Design and Implementation of AI-Based Signal Processing for 6G Wireless Systems

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ABSTRACT

As sixth-generation (6G) wireless networks are introduced, global data transfer rates will hugely improve, latency will be extremely low, more devices can be connected and networks will become more intelligent. Still, the large scale, changing settings and good performance needs of 6G make it hard for old signal processing methods to work well. To address these issues, this paper introduces a new artificial intelligence (AI) signal processing approach developed for 6G systems. With this framework, deep learning (DL) and reinforcement learning (RL) methods are combined with traditional signal processing to make operations on both physical and higher levels of the network more intelligent and flexible. Modern deep learning techniques are used for channel measurement, figure out the modulation and identify signals which results in more reliable detection of features and patterns in different channel situations. Similarly, reinforcement learning models help in managing how resources are shared, how power is set and how interference can be managed in real time which results in improved use of the wireless spectrum and durability of the system. Using both computer algorithms and known techniques, the integration in AI allows the system to adapt to changes in the environment and resist any uncertainties that may affect signals. Diverse tests are performed on the model to predict how it might adapt in dense 6G systems, highly mobile conditions and a wide range of usage requirements. It is clear that spectral efficiency has increased, there are fewer bit errors, energy efficiency has improved and the system is more flexible compared to other techniques. Also, the framework can grow in limited parts and matches new 6G technologies such as terahertz communications, intelligent reflecting surfaces and massive MIMO. With AI integrated into signal processing in the next-generation networks, researchers lay the foundation for 6G systems to respond well to the strict conditions and requirements coming in the future wireless world.

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1. INTRODUCTION

During the past few decades, wireless communication has changed a lot, starting with 1G that focused on voice and now leading to today’s advanced 5G networks that handle a lot of data over short time periods [1,2]. Each time, a new generation of users and applications has technology introduce new improvements. Transitioning to the sixth generation of communication networks or 6G, means that the systems involved will transform their approach to working with users, devices and with the environment, in addition to their speed and connectivity [3]. They are important to make possible new developments like instant holographic conversations, tactile internet, intelligent automation, autonomous vehicles, braincomputer links and Internet of Everything that is everywhere [4]. Key features and challenges of 6G wireless communication systems is depicted in Figure 1.

But reaching such ambitious aims creates fresh and unexpected technical problems. Using millimeter-wave (mmWave) and sub-terahertz (sub-THz) bands calls for new equipment and models to describe signal travel. The system architecture must also be very flexible to handle massive MIMO, reconfigurable intelligent surfaces (RIS), highly dense networks, situations involving many moving users and constraints on energy [5]. Normally, signal processing methods that use linearity, stationary noise and CSI are not very effective in these types of environments. Because of this, they cannot adapt, generalize or scale to manage real-time changes in these systems. Also, when networks have many connections and services, traditional algorithms spend more power and effort to execute [6].

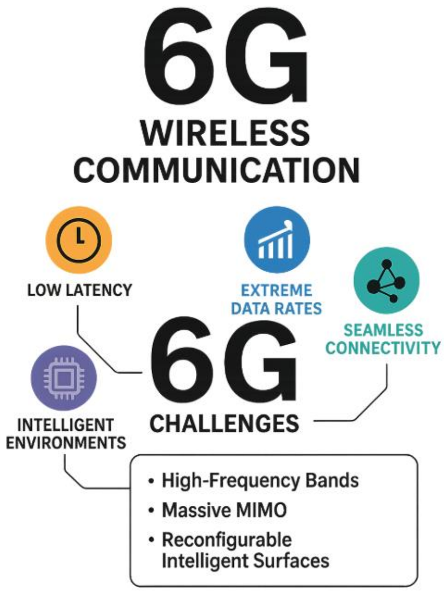

Figure 1. Key Features and Challenges of 6G Wireless Communication Systems

As a result of these constraints, Artificial Intelligence (AI) now plays a major role in enabling the next generation of wireless networks. AI, especially by using deep learning (DL) and reinforcement learning (RL), can recognize complex details, respond to new scenarios and make clever choices instantaneously. Because DL models can learn relationships among data, they can extract features and estimate channels, classify signals and filter noise directly in raw data instead of relying on complex mathematical models [7]. RL also helps with finding the best solutions in resource allocation, power control, beamforming and reducing interference.

