.	Q-learning offers a perspective on D2D, and in combination with RL-LCDC, offers a practical algorithm for decision making under uncertain network conditions.	[332,333]
RF	Designing a learning-based resource allocation strategy which incorporates simply position information is utilised.	Design parameter modifications, the suggested system is fairly resilient to inaccurate user positioning.	[334]
RF	Cartel, a collaborative learning platform in edge clouds.	Add other ML models to the system.	[335]
TL	Presented an ML approach that enables semi-blind UL and DL decoupling in mixed sub-6 GHz/mmWave cell-free 5G networks.	95% of accuracy in just a few training samples, with a quick and reliable solution to UL and DL decoupling in 5G networks.	[336,337]
SVM	Evaluate the predictive performance of four significant predictors that are crucial to achieve mobile traffic management, manage mobility, and conserve energy in future cellular networks.	Study robustness of these predictors versus varying training dataset sizes. Benchmark performances base on mobility traces from network CDRs.	[338–340]
SVM	In order to develop a deep encoder model, a preliminary experimental environment is constructed to collect data on the Multi faces.	Designing an algorithm to discover the ideal deep auto-encoder model and improving the proposed dependability assessment method.	[341]
DL	Following positive DL assisted communication results, committed to exploring a unique DL-based strategy for SCMA systems, motivated to increase BER performance.	Proposed schemes must be implemented and verified in a real environment system. An in-depth study of the structure of the learnt codebook may result in a higher decoding accuracy.	[342,343]
DL	Proposed an unsupervised DL strategy for cell outage detection and compared the results to a technique termed the nearest neighbour.	Mobility load balancing and intrusion detection are both DL concerns.	[344–346]

Table 6. *Cont.*

ML	Core Idea	Limitations	Ref.
DL	Important problems with regard to dynamic resource scheduling design and offered a data-driven scheduling strategy.	Additionally, improving the physical network's resource usage while guaranteeing QoS.	[347,348]
DL	ANN models include feed-forward NN and radial basis function neural networks.	Validation of simulation findings has proven that ML algorithms can be powerful analytical tools for future measurement-based channel modelling.	[349,350]
DL	Path loss prediction with better generalisation using satellite pictures can be done with twisted NN.	Proposal stands to benefit from increased data since more information can be used to quantify the generalisation reached.	[351,352]
K-means	Proposed two NN-based MLP models to aid in proactive auto-scaling of VNFs using commercial traffic traces.	To tackle the above mapping problem, ILP is able to solve it in seconds rather than hours.	[353]
NN	Binomial distribution-based power coefficient allocation procedure; Pascal's triangle.	Adaptive modulation and coding techniques significantly enhanced the system's BER performance.	[354]
NN	Facilitate automatic network adjustment and intelligent resource allocation optimization.	Downlink communications and the interference-elimination resource allocation mechanisms that go along with it will be examined.	[355]
2-	Quality of Service (QoS)		
ML	Results on how the model functions in the real world are provided.	N3AC scales to huge scenarios and is useful in real applications.	[317]
ML	To test the suggested framework architecture, a case study of QoS anomaly root cause tracking was given.	ML mechanisms, with the skills to train a computer to learn knowledge and concepts from data, can react intelligently to changing environments.	[318,319]
ML	Shows that ML can be integrated into an SDN controller to estimate resource need and behave appropriately, which this one is learning to implement by way of KPIs.	Design and implement new QoE measures specifically related to delay stall time, and the number of quality transitions.	[320,321]
ML	System, based on RL algorithms, allowing online learning of a dynamic and partially visible environment with delayed feedbacks.	Improving the GOL architecture includes employing fuzzy numbers and fuzzy RL.	[322–324]
RL	Developed a distributed approach for managing QoS radio resources in a dense heterogeneous network.	To dynamically react to changing traffic types.	[330,331]
3-	Big Data		
ANN	Tests show that CNN and RNN can find spatial and temporal traffic information.	More accurately projected traffic loads for proactive management are found in 5G networks.	[356]
DL	Implies the unnecessary waste of valuable resources, which ultimately disrupts operations.	Implemented algorithms must be faster, more efficient, and less complex: attempts can be made to study ameliorative strategies in the future.	[357]
ML	Traffic forecasting, thanks to big data, ML, and network KPIs, can estimate accurate statistical traffic characteristics of different types of cells over both short- and long-term forecasts.	The model makes use of a few critical network KPIs, yet it is effective and does not affect the model's cost during training and forecasting.	[358,359]
ML	Found a substantial association between cell load and the user quality of a cell. It can be used to identify and implement interference pairings using ML approaches.	More powerful More data analytics methods are being researched to solve the issues of 4.9G and 5G mobile network optimization.	[360–362]
ML	Used proactive caching techniques to collect large amounts of existing data and use ML to ascertain content popularity.	Cache location at base stations is also essential in the design of ML tools.	[363–365]
ML	Documented a powerful framework for 5G network slicing and the architecture of 5G.	Edge computing, CORD applications, and SDN-based E-CORD, RCORD, and M-CORD must be given priority.	[366–368]
ML	5G-oriented cyberdefense architecture to swiftly and efficiently identify cyberthreats in 5G mobile networks.	To detection and classification to help establish which DL models from a set and the optimal hyperparameters are more appropriate for each configuration and throughput need.	[369,370]
DL	Estimate a power delay profile of a sub-6 GHz channel, which is an input to the DNN.	Developing multi-user beam selection, perform a comparative investigation of other DL-based beam selection algorithms as well.	[374]
4-	Security		
DL	Huge antenna arrays as well as millimetre Wave antenna arrays are being utilised.	Solid set of coding algorithms is available.	[371–373]

