GENERATIVE AI & ML MODELS FOR 6G COMMUNICATIONS AND INTERNET OF EVERYTHING (IOE)

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Abstract

At a faster rate than any previous mobile generation, 5G is expanding. Our independent is to role of service providers in managing this ongoing significant traffic growth while lowering energy consumption as new use cases emerge. For industries like manufacturing, minerals extraction, energy utilities, marine and processing, airports, shipping terminals, smart cities, the health care sector and more, outstanding performance communications are the building blocks of digital transformation. In order to enable the acceptance, use, and expansion of new and developing, data-driven technologies, private 4G and 5G networks offer dependable, secure, and agile connection. Wireless communication service providers are facing new hurdles with the arrival of 5G and incorporating Artificial Intelligence capabilities into networks is one way the sector is addressing these complications. Researchers are now focusing on 6G as the rate of deployment of fifth generation (5G) infrastructure rises and standards move further to steady state. The buzz in the field of research has been sparked by new use cases and the possibility for performance gaps. Early efforts are focused on important foundational research that will help achieve target objectives for the next generation of communication networks. Our objective is to assist service providers in controlling this persistently significant traffic growth while lowering energy usage. To develop cutting-edge network solutions that let service providers launch new services while emitting fewer greenhouse gases. This paper focuses on ubiquitous AI, which could significantly alter the upcoming 6G network. An effective network is needed to deliver the higher rates and reduced latency performance improvements. Cutting-edge a situation when there is a lot of interference, the network's infrastructure must dynamically distribute resources, modify the flow of traffic and process signals. By enhancing networks and developing new waveforms, Artificial Intelligence (AI) as well as Machine Learning (ML) models will serve as a key enabler of 6G technology. The goal of the work items under consideration for this research is to give the Indian industry the boost it needs to establish an ecosystem through requirement and awareness building, validation, the incubation process and product-market acceleration in the areas of 6G, green technologies, quantum communication and future oriented Passive Optical Network Architecture.

Keywords: Artificial Intelligence, Machine Learning, 6G, Quantum Communication, Passive Optical Network.

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1. Introduction

Wireless data traffic has significantly expanded as a result of the swift advancement of smart interfaces and developing new applications including real-time and active services and current cellular networks even the upcoming 5G cannot fully keep up with the escalating technical demands [1]. In order to meet the upcoming challenges, the sixth generation (6G) mobile network is expected to cast a high technical level of new frequency and energy-efficient transmission methods. In this article, we outline the potential needs and provide a summary of the most current studies on the 6G-related techniques that have recently drawn a lot of interest. Additionally, we list a number of 6G's major technical issues along with possible fixes, including physical-layer transmission methods, network layouts, security strategies, and testbed advancements [2,3]. Several use cases are currently being considered that have the potential to outperform the capabilities of the present network evolution. As fifth-generation technology continues to take root through greater deployments and standards stabilization, these use cases are expected to demonstrate significant advancements. Researchers are now focusing on the sixth generation network as a result of this. Early signs point to 6G being a mixof technologies that draw from earlier generations, however with new enablers that are expected to spur advancements. We quickly summarize 5G in order to better grasp and frame 6G. [4,5]

Study on 5G Technology Performance

The fifth generation of mobile telephone networks improves energy efficiency, latency, and data transmission rates significantly. As a result, new service classes such as enhanced mobile broadband, massive machine-type connectivity, and ultra-reliable low-latency communicationhave emerged. The world is moving toward an intelligent, information-driven society, but there are still restrictions that call for additional development of wireless communications technologies for the purpose to fulfill the increased need for reduced latencies, larger data transmission rates, and better reliability. The convergence of diverse business advancements with communication platforms, initiated by 5G, will magnify and highlight areas where the performance criteria for 5G are not met by its current capabilities. Future networks, advances, and technological improvements for wireless communication that go beyond fifth-generation systems are being created as a result of the emergence of applications that operate in large connections [6]. In this context, very immersive applications are required, such as digital twins, huge extended reality/virtual reality apps, or three-dimensional communications. These applications will require 6G capabilities to be implemented at scale in order to be financially viable. We believe that only 6G networks will be able to provide high-speed, low-latency connectivity with massive numbers of devices in difficult environments

