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# A Roadmap for AI-Enabled System Design for 5G, 6G, And Beyond Communication: Issues And Challenges

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***Abstract*— The advancement of communication technologies has led to the development of 5G networks, with 6G and beyond already on the horizon. These advanced networks offer faster data rates and lower latency, which require new system design approaches to fully harness their potential. The integration of artificial intelligence (AI) into system design is crucial for realizing the full potential of these networks. However, the integration of AI brings a new set of challenges and issues that need to be addressed. This research paper presents a roadmap for AI-enabled system design for 5G, 6G, and beyond communication networks. The paper identifies the challenges and issues associated with the integration of AI into communication networks and proposes a systematic approach to overcome them. The proposed roadmap includes four stages: system modeling, data management, AI algorithm selection, and hardware implementation. The paper discusses the challenges and issues associated with each stage and provides possible solutions. The proposed roadmap can guide researchers and practitioners in the development of AI-enabled communication networks, providing a foundation for the design of the next generation of communication systems.**

***Keywords*— *Artificial Intelligence, Machine Learning, 5G, B5G Network, Wireless Communication***

## I. INTRODUCTION

In The need for wireless networking system is rising globally, mostly because of the expanding number of wireless users and newly developed wireless services. In the future, it is anticipated that 5th gen (5G) &even apart from5th gen (B5G) wire-free systems will be created. These networks will provide greater data speed, better extension, low expanses, better resource usage, protection, versatility, and expandability [1]. In the construction &maximization of 5G& B5G wire-free systems, unpredictable and seemingly unsolvable challenges involving massive volumes of data must be addressed.

AI, according to definition, is "the simulation of human intelligence processes by machines, especially computer systems"[2]. The knowledge of having supercomputers execute jobs that need cleverness on par with humans is how it is typically characterized. While artificial intelligence (AI) is a more general approach of robots equipped to perform operation intelligently. By learning from vast amounts of data, machine learning is the currently prevalent (and well-known) feature of artificial intelligence. Deep learning, a specific sub-group of machine learning (ML), examines artificial neural networks (ANNs) with multiple hidden layers that "stimuli" the brain cells. Deep learning being known the most general ML techniques right now since it has been effectively used in a variability of productions, counting bioinformatics, computer vision, and speech recognition.

By building real-time reliable decisions designed to operate on predictions of the behaviour of the networks and subscribers, AI advancement won't just decrease or it will in fact eventually outshine human operations for system building, pattern, and control, but they will even improve connectivity system responsiveness, flexibility, and operation of the system. It is commonly anticipated that ML, a typical AI technology, will quickly establish itself as a crucial element of B5G communication networks. In order to overcome the difficulties of planning and running B5G networks, it will fully utilize big data. The following are potential advantages of ML integration in communication systems. First, because cellular connectivity mediums are fluid, especially in B5G situations, route & interfering designs are exceedingly difficult to implement in practice. By studying communication data and existing knowledge, machine learning techniques can automatically extract information from unknown channels. Second, with an abject requirement for the worldwide maximization of connectivity requirements & fine-compatibility of network programs as the density of wireless access points keeps rising. However, these jobs are extremely challenging to complete using current methods due to the vast amounts of assets, the network characteristics that must be maximized, & its associated interrelations. The very nonlinear interactions, however, may be modelled and the (sub-)optimal system parameters may be estimated by more modern machine learning methods (for example deep learning & conditional learning approaches). Finally, ML will learning-dependent adaptive system configuration that recognizes behavioural trends as well as adapts quickly & dynamically in various situations, they are unable to keep up with the information overload while ensuring the necessary capacity, reliability, and adaptability.

And the basic complexion of the created information. As a result, the network is unable to immediately respond to or foresee events that could degrade communication capabilities in real time. It is challenging to distinctly deploy current AI methods to B5G systems, nevertheless, since most artificial intelligence (AI) applications and technologies weren't developed expressly for wireless networking systems.