8. Discussion

This research investigates the most important studies in state-of-the-art 5G and 6G networks that make use of IoT, energy and machine learning technologies. The purpose of this analysis is to draw attention to certain research tendencies in this field. This research is not up to date, and it would not address implementation, only the literature on the subject matter. This study differs from prior estimates in several ways. It is advised that the surrounding material be used as a taxonomy. Creating a literature taxonomy in a research subject may provide a number of advantages, some of which are evolving. On the one hand, the taxonomy of literary works is widely disseminated, while on the other, it is hardly discussed. The results of the survey revealed three aspects of the content of the literature, namely, challenges in the successful utilisation of these applications, recommendations to alleviate these difficulties, and the motivations for a general framework for the search and browse procedure that was proposed.

8.1. Challenges

6G will be built on a set of technology enablers that will allow it to meet the demanding requirements of these new services. The following are the primary thrusts that we foresee (see Figure 6).

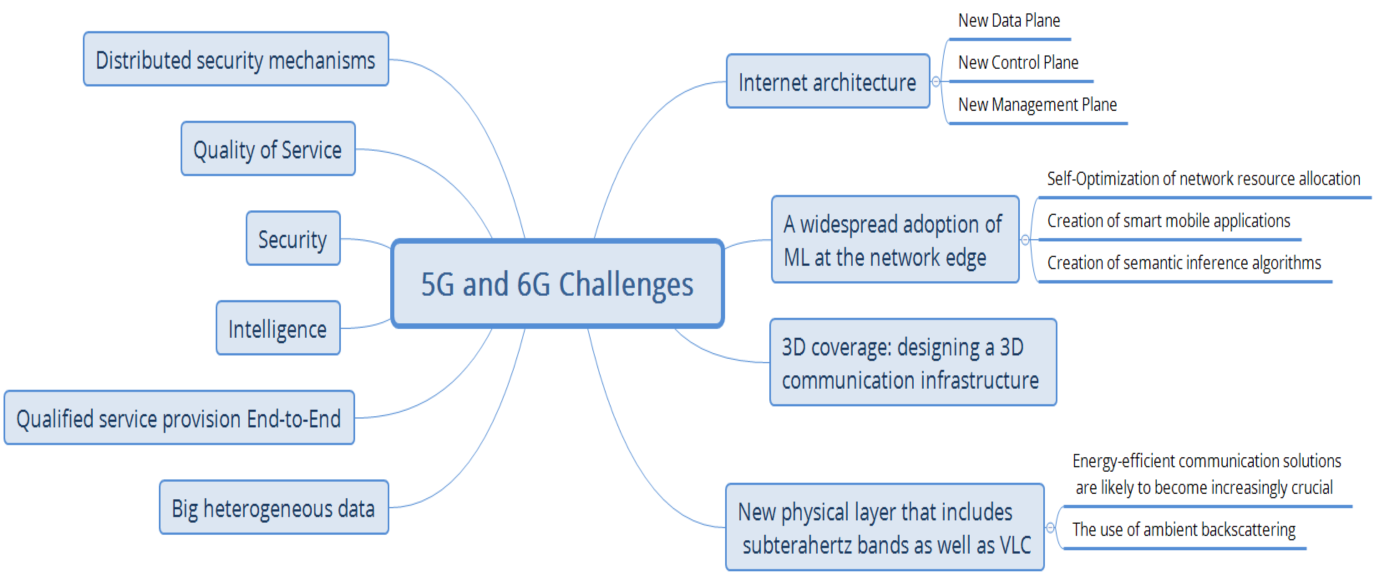

Figure 6. 5G and 6G Challenges.

8.1.1. A New Internet Architecture

The need to support nearly deterministic services, such as in high-precision manufacturing, while also ensuring very tight physical constraints such as latency and energy consumption, necessitates a new Internet architecture that brings together different resources, such as communication and computation, into a single framework.

(1) a new data plane that can adapt to different operating modes dynamically and support holographic communications. (2) a new control plane that allows for the synchronisation of concurrent streams for holographic communications, as well as the use of preferred path routing protocols to provide almost deterministic networks for high-precision manufacturing. (3) a new management plane that incorporates self-configuration and self-optimization capabilities and takes advantage of machine learning's strong support.

8.1.2. Widespread Adoption of Machine Learning at the Network Edge

Distributed machine learning algorithms, which may operate under severe time restrictions, are likely to play a vital role in a number of ways:

(1) self-optimization of network resource allocation, with proactive solutions based on network learning and prediction being considered. (2) creation of smart mobile applications that learn from user behaviour and operate as a context-aware virtual intelligent assistant, running either directly on mobile devices or remotely via computation-offloading techniques. (3) creation of semantic inference algorithms and semantic communication strategies to integrate knowledge representation into communication. This will be very helpful in deploying holographic communications effectively.