2. Evolution from 1G to 5G

The transmission of data between two or more places wirelessly is known as wireless communication. It's a broad phrase that covers a variety of technological advancements, such as radio, television, cellular networks, Wi-Fi, and Bluetooth. When scientists began conducting research with electromagnetic waves in the late 1800s, wireless communication became possible. Guglielmo Marconi created a radio wave-based wireless telegraph system in 1894. The way persons communicated was transformed by this, which was wireless communication'sfirst practical use. Wireless communication was employed for military operations in the early 1900s, including the transmission of communications between ships and aircraft. Additionally, it was employed for commercial functions including the transmission of radio and television transmissions. Mobile phones started using wireless communication in the 1970s. Mobile phones from the first generation (1G) had constrained capabilities and utilised analog signals. The 2G, 3G, 4G, and 5G mobile phone generations, on the other hand, utilised digital signals and offered a growing range of capabilities, including faster data rates, greater voice quality, and more functionality. Mobile phones, laptops, tablets, televisions, and even automobiles are just a few of the modern devices that utilise wireless communication. It is a crucial componentof our contemporary world and is still rapidly developing [7,8,9,10].

Here are the five generations of wireless communication:

- **First Generation:** Cellular network technology's first generation was known as 1G. It employed analog signals and first became available in the late 1970s. 1G networks were unreliable and had few features.
- **Second Generation:** Using digital signals, 2G was first launched in the early 1990s. 2G networks featured a greater range of functions, including messaging via text and basic internet access, and were quicker than 1G networks.
- **Third Generation:** In the latter half of the 1990s

and early 2000s, 3G was first offered. 3G networks offered a greater range of functions, including calling via video and high- speed internet access, and were even quicker than 2G networks.

- **Fourth Generation:** In the early 2010s, 4G was launched. In addition to being quicker than 3G networks, 4G networks provide a wider range of capabilities including gaming and streaming video.
- **Fifth Generation:** The fifth generation of wireless cellular networks is known as 5G. It was released in the latter part of the 2010s and is currently being worked on. In comparison to 4G networks, 5G networks are anticipated to be substantially quicker and to offer a greater variety of services, including ultra-high-speed access to the internet and the capacity to connect to a massive number of devices.

Table1: KPI for Network Communications

KPI	**4G**	**5G**	**6G**
Peak Data Rate	1 Gbps	10 Gbps	100 Gbps
Latency	50 ms	10 ms	1 ms
Coverage	10 km	100 km	1000 km
Number of devices supported	100,000	1 million	10 million
Spectral efficiency	1 b/s/Hz	5 b/s/Hz	10 b/s/Hz

Human culture has experienced a significant change as a result of wireless communication's development. We can now access information, do business, and keep in touch with relatives and friends from every corner of the world thanks to it. New technologies like the Internet of Things or Everything and autonomous vehicles, smart farming have also resulted from it. Wireless communication has a very promising future [11]. Wireless communication will grow to be even more common and effective as new technologies are developed. Future wireless networks which will be even quicker and more dependable than 5G are probably in the works. New wireless technologies that are substantially more potent and portable might possibly be developed. 6G network structures exhibit incredible heterogeneity, dense deployment, and dynamism. When combined with strict quality of service requirements, these complex structures render legacy network operation procedures obsolete. Consequently, artificial intelligence, particularly machine learning, emerges as a crucial solution for achieving fully intelligent network integration and management. AI/ML enabled channel estimation and spectrum management will enhance the outstanding reliability of ultra-broadband approaches like terahertz communication by learning from volatile and dynamic environments. Furthermore, AI and ML techniques can effectively address the challenges posed by ultra- massive access concerning energy efficiency and safety. [12].

In addition, intelligent mobility and resource management will ensure ultra-reliable and low-latency service. With these challenges in mind, this article presents and surveys some cutting-edge AI/ML based techniques and their potential applications in 6G for enabling ultra-broadband, ultra-massive access, and ultra-reliable and low-latency solutions. AI helps 6G communication provide high QoS by enabling high data rates, ultra-reliable low-latency connectivity, enhanced mobile broadband, massive machine-type communications, extended distances and high-mobility communications, and highly low-power communications. [13].

3. Pervasive Artificial Intelligence & Machine Learning

In this paper, we underscore the significance of pervasive AI in shaping the future of 6G networks. A robust network infrastructure will be crucial in achieving higher speeds and lower latency. Particularly in an interference-rich environment, the network must efficiently allocate resources, adjust traffic flow, and manage signals [14]. Pervasive AI stands out as a strong contender to fulfill these tasks. Through optimizing wireless networks and introducing new waveforms, AI and ML will play a pivotal role in enabling 6G technology. Researchers have already explored and studied AI applications in various aspects of the proposed network. A useful way to summarize this is by mapping AI applications to the standard Open Systems Interconnection network layers model. Early research targets encompass all layers, including physical, data link, network, and application layers."