This research paper, in contrast to exploring the benefits of integrating AI technology with B5G wireless connections is the focus of previous assessment articles like [3], taking advantage of the capability of AI methods to take on difficulties which can't be resolved by having mainstream network systems. As seen in Figure 1, this research paper emphasis on 5 elements that integrate AI methods into B5G wire-free systems. The rest of the article is set up in the following manner as a result. We go over medium measures, modelling, & prediction for B5G networking by means of AI methods in the part that follows. Then, using AI technology, we look at research on real layers for B5G systems. A review of network management and optimization for 5G networks is then presented utilizing AI technology. Following that, applications of AI for B5G networks are given. Next, we provide a brief review of recent developments in machine learning and AI for 5G networks. In the summary, conclusions are taken, and potential problems are explored.

## II. B5G NETWORK

Considering the diversity of B5G wireless networking topologies and the use of regularity groups such as sub-6 GHz, terahertz (THz), and visual groups, circuit simulation has become increasingly challenging. In order to satisfy B5G channel modelling requirements, prior medium designs have been enhanced with much larger processing capacities. Understanding channel properties and modeling for new conditions requires channel measurements.

There aren't many studies that look at the advantages of using AI in channel modelling, and the majority of extant works only use very basic AI approaches on a relatively small portion of the channel modelling process, with the exception of a recent study. The use of AI technology for channel measurements has not been thoroughly studied in any paper. Because of the high difficulty of simulating the signal transmission under a variety of conditions, traditional approaches use a lot of computation. The vast amount of measurement data currently available can be used to extract wireless channel properties, & with concurrent time, the medium modelling issue can be handled using data-driven approaches that easily integrate with model-based techniques. Computation precision-complexion trade-off& modelling methods will be kept in a fair balance.


Fig. 1. A framework for AI technologies to B5G wireless networks [4].

Constructed on frequency amount information and environmental data, ML can be used for scenarios arrangement, multipath component clustering, channel statistical inference, and channel characteristics prediction.

Using feedforward nervous networks (FNNs) and radial basis function neural networks (RBF-NNs), the authors of [5] proposed a huge data-enabled channel model. The system can predict input specifications, Tx-Rx lengths, and carrier frequencies (ASs) based on transmitter and receiver coordinates to provide input specifications, delay spread (DS), root mean square (RMS) and root mean angle spreads (ASs) angle spread (RS). Performance of FNN and RBF-NN was carefully examined utilising both simulated and actual channel measurement data. The measured, predicted, and RMS DS path loss are depicted in Figure 2. FNN and RBF-NN can both be used to model channels. The channel's CIR was modeled using principal component analysis (PCA) in [6], and noise was removed from the measured CIR using artificial neural networks (ANN). A number of clustering strategies were explored in [7] for noise-laden applications grouping and monitoring, including fuzzy C-means (FCM), K-means, fuzzy C-means (FCM), and concentration-dependent spatial grouping. Based on a variety of wireless channels, a convolutional neural network was performed to used in [8] to automatically detect the relevant radiocommunication channel characteristics. CNN generated the group of wireless networks using the recovered MPC characteristics as input parameters, including amplitude, latency, and Doppler frequency.

## III. ESTIMATION OF CHANNEL

Blind and pilot-dependent channel estimate approaches can be used to obtain the channel state information (CSI) in wireless communications.

Fig. 2. (a) Path Loss Was Evaluated and Forecasted, (b) RMS DS Calculated and Projected [9]

Barriers in channel estimation include, among others. For huge multiple-input multiple-output (MIMO) mediums & extremely complex system, the pilot overhead may be unacceptable (UDNs). Therefore, it is important to weigh the compromise among channel estimate & pilot duration precision. Accurate CSI is challenging to get because to the nonlinear features of the mm Wave route and the visible range transmission (VRT) line. Accurate channel assessment is also necessary to provide quality of service (QoS) and effective information transmission as high-speed trains (HSRs) increase.