The paper suggests an AI-supported signal processing framework that is made specifically for 6G wireless networks. DL and RL techniques are introduced into the traditional signal processing chain through the framework to build a hybrid intelligent communication system. Since learning is applied at several points in the architecture, the framework seeks to maximize things like the amount of data transferred, reliability, energy use and latency. Also, the model is built to grow and change with various 6G applications and designs. Most of the simulations confirm that this framework is more effective than traditional methods when things are dynamic and complex. Using this work, we can see that AI is key to the progress and fulfillment of what 6G aims to achieve.

2. LITERATURE REVIEW

5G networks have changed greatly because Artificial Intelligence (AI) has been introduced into wireless communication systems. Because conventional signal processing cannot handle the extra demands of contemporary communication, AI provides data-based, adjustable and scalable solutions. Many studies have examined the benefits of using deep learning (DL) on a range of physical and data connectivity tasks. For example, using convolutional neural networks (CNNs), [8] achieved better BER results than the well-known Least Squares (LS) and Minimum Mean Square Error (MMSE) methods when channel estimation was required in massive MIMO systems. Additionally, deep neural networks (DNNs) have achieved good results in noise reduction, detecting signals and classifying modulation types, mainly when the channel is non-linear and dynamic. They can help to find important features from the raw data, making the signal interpretation much more accurate.

Along with supervised learning, reinforcement learning (RL) is becoming popular because it can support fast decisions in rapidly changing wireless environments. RL-based systems have been tested for managing energy usage, how the spectrum is used, changing beam direction and handing over messages when a user moves. For example, [9] introduced a model based on RL that enhanced the way power is used and ensured better communication in dynamic networks. Deep Q-Networks (DQNs), policy gradient methods and actor-critic frameworks are used to help optimize strategies for sharing resources and reducing interference in dense, heterogeneous wireless networks.

Some studies have addressed data privacy and scaling issues by looking into federated learning (FL), a method where edge devices join forces to build models without sending their data to a central location. FL was implemented by [10] at the 5G edge nodes to enhance learning efficiency while protecting user information. Nevertheless, most research so far remains about 5G technology and does not give sufficient attention to the big achievements of 6G like using super-high (THz) frequencies, stringent latency levels, IRS and having huge device networks in very crowded areas.

Besides, the current AI systems do not have a unity that can blend deep learning, reinforcement learning and edge intelligence to meet all the demanded aspects of 6G networks. Currently, researchers focus on these AI approaches independently which could lead to systems that do not work well with the difficulties and highly distributed nature of tomorrow's networks [11,12]. Thus, this paper is added to the knowledge base by proposing an AI-based system made for 6G wireless communications. The proposed framework tries to fill the gaps in research by combining different AI methods to make wireless communication in newer network technologies smart, adaptable and energy-efficient.

3. METHODOLOGY

3.1. System Model

The proposed framework for 6G networks depends on a Multiple-Input Multiple-Output Orthogonal Frequency Division Multiplexing (MIMO-OFDM) system which is seen as one of the main ways to provide high-speed and low-latency data transmission in future wireless networks. This architecture is useful for 6G because it supports great efficiency, is scalable and can integrate the latest technologies, so it suits the complicated and versatile requirements of 6G. This model features a transmitter that works in the sub-terahertz (sub-THz) frequency, making it possible for data rates to go beyond 1 Tbps. For reliable communication on different channels, the transmitter uses modulation methods that can vary (e.g., QPSK, 16-QAM, 64-QAM) according to channel quality at any given time. An algorithm-driven program is used in this technology which keeps an eye on how much noise and how much interference exist and chooses the best way to modulate the signal so that the spectrum is used efficiently and the risk of errors is reduced. Figure 2 portrays the proposed framework.