8.1.3. 3D Coverage

By designing a 3D communication infrastructure that includes terrestrial and aerial radio access points as well as mobile edge hosts, cloud functions can be provided on demand.

This system is far more cost-effective than the existing approach, which relies on a fixed infrastructure, when requests fluctuate greatly over place and time, as they do with periodic events that draw large crowds or in remote areas, such as in the case of disasters. The idea is to manage a variety of aerial platforms, such as unmanned aerial vehicles, high-altitude (approximately 20 km) platform stations, and constellations of Very-Low-Earth-Orbit satellites flying at a few hundred kilometres in space, in order to provide cloud functionalities while maintaining controllable delay constraints.

8.1.4. A New Physical Layer That includes Subterahertz Bands as Well as VLC

The use of sub terahertz bands and VLC is required to support very high data speeds (as much as terabits per second) to enable, for example, holographic communications.

(1) Energy-efficient communication solutions are likely to become increasingly crucial, especially as the Internet of Things (IoT) becomes more widely deployed, with a plethora of tiny sensors. Ref. [388] discusses energy-harvesting mechanisms, sophisticated wireless charging methods, and their fundamental limits, with a focus on potential distributed laser charging approaches that demonstrate wireless charging can transfer up to 2 W of power over a distance of about 10 m. (2) The use of ambient backscattering, which allows tiny devices to run without a battery by redirecting ambient radio-frequency (RF) signals without requiring active RF transmission [389], will be an even more radical approach.

8.1.5. Distributed Security Mechanisms

The concept so far outlined envisions a massive exchange of data to enable widespread adoption of machine learning techniques. Clearly, this poses a significant problem in terms of security, privacy, and trust, which 6G networks must address appropriately. To establish an effective compromise between ML and privacy, innovative cryptographic techniques should be applied. A mobile user, for example, may utilise homomorphic encryption [390] to execute a distant ML algorithm on its data. Instead of transmitting raw data, the user may send encrypted data, run the remote ML algorithm on the encrypted data, and still get the desired result. Existing techniques are now impractical due to their enormous computational complexity, but we can expect this to change in the next decade or two. Another important issue, particularly in the IoT situation, is decentralised authentication. Using blockchain-like methods, distributed ledger technologies are likely to play a crucial role in distributed authentication [391].