To address the aforementioned issues, researchers use ML approaches according to research, a 2D nonlinear complicated gradient boosting analysis of fast fading time-varying multiple path channels was used to address the issue of channel estimation. For beam space mm Wave large MIMO systems, a deep-learning-based channel evaluate was put forth in [10]. From a huge quantity of training data, it can learn the channel topology and estimate the channel. For mm Wave massive MIMO uplink, estimating a patchy off-grid route using Bayes learning approach was put out in [11]. By taking advantage of the spatially sparse structure in mm Wave channels, it can determine the inclination & make of the dispersing routes. The normalized ML-dependent medium analysis approach for this subject, which can be applied immediately in various contexts without additional training, is one direction for the future. Machine/deep learning algorithms must employ a sizable amount of previously gathered communication data to understand the channel feature of various environments in order to construct this generalized scheme.

## IV. Research At The Physical-Layer

### A. Using AI technologies, 5G networks use large-scale sensing via massive radio interfaces

Massive MIMO, which makes use of gigantic antenna arrays, delivers not just previously unheard-of reliability and high-rate communications performance, but also colossal volumes of baseband-level data which should be utilized to draw conclusions regarding the nature. Inference problems, such as the identification of the existence of motional entity, assessment of the volume of hustle & rush on the path, calculating quantity of people present in the closed area, and protection from invasion in secured places, are further interesting emergent application cases. Sensing of open environments, interior venues, & indeed via walls are specific technical problems that can be overcome. There are several utilization in protection, security coverage, &controlling and looking after as well as rising commercial use cases. Since parametric models are frequently either unavailable or wrong, traditional estimation/detection methods cannot be used to analyses the enormous volumes of data provided by big antenna arrays, including gigantic MIMO arrays. The most interesting methods might be found in deep learning networks and visual & picture processing, which are based on algorithmic techniques. With conventional radar imaging, the goal is to draw inferences about particular events by analyzing the movements of the environment. This technique extracts key elements from the movements of the environment. It is the objective of conventional radar imaging to generate an copy or plot of the surroundings.

The development of an appropriate physical model and relevant physical modelling studies should be important future research objectives.

In this context, trained deep neural networks are a key technological element, but different approaches to dictionary learning may also be applied. Real data gathered from experiments should be used for evaluation, coupled with simulated channel models. The current state of the art in available area, interior, and behind the wall monitoring allows these methods to greatly enhance the detection of problems which are not possible with conventional prototype signals. Furthermore, the technology may be used to identify gestures, particularly when high frequencies are used.

### B. Signal Processing

The 5G communication networks have incorporated giant MIMO technologies. It is one of the most straightforward applications of AI. Giant MIMO can generate a lot of data despite its many benefits, including spectrum efficiency, energy efficiency, protection, and durability. A massive MIMO system, for instance, with 3256 antennas and 100 MHz of bandwidth, may produce more data than 30 GB in channel assessments. Both detection and channel estimates are often time-consuming processes for large-scale MIMO systems that need a lot of processing power.

In [12], massive MIMO systems are represented using giant random matrices and subjected to a single ring law analysis of their enormous data. Pilot contamination has a significant impact on how well massive MIMO systems perform. It is possible for systems to receive incorrect CSI data when pilot contamination occurs between close cells. As the amount of projections rises, stations in beam space become relatively sparse, which implies that the majority of the MPC control comes from a rare routes that have grouped together in the space and the network atmosphere comprises only a few non-zero components [13]. By calculating the CSI of huge MIMO structures consuming the beam space channel sparsity attribute, the authors use a sparse Bayesian learning technique. As compared to traditional CSI estimators, Bayesian learning can achieve superior results in pilot examinations. The sparse retrieval challenge is an important aspect of Bayesian comprehensive sensing. For the estimation of a non-negative squeezable direction based on a collection of noiseless measurements, a collection of soundless dimensions must be collected.