Although the 6G mobile network communication design is still in development, several keyfeatures are expected to be included. Here are some shown for instance:

- **Heterogeneous Networks:** 6G networks will use a change of radio frequencies,including sub-6 GHz, millimeter wave (mmWave), and terahertz (THz) bands. This will enable 6G networks to provide a broader range of support and services for a broaderrange of devices.

- **Massive MIMO:** Massive MIMO is a technology that utilizes a substantial quantity of antennas to transmit and receive data.. It is expected to be used in 6G networks, which will enable them to accommodate a much larger number of devices while also providing significantly greater data speeds.

- **Cell-free networks:** A novel wireless network architecture that diverges from traditional base stations is the cell-free network. In this approach, a multitude of small antennas is employed to transmit and receive data. By adopting this approach, 6G networks can achieve significantly improved coverage and accommodate a wider arrayof applications.

- **Artificial Intelligence:** AI is a key enabler for the next generation of wireless networks. AI will be used to optimize network resources, improve user experience, and deliver new services.
- Aside from the previously mentioned features, the 6G network architecture is projected to be more adaptable and flexible than the current 5G architecture. This will allow 6G networks to support a broader range of use cases and meet the needs of a wider varietyof users. Despite the fact that the 6G network architecture is still in its early stages, it isclear that it has the potential to revolutionise the way we connect with one another andwith the rest of the world. [15].

AI and Machine Learning will likely have a significant role in the advancement of 6G communications. AI and machine learning can help 6G networks perform better in a variety of ways, including:

- **Improving Network Efficiency:** AI can be used to improve 6G network performance by randomly assigning resources among various users and applications. This will enable 6G networks offer the best possible accomplishment for everyone on thenetwork, irrespective of location or application type.
- **Traffic Management:** AI can be used to handle traffic in 6G wireless networks by forecasting traffic flow and assigning resources accordingly. This will help to ensure that 6G wireless networks never become congested, regardless of whether traffic is high.
- **Personalised Services:** Artificial Intelligence may be applied to provide personalised services for 6G users. AI can, for example, be used to recommend information to users according to their preferences or to provide instantaneous information on their surroundings.
- **Network Security:** AI can be used to protect 6G networks by identifying and avoiding cyber-attacks. AI can also be used for monitoring network traffic and detect anomalies.

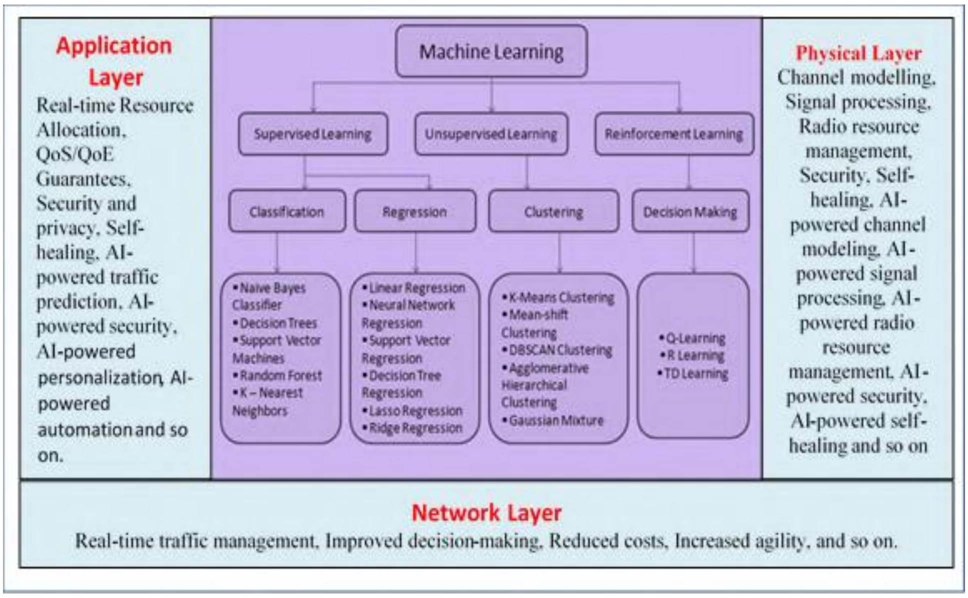

Figure 1. AL & ML Driven 6G Network Communications OSI Layer

4. AI & ML driven OSI Physical Layer

The physical layer of traditional wireless communications is typically designed using mathematical models, and various major modules are represented and optimized independently. While this design approach can accommodate the rapidly changing physical layer characteristics, certain non-linear physical layer factors often defy modelling. To make significant advancements, it is essential to integrate Machine Learning into the physical layer of 6G communication networks. The 6G connectivity for broadband offers an overview of the technologies that support the physical layer.