8.1.6. Quality of Service

In contrast to 5G, 6G's QoS will include additional metrics. Latency, throughput, and packet loss rate are some of the most used QoS KPIs. Because intelligence will become the primary necessity in the 6G era, compute capacity and storage will also need to be considered. Furthermore, rather than needing outstanding performance in a single area, future 6G systems will focus on the optimization of numerous measures, for which the complexity of determining the relationship exceeds the capabilities of current mathematical models. To overcome this issue, a variety of purpose-based learning models should be widely used.

8.1.7. Security

Since the Internet has become an increasingly significant part of people's lives and work, security has gotten a lot of attention. Despite the fact that DL has proved its effectiveness in threat detection [392], future communication services will necessitate context-aware security protection using a variety of data created in people's lives and work. Furthermore, when new strategies are developed to maintain message security, the choice of security configuration will become an even more difficult problem, as security protection usually entails some loss of network QoS.

8.1.8. Intelligence

Because future cellular networks will be more dynamic, system knowledge of potential congestion and environmental changes will be necessary to provide qualified services, with three obstacles. To begin, the communication system necessitates the ability to federate learning in order to meet the changing service requirements of mobile users in a timely manner. Second, automated and unexpected system upgrades are essential for adapting to new conditions. Third, in order to fully realise the potential of machine learning, the difficulties of heterogeneity in software and hardware must be addressed.

8.1.9. Qualified Service Provision End-to-End

Computation Oriented Communications (COC), Con-textually Agile eMBB Communications (CAeC), and Event Defined uRLLC (EDuRLLC) [393] are three types of newly supported 6G services, similar to 5G. Despite the fact that the exact service types enabled by 6G have yet to be determined, the standards will undoubtedly be more strict. For starters, future 6G services would require end-to-end assurances, which means the metric should be measured from the transceiver to the receiver rather than just the main network element in the 5G system. Second, in addition to typical measurements like link bandwidth, latency, and security, other KPIs should be considered. Future services will be evaluated in terms of situational awareness, learning capability, storage cost, and computing capacity. Furthermore, the heterogeneity of communication technologies and infrastructure hardware, as well as the complex requirements on numerous metrics, would hasten the adoption of machine learning in networking.

8.1.10. Big Heterogeneous Data

There are many various types of big data sources, each with its data rate, mobility, and packet loss. In wireless networks, analysing diverse data is difficult. Spatial and temporal dynamics are brought about by heterogeneous data. As a result, for massive spatiotemporal data processing in mobile networks, unusual methodologies are necessary.

8.2. Recommendations

This section gives some recommendations for addressing the concerns and challenges that have arisen in 6G through the application of machine learning techniques (see Figure 7).

When two primary tracks come together, a new generation is born: (1) a technological path that brings new, ground-breaking technologies to maturity; and (2) a societal path that encourages the introduction of new services which cannot be efficiently provided by current technology. We begin by introducing new services and then highlighting some of the primary enablers of those services.

8.2.1. Holographic Communications

will become obsolete within ten years. New modes of engagement emerge that allow for a real immersion into faraway worlds, displacing the current means of remote contact among human beings. In conjunction with holographic communications, it is envisaged that 5D communications and services, which integrate all human sense information (sight, hearing, touch, smell, and taste), will emerge, resulting in a totally immersive experience [394]. In order to implement holographic communications using multiple-view cameras, data rates on the order of terabits per second will be required [395], which will be insufficient for 5G.

8.2.2. Manufacturing with High Precision

One of the most important goals of Industry 4.0 is to eliminate the need for human intervention in industrial processes through the use of automatic control systems and communications technology. For high-precision manufacturing, this results in extremely high dependability (on the order of 1–109) and extremely low latency (0.1–1 ms round-trip time) [396]. Aside from that, industrial control networks demand real-time data transfer and excellent determinism, which translates into extremely low delay jitter, on the order of 1 ns, which is translated into extremely low delay jitter.