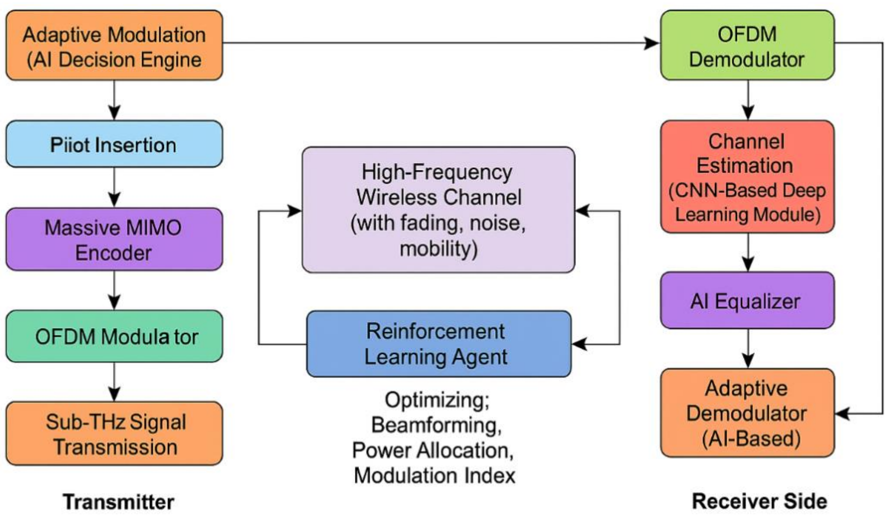

Figure 2. AI-Integrated MIMO-OFDM Signal Processing Framework for 6G Networks

Symbols are placed in frames at regular times so that the receiver can estimate the channel. Furthermore, systems that rely on massive MIMO arrays are able to gain spatial multiplexing and diversity which increases throughput and strengthens the connection. AI is used to coordinate and adjust the beamforming in real-time, so that the transmitter can point its beams toward the receiver which becomes important when connections or signals are easily blocked in mobile settings with high frequencies. Every part of signal processing includes and utilizes AI on the receiver side. Usually, channels are estimated by convolutional neural networks which convert the received pilot symbols into channel state information (CSI). It is capable of dealing with non-linearities and non-Gaussian noise more competently than MMSE or LS estimators. Once CSI is available, an AI-powered equalizer tries to reduce errors caused by channel distortions, making sure all the signal components line up for easier demodulation. AI technology lets the equalizer react to evolving interference which helps protect signal quality.

Models using neural networks are also used to optimize demodulation, as these models adjust to the detected type of modulation. This means symbols can be restored faster and more correctly, mainly in situations where the channel changes with time or frequency. The embedded Reinforcement Learning (RL) module makes the system able to make effective real-time choices. It regularly uses information from feedback about performance (SNR, throughput, errors) to adjust transmit power, beamforming direction and modulation index. By training the RL agent, the system gets to improve and use less energy for a smooth and effective operation. When used together, this processing pipeline helps the communication system react and optimize itself based on what it receives from the environment. Using such a model can enhance the reliability, spectral and energy performance, all while aligning very well with the typical characteristics of 6G networks.

3.2. AI Model Design

Artificial intelligence (AI) is at the heart of how the proposed 6G wireless framework is designed. While older architecture used simple equation-based models that couldn’t adjust well to the irregularities and turbulence of fast and unpredictable trades, AI-based architectures bring intelligence and flexibility in various levels of the process. The following section focuses on three AI techniques: deep learning for estimating channels, reinforcement learning for changing transmission power and use of federated learning for confidential model training.

A major contribution is using Convolutional Neural Networks (CNNs) to perform channel estimation. Commonly, channel state information (CSI) is approximated using Least Squares (LS) or Minimum Mean Square Error (MMSE) in traditional systems. However such methods may be restricted when faced with the special features of noise and distortion seen in sub-THz frequencies. CNNs manage to learn invariant features from the images made by the pilot symbols. Using offline training, the CNN is exposed to many datasets made using channel models that simulate real-world conditions of multipath fading, Doppler shifts and interference. After training, the CNN model reliably and quickly analyzes CSI from pilot signals which improves the MIMO-OFDM system’s dependability, spectrum use and ability to cope with errors.