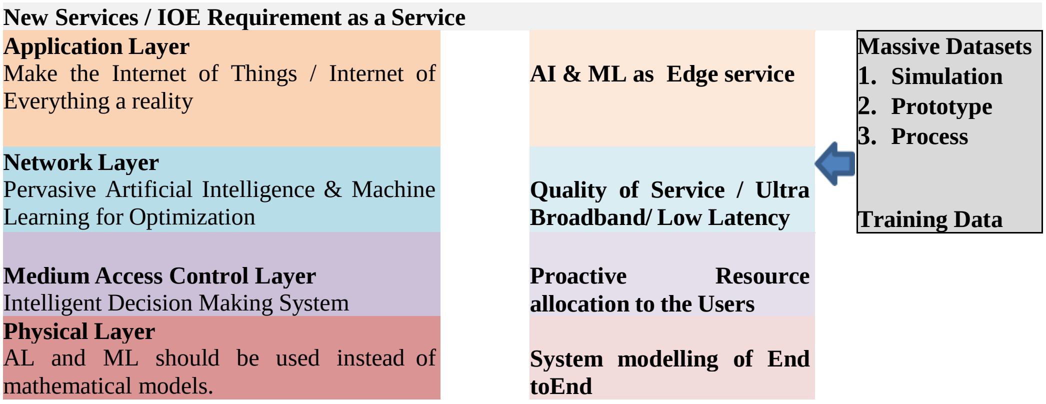

Figure 2: Representation for AL & ML driven 6G Communication Methods

Machine learning can be integrated at multiple levels in a 6G wireless communications system. In frequency division duplex systems, for example, machine learning can be used to identify and mitigate interference, predict channels, and improve reciprocity between the uplink and downlink. Because of the lack of accurate models or the presence of nonlinearity, these tasks present challenges for traditional methods. Machine learning can be used to update existing discrete modules at the second level of integration. Each module's design is typically based on a linear model, which can result in suboptimal performance when strong nonlinear factors are present. Machine learning can improve the performance of these modules by incorporating nonlinear effects into the model. The joint optimisation of physical layer modules is the third level of machine learning integration. Decoding, modulation, and waveform design are traditionally divided into separate modules and optimised individually in the physical layer design. However, when these modules are considered together, the receiver complexity frequently becomes too high for holistic optimisation. Machine learning allows for a more adaptable approach, removing the need for meticulous design of each coding scheme or constellation pattern. Learning algorithms, on the other hand, can achieve near-optimal end-to- end mappings automatically. Future research should concentrate on determining which specificmodules benefit from machine learning for joint optimisation in the physical layer. The fourth integration level entails combining machine learning with existing model-based techniques. Although traditional model-based techniques can be overly idealised at times, they can still describe the main features of a process. It is possible to overcome some inherent machine learning limitations, such as the need for extensive training data, issues of underfitting or overfitting, and slow convergence, by using certain existing model features as references in the machine learning design process and inputting them as additional information. [16, 17]

Machine learning is being used to research and develop new methods for channel coding, synchronization, positioning, and channel estimation in the physical layer of communication systems.

4.1 AI & ML driven Channel Coding

Channel coding is essential to overcome imperfections in wireless channels and rectify errors that may arise during transmission. Recent research has concentrated on turbo coding, which approaches the Shannon limit, as well as channel codes like low-density parity check and polar codes. The focus of recent channel code research has shifted towards enabling fast coding and decoding to support low-latency services while maintaining high-fidelity error correction capabilities. Replacing the channel coding component of the communication network with deep learning necessitates training for code word lengths of at least several hundred bits (assuming a control channel). However, the current output from such training efforts has been limited to the tens of bits.

4.2 AI & ML driven Synchronization

As a consequence, nearly all standards, including

4G Long Term Evolution and 5G New Radio, initiate with system-compliant synchronization. Hence, it is crucial to have synchronization technology that fulfills system requirements for accuracy, even in challenging radio channel environments, high-speed mobile scenarios, and environments with significant carrier frequency offsets. An end-to-end autoencoder based communications system, comprising a transmitter, channel model, synchronization utilizing a synchronization signal as a reference, and receiver, is expected to attain globally optimal performance.

4.3 AI & ML driven Positioning

Presently, mobile positioning technology utilizes mathematical algorithms to accurately determine users' locations in indoor and outdoor settings by analyzing signals acquired throughmobile devices or wireless communication channels. Machine learning techniques, specifically deep neural networks, play a pivotal role in solving this problem. Notably, deep learning technology is at the forefront of location technology advancements, and functional fingerprintmethods stand out for employing deep learning models. These methods can utilize various inputs, such as received signal strength, channel state information, or hybrid information, to facilitate fingerprint-based deep learning approaches.