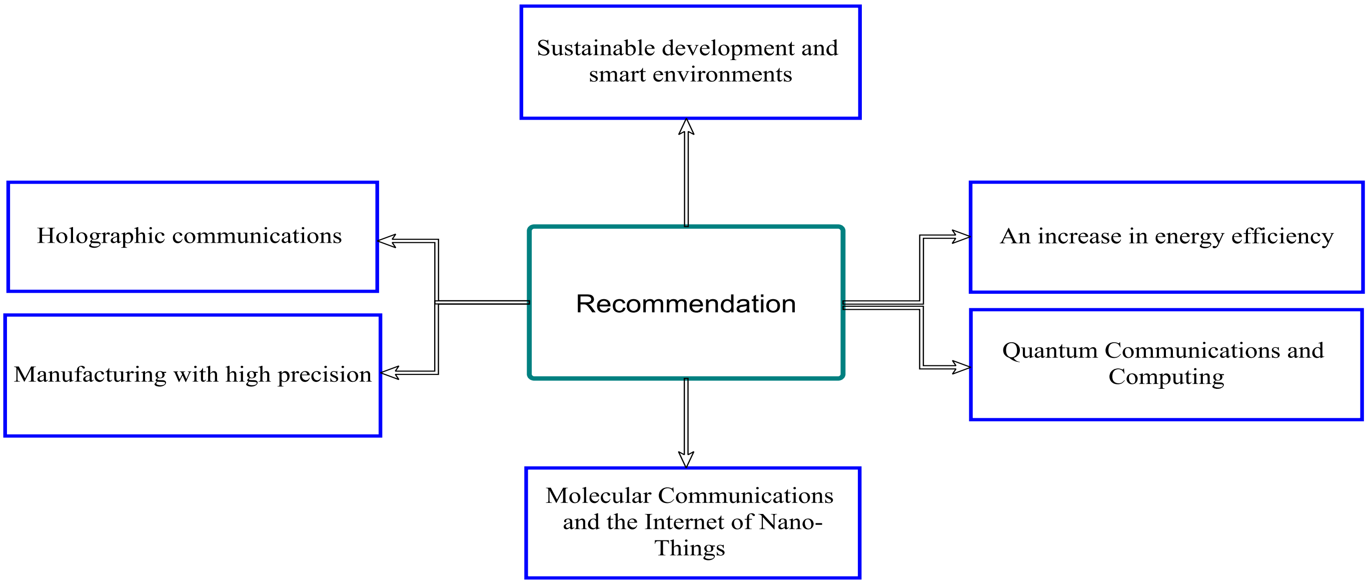

Figure 7. Categories of Motivations.

8.2.3. Sustainable Development and Smart Environments

Information and communications technologies (ICTs) incorporating wireless communications, cloud computing, and the Internet of Things (IoT) are expected to play a critical role in advancing global sustainability and improving the quality of life for all people. These technologies have the potential to make significant contributions to improving health care and enabling the creation of smart cities, which may include the construction of intelligent transportation and energy distribution infrastructure. A pervasive sensing framework, as well as a distributed decision and actuation system, are required to achieve some of these objectives. 6G will make a substantial contribution to this by depending on 3D communication platforms that can enable almost instantaneous distributed edge cloud features, such as distributed decision procedures, to be implemented. When it comes to situations such as autonomous driving, reliable safety procedures are critical in reducing the likelihood of an accident. This will necessitate extremely high levels of communication reliability (i.e., greater than 99.9999%) as well as low end-to-end latency (below 1 ms). Furthermore, intercommunication among automobiles will be critical in lowering the likelihood of a collision. To do this, high-speed data linkages between vehicles and between vehicles and roadside equipment will be required.

8.2.4. An Increase in Energy Efficiency

It goes without saying that any sustainable growth must pay strict attention to energy use. As a result, 6G will need to design communication tactics that are both effective and energy-efficient. In order to provide battery-free communication whenever possible, the goal is to achieve communication efficiency on the order of 1 pJ/b. Some key performance indicators (KPIs), such as delay jitter and energy per bit, are not stated in 5G since they do not represent a primary focus of 5G, although they are critical KPIs for 6G.