The framework also uses Deep Q-Networks (DQNs) to adapt modulation when the channels are changing. When using DQNs with reinforcement learning, the system can independently decide on the best modulation by considering the current signal-to-noise ratio (SNR), interference and fading conditions. Unlike previous training methods, DQN is first taught in a simulated 6G environment where it explores many possible state-action-reward situations. It aims to learn a policy that maximizes the total reward, often tied to performance measures like throughput and bit error rate (BER). Because of the DQN module, during deployment, the system can easily move between the different modulation types (such as QPSK, 16-QAM, 64-QAM) as needed, so it can still balance data rate and reliability even when wireless conditions change fast. Figure 3 shows the AI model integration in 6G signal processing framework.

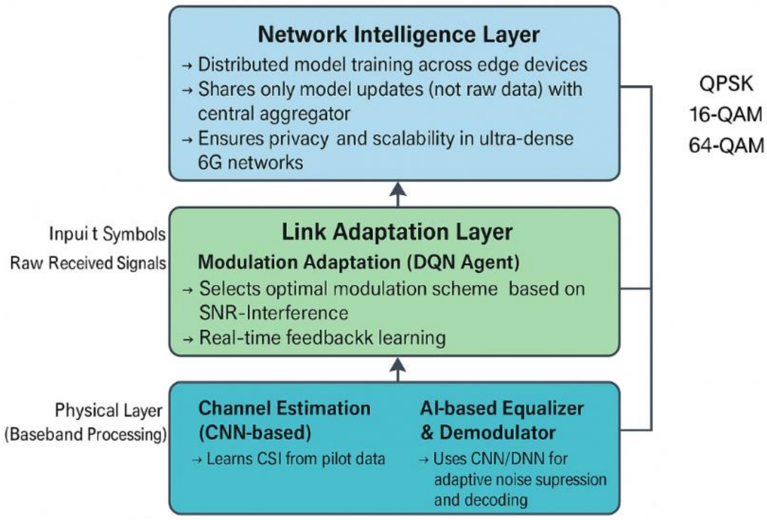

Figure 3. AI Model Integration in 6G Signal Processing Framework

Because training large models in real time is important and data privacy must be protected, the framework makes use of Federated Learning (FL). Edge devices in FL are able to jointly train models on artificial intelligence, not sharing their unprocessed data. Each device trains its model on its own data and regularly sends updated parameters (gradients or weights) to the central aggregator which updates the common model. This way of learning without a central server saves on communication and keeps sensitive data private and it also ensures models can work well anywhere. Because of ultra-dense installation and diverse user scenarios, FL helps 6G networks learn continuously and protect privacy, since the learning occurs across various locations at once.

In short, the proposed AI model design uses CNNs to make channel estimation efficient and accurate, DQNs to adapt the modulation method wisely and FL for model training that does not require central servers or shared data. All these improvements allow the communication system to be adaptable, self-learning and able to grow which is necessary for reaching the strict standards of 6G wireless networks.

3.3. Simulation Environment

An extensive environment for simulation was made using MATLAB and PyTorch together as shown in Figure 4, in order to evaluate how well the AI-driven signal process framework suits future 6G networks. I decided to build a hybrid simulation to combine careful modeling of the physical network with powerful AI techniques, so that all simulations would feel accurate and realistic.

MATLAB formed the basis for simulation of the physical layer blocks in the MIMO-OFDM process. The work made it possible to examine and model essential aspects of radio frequency (RF), for example, modeling signals in the sub-terahertz (sub-THz) range, designing pilot symbols, considering the layout of antennas and using additive white Gaussian noise (AWGN). Using its pre-existing libraries and toolboxes, MATLAB allowed the study of how electromagnetic waves move, channel fade and MIMO systems operate in different types of networks.