4.4 AI & ML driven Channel Estimation

Channel estimation plays a crucial role in various communications standards, including LTE and 5G NR, as it provides vital information about how the channel affects the transmitted signal. However, real channels can be unpredictable and non-stationary. Despite these challenges posed by complex channel environments, deep learning-based channel estimation can be enhanced through neural network training. Moreover, it is possible to implement channel estimation and other modules like equalization within a single neural network. This joint optimization of components in traditional communication networks can lead to improvedefficiency.

One promising solution to address this is online training, along with the generation of trainingdata that accurately reflects real-world channel conditions. This approach can help optimize deep learning models for channel estimation and contribute to more reliable and effective communication systems.

4.5 AI & ML driven Beam forming

Intelligent beamforming and smart antenna solutions play a pivotal role in enhancing performance, ensuring stable throughput, minimizing interference susceptibility, extending coverage, enabling highly mobile applications, and reducing physical layer energy consumption. This evolution is already underway in 5G networks and is expected to be furtheraccelerated by 6G communications. In the 6G era, all components of the communication chain will possess a level of intelligence, or at the very least, the capability to operate optimally after undergoing some training.

5. Intelligence system for Optimization in OSI Physical layer

Several optimization challenges exist at the physical layer, encompassing non-convex problems like maximizing throughput through power control, multi-user spectrum optimizationin multi-carrier systems, cognitive radios' spectrum sensing optimization, and the efficient beamforming problem formulated as a sum-rate maximization with a total power constraint, among others. To tackle these issues, heuristic solutions have been proposed for certain physical layer problems, such as beamforming design, to alleviate the substantial computational overhead and latency associated with current iterative algorithms. However, while heuristic approaches offer minimal computational delay, they often compromise on performance [18].

In contrast, deep learning techniques show promise in solving these problems in real time while maintaining high accuracy and reducing computational latency. Consequently, deep learning emerges as a powerful approach for designing, optimizing, and enhancing one or more physical layer functions for 6G networks. Convolutional neural networks are particularly useful for signal classification, while deep neural networks excel in tasks like channel estimation and signal detection.

<table>
<tr><td colspan="3">Advancing AI & ML to make efficient System</td><td rowspan="5">A Platform to scale overall efficiency in Wireless Communication technologies</td></tr>
<tr><td>Efficiency ofPower</td><td>Personalization of the System</td><td>Robust Learning / OnSystem Learning /</td></tr>
<tr><td colspan="3">Learn Insight of the System</td></tr>
<tr><td colspan="3">Understanding the behaviour / Prediction of the System</td></tr>
<tr><td colspan="3">Decision / Intelligent System / Reinforcement Learning</td></tr>
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Figure 3: Framework for Intelligence system for Optimization

The autoencoder paradigm is used in a deep learning-based end-to-end physical layer architecture in the later stages of physical layer optimization with machine learning. In this approach, the receiver and transmitter are jointly optimized in the presence of a specific channel. When building end-to-end physical layer modules, deep learning autoencoders consider designing a communication network as an end-to-end reconstruction optimization task. Without the need for expert knowledge or modules, the autoencoder would jointly learn the transmitter and receiver implementations. Given the difficulty of constructing end-to-end physical layers, deep learning methods can now be used to design, enhance, and optimize any number of physical layer functions for 6G.

5.1 AI & ML Proposal at the OSI physical layer

While the following power for system, cost of system and size or volume are always essential factors in neural network implementation, these factors hold particular significance when deploying machine learning systems in user equipment or at the network's edge. Nevertheless, to attain satisfactory battery life while processing real-time data, a hardware-centric approach is essential. The subsequent sections delineate the three primary stages of development and the expected role of an artificial neural network in each of them. During the computer simulation and prototype phases, training is anticipated to occur. [19].

5.1.1 Computer Simulation

The first step in designing a wireless modem typically involves a software simulation of the physical layer. This simulation employs a channel model to replicate real-world conditions, including disturbances, fading, multipath interference, Doppler spread, and path loss in the air interface. Within this simulation, artificial neural networks can be utilized to implement variouselements of the receiver. Machine learning is integrated into ANNs, allowing flexibility in terms of the number of nodes, layers, connections, activation functions, and back propagation loss functions. During this initial stage, tuning the parameters and features of the ANN becomes necessary, involving trade-offs between performance and computational resources. An essential task during the simulation is to identify the structure and properties of the neural network. In this context, comparing the effectiveness of different activation functions or adjusting the number of nodes per layer highlights the significant computational power required during the simulation stage.