8.2.5. Quantum Communications and Computing

With the support of entire applications/scenarios, 6G will meet higher security needs than current technologies. With the application of a quantum key based on the quantum no-cloning theorem and the uncertainty principle, quantum communications can give extremely robust security [397]. Whenever eavesdroppers attempt to carry out observations, measurements, or copy activities in quantum communications, the quantum state is disrupted, and the eavesdropping activity may be easily identified. Theoretically, quantum communications have the potential to provide complete security. While Tb/s data transmission and full applications/scenarios provide obstacles for wireless computing in 6G, they also present opportunities [397]. When compared to traditional computing, which uses 0–1–b operations, quantum computing, which relies on quantum superposition and entanglement, can significantly increase computing capabilities by utilising unitary transformations in the form of qubits. As a result, quantum computing has the potential to greatly accelerate and improve artificial intelligence algorithms that require large amounts of data and extensive training. Furthermore, by combining quantum theory and machine learning, it is possible to construct more powerful and efficient machine learning algorithms to meet the requirements of 6G.

8.2.6. Molecular Communications and the Internet of Nano-Things (Molecular Communications and the Internet of Nano-Things)

Advanced nanotechnology has the potential to enable the production of nanodevices such as nano-robots, implantable chips, and biosensors, which have vital applications in areas such as nanoscale sensing and biomedicine [398]. The use of nanotechnology in biomedicine, in particular, has piqued interest because it has the potential to accomplish tasks such as intelligent drug distribution through blood vessels and monitoring of body organs, both of which have the potential to enhance significantly human healthcare outcomes. It is possible to achieve effective communication and information transmission by connecting nanodevices to the Internet or by forming networks (i.e., the Internet of Nano-Things); in biomedicine, the Internet of Bio-Nano-Things (IoBNT) can enable the connection of nanodevices and biological entities. In the Internet of Things, molecular communication is an enabling approach for the IoBNT, in which biological molecules are used to communicate and transport information amongst nanodevices [398]. A further benefit of combining the IoBNT with body area networks, which are short-distance wireless networks made up of wearable monitoring devices/sensors and sensing devices embedded in or on the body, is that they can give comprehensive solutions for healthcare enhancements.

8.3. Motivations

The future 6G network will not only concentrate on the pure communication area, but it will also be interoperable between diverse but related fields like electronics and materials, wireless communication, computer science and engineering, and computer science and technology [399]. Nanoelectronics for the Internet of Things, RF modules and packaging, high-frequency materials, radio transceivers, energy harvesting, THz imaging, and 2D/3D imaging will all be covered in the topic of electronics and materials. While in the field of computer science and engineering, the professionals can make contributions in a variety of areas such as image and signal analysis, mobile apps, security and privacy, big data analysis, smart sensor analytics, smart environments, and ubiquitous systems to name a few. In addition to their work in the field of wireless communication, experts in RF and antennas, 5G baseband technology, Internet of Things applications, future radio access, network optimization and management, spectrum regulations, and channel modelling are also actively involved in a variety of other fields (see Figure 8).