## V. Localization Of Wireless Networks Based On Data

For context awareness, site-dependent network management, and other services, wireless positioning systems must be able to estimate positions based on channel information and fingerprints. Channel information must be updated frequently in order to accurately reflect the underlying channel characteristics due to the energetic and time-varying nature of communication obstructions [14]. Regular and continuous preservation of large-scale B5G networks requires considerable time and effort. Due to the explosion of communication and sensing data in B5G systems, machine learning algorithms can be used to place devices and users using data-driven localization. Data-driven clustering algorithms will evolve over time and adjust automatically to transmission obstacles in dynamic systems. By crowdsourcing massive amounts of information from a large quantity of portable systems, wireless channel positions can be endlessly restructured and enhanced [15]. Uutilizing AI-based B5 network optimization strategies, including model-based and data-driven UDNS optimization, location-based services will be improved due to the precise localization findings. The method of administration and optimization of cellular systems utilizes "models" that address all aspects of network functionality, including physical architecture and network technology infrastructure. For the future design of networks, which will be built on numerous and different radio access technologies, distributed fairly densely, and required to a variety of submissions and demands, this method is not sufficient. Constructed on "models" that individual partially mimic real system installations, a complex network ecosystem cannot be effectively built or operated. A model is the basis of both the physical level architecture as well as the network technology infrastructure in the current approach to managing and optimizing cellular networks. As a result, it is inadequate for the project of systems that drive be used in the future, which drive be constructed using a variety of wireless admission skills, dispersed rather closely, and required to support a broad array of applications. A complex network ecosystem cannot be properly developed and controlled based on "models" that only loosely mirror real network installations and are incorrect. As an example, consider the deployment of unmanned aerial vehicles (UAVs) in an on-demand network for disaster recovery and rescue missions. When deploying such a network, it is impossible to trust on reproductions that organize even occur for the definite circumstances at hand [16]. Consequently, future networks must be planned and optimized radically in light of these assumptions. Future networks will be required to exceed the concept of network design models and utilize a wealth of "data" available at their disposal in order to satisfy a variety of needs. For the design of effective B5G networks, a paradigm shift is required to yield gain of big data analytics, increase situational responsiveness, and improve complete system performance by utilizing artificial intelligence and machine learning. As a result of artificial intelligence, a complete functioning picture of the vast sum of systems in the link can be obtained from vast sums of information gathered from various foundations, such as radiocommunication network assessments, sensor readings, drones, and surveillance images gathered from various sources. As well as defect monitoring and user tracking, it can also be used to optimize wireless network functions. Since AI-based resource management systems are constantly learning about the wireless environment and the users on the network, they can be operated entirely online. By implementing these procedures, network decision-making becomes increasingly complex and dynamic as time passes. We consider the improvement of a typical tipping point-oriented decoder for Poisson routes, which can be used also in molecular & photonic networking systems, which are typically challenging to build due to the availability of cross intervention, to enhance the prospect of using ANNs in networking system design [17]. Based on the standard networking approach, the adaptable demodulation threshold is determined by minimising the exact solutions to the error probability incorporating the ISI. Accordingly, the information-based approach assumes that the channel type is unknown, and determines the best demodulator based on ANNs, resulting in the effective demodulation tipping point without prior notification [18-20]. An ANN is programmed using a learning algorithm under supervision when using a data-driven approach. Through the Bayesian regularization back propagation method and the Levenberg-Marquardt optimization strategy, the weights and inclinations of the neural network are altered. Soft computing techniques have also been applied to power sector optimization. Figure 3 illustrates the appropriate demodulation threshold for varying signal-to-noise ratios at modest and substantial ISI values.

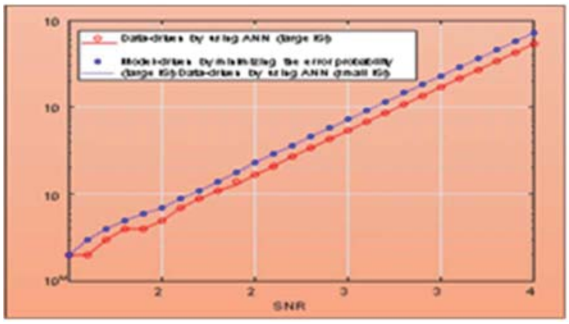


Fig. 3. Maximum Demodulations Point of Threshold for Lower and Higher ISI Values [19]

In both instances, we observe that a data-driven method offers the similar demodulation threshold-point and, as a result, the similar error probability by forgoing the requirement that the system developer have complete knowledge of the network/medium structure.