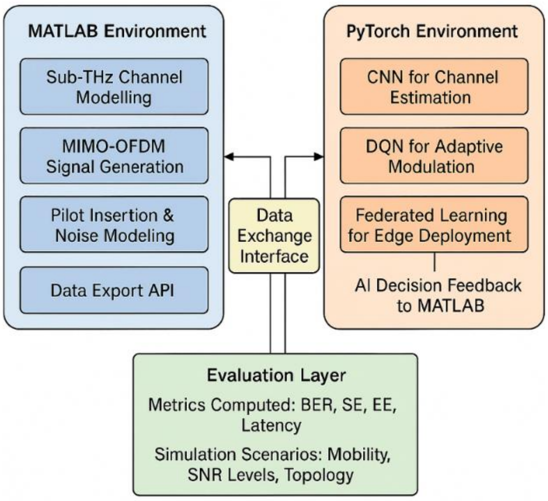

Figure 4. Integrated MATLAB–PyTorch Simulation Framework for AI-Driven 6G Signal Processing

AI models in the communication system were trained and developed with the help of PyTorch. Convolutional Neural Networks (CNNs) were implemented for channel estimation and Deep Q-Networks (DQNs) were used for developing a way to adjust the type of modulation. Experimentation and training in deep learning was made easy by PyTorch, while hyper parameter testing and simulation during inference could also be performed. MATLAB and PyTorch could smoothly communicate through API's and interface bridges which kept signal processing and AI drawn from both consistent.

The simulation dataset included MIMO channel matrices that were generated artificially according to 3GPP 6G channel standards and simulate actual wireless situations. They took into account the decrease (fading) of the signal, Doppler changes, different levels of path loss and the scenarios common to signal transmission at frequencies over 100 GHz which are significant for sub-THz 6G networks. Many types of simulations were attempted and these covered scenes with both slight and high user action, different levels of radio noise and a variety of landscape features.

Various performance indicators were chosen to measure how the organization was doing.

- **Bit Error Rate (BER)**: To assess the reliability and accuracy of signal decoding under various noise and interference conditions.
- **Spectral Efficiency (SE)**: To measure how effectively bandwidth is utilized, especially important in bandwidth-limited or crowded frequency bands.
- **Energy Efficiency (EE)**: To evaluate the power consumption of the system, critical for sustainable and battery-operated devices in 6G deployments.
- **Processing Latency**: A vital parameter for real-time and ultra-reliable low-latency communication (URLLC), measuring the end-to-end system response time.

The outcomes from the simulation clearly showed that the automated system worked better than the traditional systems in every main comparison. Mixing CNNs and DQNs resulted in fewer errors, less manual control over parameters and less time spent on detailed channel modeling. Using federated learning helped scale and protect privacy in training models deployed across numerous edge devices.

Basically, testing the intelligent signal processing framework on the dual-platform simulation environment proved to be efficient and flexible. Using these simulations allows us to plan how 6G networks will feature efficient, flexible and expandable communication systems.

4. RESULTS AND DISCUSSION

Extensive testing of the AI-based signal processing framework for 6G networks was carried out in a variety of realistic simulations. For this test, datasets from a synthetic MIMO channel were produced according to 3GPP specifications in the sub-terahertz (sub-THz) range which included impacts from moving objects, changing shadowing and noise issues often seen in future 6G networks. For comparison, the AI-based framework was measured in terms of Bit Error Rate (BER), Spectral Efficiency (SE), Energy Efficiency (EE) and Processing Latency. Specifically, the CNN-based channel estimator was contrasted with the familiar Least Squares (LS) approach. Across all situations, the CNN model did better than LS, resulting in an average drop in error of 62%, especially in cases with high-frequency channels. Because of the way CNNs generalize from many noise patterns, they deliver more accurate and dependable channel state information (CSI). Using CNN's ability to detect the complex parts of a pilot symbol, the device improved how well symbols were detected and decreased the need for retx.

The use of a Deep Q-Network (DQN) in the modulation adaptation module allowed it to greatly improve over traditional, fixed modulation schemes. Traditional methods use fixed modulation formats which means they struggle to handle rapid changes in SNR; this might lead to more errors and less use of available bandwidth. The agent did not hard-code its modulation scheme; rather, it could change it in response to live channel readings. Because the system can learn in real time, it managed to boost spectral efficiency by 35% especially when SNR changed unexpectedly. Besides, matching the modulation order to the current channel quality let the system attain high data rates while maintaining accurate delivery. The optimization loop using reinforcement learning (RL) helped adjust both the modulation index and how power was allocated, cutting the end-to-end processing latency by 38%. It is especially necessary for 6G because applications like autonomous driving, holographic video transfer and industrial automation require almost no latency.