Figure 4: Performance Simulation in Intelligence System

5.1.2 Prototyping with AI & ML Methods

After the simulation, an experimental platform is frequently developed, with a field- programmable circuit array serving as the main processing engine. ANNs can be trained in various scenarios, including different distances, rural and urban environments, varying speeds, and different weather conditions.

5.1.3 AL & ML Driven Product Phase

The inputs and outputs of the ANN must be designed to be readily accessible. Placing the ANN on a separate co-processor can increase the time it takes to transport data off chip, which may exceed the allocated timescale. Consequently, the ANN should be regarded similarly to any other physical layer working block, where data is readily available, and the neural network functions as a component of the processing chain.

6. New Developments in the Future (6G)

Deep learning technology is projected to be employed in wireless transmission within the 6G mobile communications infrastructure over the next decade. This will entail conducting real-world online training as part of the framework's trimming approach to bridge the gap between the capabilities of the learned wireless channel model and the real-life wireless channel environment. Specifically, our forecast examines the impact and uncertainty of deep learning-driven physical layer techniques.

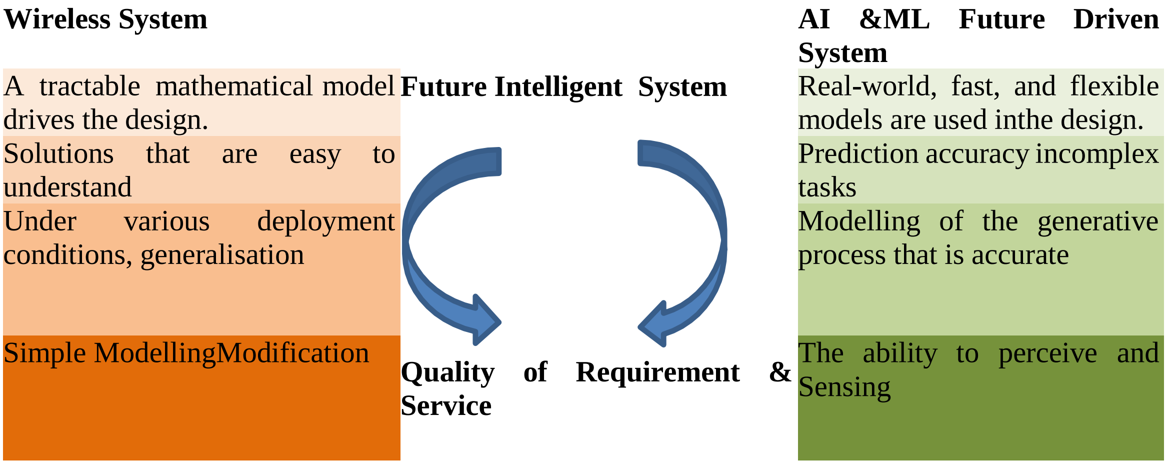

Figure 5: Bringing AI and Machine Learning Research to Wireless Communication

Synchronization is performed by conducting a correlation that is longer than the duration of the synchronization signal for a given wireless channel. This is because the correlation is less affected by environmental irregularities when it is longer. Next, we present a framework for the future of deep learning-driven physical layer technology. One approach is multi-offline training and adaptation, which involves conducting offline learning on multiple channel models beforehand, uploading them to the system, and monitoring real-world radio channel features to apply the necessary offline learning. Another approach is single offline learning and online learning, which entails identifying the performance sensitivity of each radio transmit characteristic factor, applying offline training to the actual system based on the least sensitive factors, and employing online learning to adapt to the operational radio channel-related physical characteristics. Although MOLA may require considerable time due to the extensive databases and memory requirements, it is expected to succeed in certain wireless channel conditions. On the other hand, SOLO is anticipated to be used semi-optimally in radio channel conditions not governed by MOLA. However, it is essential to note that if SOLO can match MOLA in terms of both performance and implementation, the latter will ultimately be chosen[20].

7. AI & ML Proposal for the OSI (MAC) Medium Access Control Layer

Within a cellular network, the medium access control layer is responsible for overseeing various tasks, including user selection, user pairing for MIMO systems, resource allocation, encoding and coding scheme selection, uplink power control, random access, and handover control. To achieve significant benefits in real-world scenarios, machine learning (ML) technologies must be used to dramatically improve the MAC scheduler. While there are no perfect solutions, careful consideration must be given to how to train the AI & ML models for this particular problems.