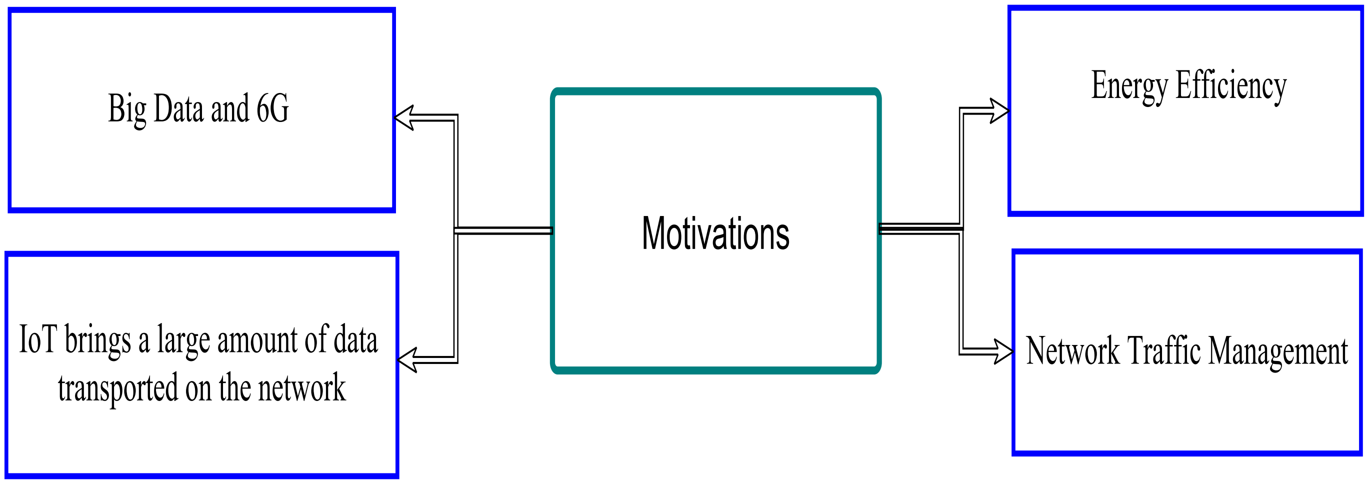

Figure 8. Categories of recommendations according to audience.

8.3.1. Big Data and 6G

In this section, we'll take a quick look at some of the outstanding questions. This also provides guidance for future advancements in research at the intersection of big data and 6G, as tackling these difficulties has the potential to provide significant breakthroughs.

Caching and computing on a proactive basis: By utilising modern big data analytics methodologies, the cost of computing and caching for future generation networks can be decreased. As a result, resources are to be efficiently allocated and utilised, which will result in a better balance between caching and computing overhead. If the intermediate and final outcomes are not significant, they should not be stored because storing all of the information would be prohibitively expensive.

Security and privacy: Big data analytics is used to unearth information that has been hidden within a large amount of data. Because of this, large-scale data analysis may result in security and privacy concerns. In order to ensure that data cannot be modified or altered during the storage, management, and processing stages, it is critical that information is properly encrypted. Furthermore, only authorised entities should be permitted access to the data, and access should be granted only through secure means. As a result, security and privacy problems are important considerations for such large-scale data analysis, and they should be addressed thoughtfully.

Big Heterogeneous data: Large amounts of heterogeneous data: Large amounts of data from a variety of sources with varying data rates, mobility, and packet loss. Analysis of heterogeneous data in wireless networks is a difficult problem to solve. Spatial-temporal dynamics are brought about by heterogeneous data. As a result, for large-scale spatiotemporal data analysis in mobile networks, novel methodologies are necessary that are not commonly used.

8.3.2. The Internet of Things (IoT)

Carries with it a vast volume of data that must be carried via the network. As a result of the addition of sophisticated sensors and controllers to their devices, several device manufacturers had already included the capacity of collecting data from their gadgets. Within this decade, it became obvious that reporting on and analysing data gathered from sensors and control devices were becoming increasingly popular among people.

Management of a smart city. In a smart city, information is available on a variety of topics, including the environment, tourism, traffic, social life, mobility, energy, and so on. A complete picture of the city is provided by the data collection and organisation provided by heterogeneous sensors, which allows for the implementation of early warning solutions and the development of predictive models, thereby increasing the city's resilience and limiting the negative effects on citizens caused by unexpected events. The environmental monitoring and structural monitoring applications are the ones that stand out in this scenario.

Management of public and private metering systems. To make the development of smart metering systems economically viable, the goal in this scenario is to integrate smart metering services into a single transportation network. For example, the citizen or company can remotely monitor the status of their house or office, allowing the system to adapt quickly to various occurrences in order to provide the desired comfort while conserving energy, as seen in the image below. In this context, data privacy and security are critical considerations: it is vital to ensure that the information gathered will not be used to violate the privacy of the user or be utilised by malevolent parties in order to do this.

Management of industrial processes as part of a whole. The requirement for integrated industrial management is a crucial component of innovation processes in the Fourth Industrial Revolution (Industrie 4.0). The establishment of dedicated network infrastructure, on the other hand, can be a considerable financial burden. It is anticipated that the 5G network would provide an infrastructure that will meet the demanding specifications required for industrial automation applications while still being cost-effective. In this scenario, the ability to meet the severe URLLC requirements will be critical in determining the outcome.