## VI. WIRELESS NETWORKING

The basic networking technologies underpinning the 5G PUBLIC-PRIVATE-PROJECT (5G PPP) paradigm of software/programmable networking, network function virtualization (NFV) and software defined networking (SDN), have begun to attract industry interest for their increasing sophistication. Network slicing is a revolutionary concept that 5G mobile systems have pushed for with the development of SDN and NFV (NS). Providers may utilise NS to cleverly build custom connection pipes in order to give the best pathway for distinct services that require a range of capabilities, evaluation metrics, and separation criteria. This is done in place of building separate networks for various services. In particular, edge caching, mobile edge computing, and similar technologies may have developed to take the role of its forwarding-only capability to a location having the capacity for computing, storage, &memory. In order to provide applications that meet such a wide range of needs like optimized mobile broadband (oMBB), that requires extra capabilities like hyper-dependable and low-latency communications (hDLLC) as well as enormous computer driven connectivity, that consume bandwidth and drive throughput, it is essential to enable future cellular structures with NS (mMTC). [21-28] The response principle, that quietly reacts to receiving requirements & delivers it on request, is the foundation upon which systems of today, including 5G technology, are designed, constructed, and maximized. Future networks will need to deliver additional service capabilities, and this approach is insufficient. Upcoming systems are going to be those defined by diverse software. Despite of various applications are smartly done separately, it's information traffic is eventually combined, creating a highly dynamic and unmanageable situation. Additionally, the demands for various applications for future networks can't be met by the present response concept. For instance, uRLLC applications might not be able to accommodate the delay brought on by this response principle. Future networks, on the other hand, require the ability to forecast the future so they may distribute system resources responsibly. System designs with NS can anticipate traffic styles and identify future off-peak periods on dissimilar spectrum bands in a proactive manner as opposed to silently receiving and fulfilling requests as they come in. This allows coming traffic requirements to be appropriately distributed over a specified time line. By anticipating user behaviour, we can better utilize network resources and allot edge-to-edge network portions in a web linked environment. Only with the assistance of Ml and AI approaches will this paradigm change from responsive to responsible network architecture be made achievable.

## VII. ML ALGORITHMS FORB5GNETWORKS

Modern communications applications often conduct signal processing and ML algorithms directly. The cloud radio access network (C-RAN), which performs combined computation &information management for all network systems at a centralized controller, is an example of an archetypal architecture (e.g., the cloud). However, different network operations must be carried out privately or with little data traded to cloud when there are a lot of systems and connectivity restrictions through the fronthaul/backhaul links. The provision of a distributed operational design that adjusts flexibly to network needs is therefore crucial. A compact deep learning approach can be used with cloud, fog, and edge computing networks, as demonstrated in Figure 4. The edge network houses a huge number of end users and devices, whereas the cloud network houses all of the information& compute. The cloud networking has numerous nodes. Hence a demand for distributed categorization, data computational,

& learning models that smoothly adapt to the quantity and variety of input sources while taking into account the available communication bandwidth exists concurrently. The benefits of centralized and decentralized algorithms should be blended balancing off intricacy, speed, & dependability in the context of a variable edge computing model. For this, techniques for encryption and decentralized judgement call need to be enhanced and combined for information fusion.

Additionally, in the dispersed environment, it is necessary to create tools that can recognize linkages between the network parameters and its time development. Scalable methods are needed, given that dynamic, like approximate message passing, in connection with Bayesian procedures.