7.1 Collaborative Learning in future wireless network

We propose a promising and innovative application of collaborative learning to address the challenges of wireless communication. This approach aims to minimize disruptions in the user's sense of presence that can cause virtual reality users to disconnect from their virtual surroundings. The model considers a cluster of base stations catering to a group of wireless VR users, facilitating both uplink and downlink communication. The uplink is utilized for data transfer tracking, while the downlink is responsible for transmitting VR images. VR users can access both mmWave and sub-6 GHz frequencies, with the sub-6 GHz band being employed for data transfer tracking and the mmWave band utilized for VR image transmission.

7.2 Proactive allocation of resources

The majority of IoT applications involve fixed or low-mobility devices, and the traffic generated by such IoT devices typically follows predictable patterns. To cater to these scenarios, the "fast uplink grant" enables ML-based anticipatory resource allocation.

7.3 Proactive management of power

Energy efficiency is a crucial consideration in wireless network design. The need for long-lasting batteries in Internet of Things (IoT) devices drives research into energy-saving solutions for future 6G networks, in response to both environmental concerns and practical demands. Energy conservation can be implemented at various system levels, with direct radio control consuming the most power, making it most effective at the medium access control (MAC) layer. Therefore, the application of machine learning (ML) algorithms to predict traffic and prioritize packets can significantly enhance the performance of adaptive power-saving systems. ML based algorithms can analyse cell-level traces from real networks to create models based on predicted traffic patterns, contextual data for different cells, and appropriate load metrics. These models learn from surrounding interfering user's behaviour and adapt their sleep schedules and transmit power accordingly. Moreover, these models can dynamically switch base stations (BSs) on and off to conserve energy at higher levels. Asymmetric data transmission is common in wireless networks, where time division duplexing (TDD) and frequency division duplexing (FDD) are the main duplexing methods. Addressing asymmetric traffic in TDD systems is straightforward and can be controlled based on downlink and uplink traffic loads. ML techniques offer a solution to these challenges by seamlessly integrating data traces collected from cells, enabling proactive medium access control (MAC) functions instead of traditional reactive ones. As ML algorithms are driven by traffic and network activity patterns, they can proactively guide such strategies, leading to improved system performance.[22].

8. AI & ML in Wireless Communications for High Level security

Machine learning will play a vital role in ensuring the safety and security of future wireless communications systems. In the context of 6G, ML based security measures require a comprehensive evaluation from an end-to-end network perspective. Currently, ML is applied in various services, network components, and networked nodes. One critical aspect is intelligent spectrum sharing, where secure sharing of spectrum information among peers competing for the same frequency slot is essential. ML can help validate the legitimacy of competing peers, enabling secure information sharing [23].

Given the wireless medium's inherent openness, it becomes susceptible to interference, whether intentional or unintentional. Defensive techniques, such as cryptography, are used to protect against interference. On the other hand, offensive mechanisms involve proactive attacks like jamming or eavesdropping, aiming to safeguard future transmissions and identify system weaknesses while undermining adversaries' capabilities. Creating real-time ML models that learn the environment and prevent adversary interference is crucial in defensive strategies, establishing a communication network resistant to attacks.

9. AI & ML in OSI Application Layer

Machine learning algorithms integrated into wireless communications nodes at the lower layers have the potential to enhance stability, reliability, data rates, latency, spectrum efficiency, and energy conservation. Integrating ML solutions at the transport or application layers, along with sensor fusion and ML-as-a-service, can further improve capability sharing, remote control, unified connectivity, and services. Context-aware applications can be developed using ML without the need for predefined context rules or elements. Such applications can deliver proactive services by leveraging multiple learning algorithms within a smart and dynamic functional domain.

By making ML available as a hosted service on mobile communications nodes, the flexibility and power of communication networks can be significantly increased. Four key trends are contributing to the increased accessibility of ML: (1) greater processing power, (2) lower data storage and processing costs, (3) increased data availability, and (4) improved methods, including cloud-based deep learning solutions. Additionally, hybrid cloud and fog computing are expected to further expand this accessibility by offering ML as a service to consumers and applications in the application layer of wireless communications nodes. Furthermore, edge computing plays a crucial role as another key component essential in 6G systems. [24].

9.1 Automation of 6G network performance using AI & ML

A novel approach is necessary to revolutionize the management and operation of radio access networks (RANs). Some key benefits of this approach include:

- Integrating machine learning into baseband operations.
- Implementing a virtualized container-based RAN compute architecture.
- Co-locating containers alongside mobile edge computing servers.