8.3.3. Energy Efficiency

Widespread adoption of cloud computing and network functions virtualization (NFV), combined with a smart, programmable management system, will result in a significant reduction in service deployment time, significant savings in energy consumption, and improved network management in general [400]. Cloud computing and NFV, combined with a smart, programmable management system, will enable a significant reduction in service deployment time, significant savings in energy consumption, and improved network management in general [401]. In this scenario, ML can be utilised to improve performance by making greater use of available network and virtual machine resources while also reducing total energy requirements and expenses. The nature of NFV opens the door to more flexible management allowing for fast, dynamic deployment to match current demand in real-time, as well as the migration of services to locations with reduced energy costs and/or footprints [401,402], When used in conjunction with a smart management system, this can result in downscaling tactics that can result in significant savings in both energy consumption and operating expenses[403–405].

8.3.4. Network Traffic Management

Accurate network traffic identification is the foundation of intelligent network management, and it is essential for effective network management. Service providers will be unable to maximise shared resource consumption and assure accurate billing and payment if they do not identify and measure network traffic flow. On the basis of past traffic data, machine learning algorithms can be used to find the most optimum network topologies. Similarly, network functions virtualization (NFV) can be used to provide the necessary resources and services to overcome exceptional or routine situations. Because of this, researchers in communication networks are increasingly relying on machine learning to optimise network architecture, control, and administration, ultimately leading to greater automation in network operations. Experts in the machine learning field, on the other hand, are collaborating with networking researchers to optimise network architecture and design. Furthermore, the rapid growth of machine learning has had an impact on many fields of wireless communication since it is capable of making judgments and extracting information from the data generated by a 5G network.

9. Conclusions

Recent research on sixth-generation wireless communication networks especially concerning IoT applications, machine learning, and energy has been reviewed in this paper. Future breakthroughs in these domains are expected to significantly impact many aspects of our life over the next several years, regardless of industry. The next-generation networks will likely be highly complicated. They will require energy that can power billions of connected devices simultaneously, making it impractical to change or recharge the batteries of so many devices regularly. As a result, energy-efficient networks and devices will be required in the future. Because of the importance of energy efficiency in future 6G networks, this paper provided a survey of recent works in 5G and 6G energy efficiency for IoT networks. This paper also reviewed the primary challenges and limitations that must be addressed to achieve energy efficiency-based huge IoT enabled by 6G. This study aims to put forward a set of guidelines to researchers working in energy efficiency, IoT, and AI for the next-generation mobile communication networks.

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Abbreviations

The following abbreviations are used in this manuscript:

3GPP	Third Generation Partnership Project
mMTC	Massive Machine Type Communications
AI	Artificial Intelligence
mURLLC	Massive Ultrareliable Low Latency Communication
AR	Augmented reality
ML	Machine learning
B5G	Beyond 5G
m2m	machine to machine
BL	Bayesian learning
MR	Mixed reality
CU	Cellular mode
NB	Naïve Bayes
EDoS	Economic Denial of Sustainability
NR	New Radio
E2E	end to end
NFV	Network function virtualization
eMBB	Enhanced Mobile Broadband
NMA	Network management automation
EHD	Extremely high definition

NN	Neural networks
eTOM	Enhanced Telecom Operations Map
XR	Extended reality
FiWi	Fiber Wireless
xMBB	Extreme mobile broadband
FL	Fuzzy logic
RF	Random forests
GPT	General purpose technology
RA	Resource allocation
HCSs	Human Centric Services
RL	Reinforcement learning
DR	Deep learning
RNN	Recurrent Neural Networks
DT	Decision trees
SG	Smart grid
D2D	Device-to-device
SINR	Signal to interference plus noise ratio Service
DRL	Deep reinforcement learning
SLAs	Level Agreements
ITSs	Intelligent transportation systems
SHD	Super high definition
IoE	Internet of Everything
SGs	Smart grids
IoT	Internet of Things
SRS	Shopping recommender system
ITS	Intelligent transportation system
SON	Self organizing networks
IMD	Intelligent medical diagnosis
SVM	Support Vector Machine
LTE	Long Term Evolution
THz	Terahertz
QC	Quantum computing
TL	Transfer learning
QML	Quantum ML
UAVs	Unmanned aerial vehicles
QoE	Quality of experience
URLLC	Ultra reliable low latency communication
QoS	Quality of service
VNF	Virtual network function
KPIs	Key performance Indicators
VR	Virtual reality
MIMO	Multiple Input Multiple Output
HSR	Hyper high speed railway
mIoT	massive Internet of Things

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