There are two ways to increase the pace of ML training. One involves the hardware implementation of ML algorithms, which should lead to minimal energy usage & good effectiveness. The alternative is to simplify ML algorithms while maintaining a respectable level of accuracy.

## VIII. Adaptible Integrated Lightweight Systems Program

Present machine learning (ML) techniques mostly concentrate on machine goal, computational linguistics, and robotics using strong real-time graphics processing units (GPUs) or central processing units (CPUs). However, resource-constrained devices, such integrated and Internet of Things (IoT) systems, are commonplace in communication networks. Therefore, ML algorithms for communications should work effectively with embedded devices have few data storage, compute capacity, and energy resources in addition to learning complicated systems, users, & gadgets are all supported by predictive methods. Creating lightweight machine learning algorithms, particularly frameworks for deep learning with integrated devices is difficult but very rewarding. Combining ML with structures for parallel programming including cloud & edge computing is one promising route in this area. The examination of a high-level ML development toolset is another significant research area.

## IX. Ml/Ai Tob 5g Systems

Though it is still in its early stages, the integration of Artificial Intelligence/Machine learning & communication system is moving forward quickly. Standardizing ML algorithms for B5G networks is incredibly challenging since the numerous transducers, systems, programs, &networks linked to this webis going to develop data in a wide range of forms &figures that must be communicated. There is no set baseline or standard ML algorithm, & uncertain to the entire transmission field that kind of ML programs work best for B5G networks.

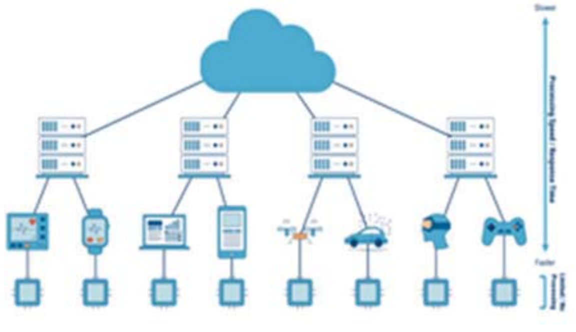

Fig. 4. Deep Learning Application in Different Computing Systems [20]

Research Team 13 at their meet from November 6th–17th in Geneva. In addition to gateways, network infrastructure, methods, algorithms, and data structures, the participant observation also will develop index for evaluation and technical studies for machine learning for next systems. Data formats, machine learning (ML) methods, parameters, application cases, & an ML-acquainted system infrastructure are the three working groups. On 22 March 2018, the 3GPP evaluation index committee developed an ML function that can be used by 5G operators to track the performance of a particular portion or outside program. The network data analytics function The 3GPP's 5G standardization activities include the network data analytics function (NWDAF), which has the potential to become the hub to analyse through the prime 5G system. Despite being in the early phases of standardization, the NWDAF may turn out to be a stimulating environment for innovation. It's being suggested that the idea of "smart-5G" & held which in order to effectively increase both the two spectrum utilization &power efficiency, enhances customers involvement, & lower costs, the 5G network needed to adopt new and next generation advance technologies like wireless big data and AI. TIP established the "AI and Integrated Machine Learning" group project.

## X. Conclusions

In conclusion, this research paper provides a roadmap for AI-enabled system design for 5G, 6G, and beyond communication networks. The integration of AI into system design is essential for fully exploiting the potential of these networks. However, this integration presents new challenges and issues that must be addressed. The proposed roadmap provides a systematic approach to overcome these challenges and issues. The roadmap comprises four stages, including system modeling, data management, AI algorithm selection, and hardware implementation. Each stage is discussed in detail, highlighting the associated challenges and issues, and providing possible solutions. The proposed roadmap can guide researchers and practitioners in the development of AI-enabled communication networks. The successful implementation of this roadmap can lead to the design of the next generation of communication systems, which will have higher efficiency, faster data rates, and lower latency. The development of these advanced networks will revolutionize the communication industry and bring about a new era of connectivity. Overall, the proposed roadmap is a step towards realizing the full potential of AI-enabled communication networks.

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