In 6G networks, real-time data from user equipment measurement reports can be utilized for ML modelling, enabling improvements in accessibility, availability, mobility, and traffic performance. This advancement will lead to enhanced and automated network performance management, maintaining key performance indicators within predefined levels. Machine learning will further automate the management of dynamic mobile networks in 6G, introducingsmart adaptive cells. This automation can bring significant benefits across various aspects, including coverage, throughput, and quality of service prediction, autonomous network configuration, power control, operation, maintenance, fault management, power savings, and beam management.

9.2 AI & ML driven Unmanned Aerial Vehicles

The control of unmanned aerial vehicles (UAVs) necessitates ensuring stability, which can only be achieved if wireless communications meet specific standards of ultra-reliability and low latency. In the initial use case, a single UAV is guided to its destination by a ground controller. The UAV's state, including velocity and distance to the destination at each time instant, is downloaded to the controller during each control cycle. Subsequently, the controller utilizes an artificial neural network to determine the optimal action (acceleration), which is then uploaded (UL) to the UAV within a given deadline. For every autonomous UAV, a pair of ANNs is utilized. The first ANN is used to acquire mean-field approximations of other UAVs' states. The second ANN, known as the action ANN, calculates the UAV's optimal action. When the distance between pairs of UAVs becomes small or their relative speed increases significantly, the action ANN is activated to limit the chances of collision. This control mechanism's stability is guaranteed even when the UAVs' starting states are modified. Additionally, this ANN-based control approach has the potential to reduce transmission powerconsumption.

9.3 Automobile systems, spontaneous data transfer

As 6G networks and connected and automated vehicles (CAVs) advance, they will collaboratively enhance traffic safety and efficiency. Leveraging the diverse sensing capabilities of CAVs, they will function as moving sensor nodes, covering extensive areas and delivering highly precise measurements. By utilizing crowd sensing-enabled services, such as the distributed creation of high-definition environment maps, CAVs will be able to elevate theirsituational awareness significantly. However, data transfer in automotive networks presents challenges due to various external and environment-specific factors influencing channel dynamics. Vehicle communication systems must cope with high speeds on highways and irregular line-of-sight conditions in cities. This leads to frequent encounters with low- connectivity areas, where link loss and packet errors are common, necessitating retransmissions. Despite these challenges, the combined efforts of 6G networks and CAVs promise to foster remarkable advancements in traffic safety and efficiency.

9.4 Aspects of building software

Engineering research for machine learning solutions in wireless communications must also encompass implementation considerations. As the wireless system software development trend leans more towards ML-based methods, the primary challenge lies in the engineering paradigm shift. Moving from deterministic, traditional requirements-driven tasks and procedures, the focus now shifts to data-driven monitoring, data extraction, learning, and cycle prediction in system and service development. A crucial initial step involves evaluating the adaptation of existing engineering tools, methodologies, and procedures to accommodate the aforementioned ML-driven development loop. This assessment will offer valuable insights into the scale of evolution and investment required across various industry sectors. [25].

10. Conclusion

Artificial intelligence (AI) and machine learning (ML) are considered crucial catalysts for advancing the capabilities of enhanced mobile broadband, massive machine-type communications, and ultra-reliable low-latency communication in 5G, elevating them to a more powerful and intelligent level. This article delves into various methods that utilize AI and ML tools to optimize 6G networking and resource management. We demonstrate ground- breaking intelligent terahertz approaches, such as AI and ML enabled THz channel estimationand spectrum management, to achieve ultra-broadband transmission. Additionally, we explore AI and ML applications in energy management, particularly for large-scale resource-harvesting networks. Furthermore, we investigate AI and ML based security augmentation strategies, including authentication, access control, and attack detection, for super IoT systems. These energy and security intelligence solutions contribute to efficient and reliable ultra-massive access. In addition, we present efficient mobility and changeover management algorithms based on deep reinforcement learning, deep learning, and

Q-learning. These algorithms are designed to establish ultra-reliable and stable transmission connections while accommodating the high dynamics of 6G. Lastly, we explore adaptive resource allocation solutions, encompassing traffic, storage, and computing offloading methods, to fulfill the ultra-reliability and low latency requirements of 6G services. As discussed in this article, AI and ML enabled techniques have the potential to enable future 6G networks to learn from uncertain and dynamic environments, intelligently and automatically adapt to unpredictable changes, and significantly enhance performance in areas like ultra-broadband, ultra-massive access, ultra-reliability, and low latency. However, challenges remain to implement comprehensive and mature AI and ML applications in 6G. These algorithms, with their complexity and computation demands, need to be made more practical for implementation, especially on contemporary computer systems with limited power, memory, storage, and processing capabilities. Additionally, diverse application scenarios and emerging AI and ML methodologies may pose challenges to the adoption of intelligent technologies in 6G.

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