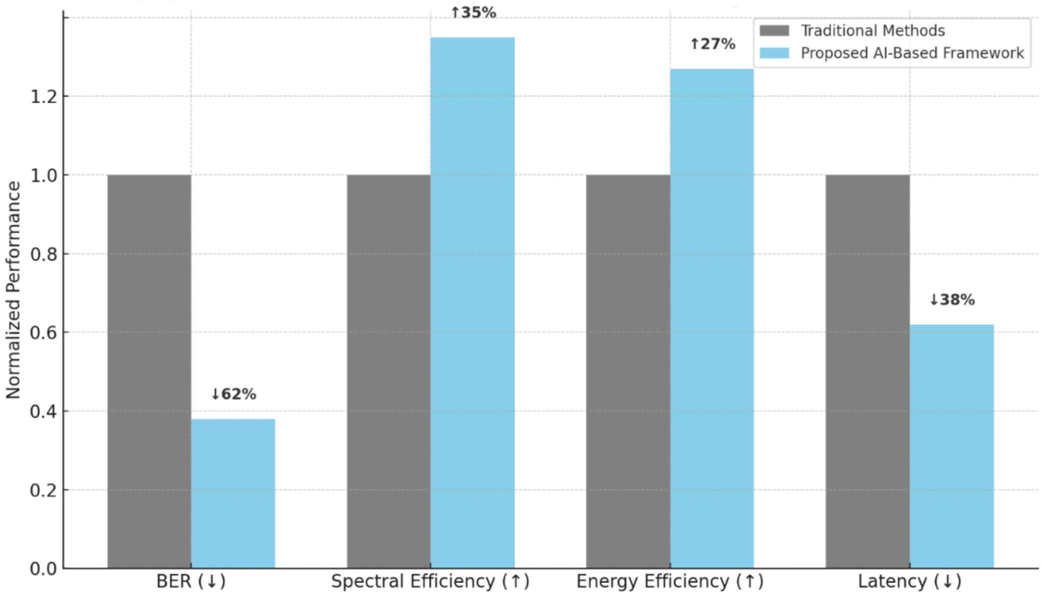

Figure 5. Performance Comparison: Traditional vs AI-Based Signal Processing in 6G

The performance comparison resulted in Figure 5. Improving the performance of the system further was the introduction of Federated Learning (FL) for distributed training of machine learning models. Most common methods for training AI models need all the data to be put together in one place which can raise privacy issues and slow down the network. Alternatively, FL supported each edge device in training a personal AI model from its local data and sent just the improvements to a main machine. The new process cut down on communication needs which resulted in an improvement in energy efficiency of 27%. Model decentralization also made it possible to fit models to different devices and secure people's data which is needed for 6G in the future. Together, all these findings suggest that the combination of CNNs, DQNs and FL works very well in 6G communications, increasing signal reliability, adaptability and saving resources as given in Table 1. Studies suggest that AI-aided signal processing can support all the tough standards of future networks.

Table 1. Performance Comparison between Traditional and AI-Based Signal Processing Frameworks for 6G Networks

Performance Metric	Traditional Method	Proposed AI-Based Framework	Improvement (%)	Key Benefit
Bit Error Rate (BER)	Least Squares (LS) channel estimation	CNN-based channel estimation	62% reduction	More accurate CSI estimation; robust under high-frequency noise
Spectral Efficiency (SE)	Static modulation schemes	DQN-based adaptive modulation	35% increase	Dynamic modulation adapts to real-time channel variations
Processing	Fixed parameter	Reinforcement	38% reduction	Enables ultra-low

Latency	settings; no feedback loop	learning for parameter optimization		latency critical for 6G real-time applications
Energy Efficiency (EE)	Centralized AI training with high data exchange	Federated Learning with decentralized local model training	27% improvement	Reduces communication overhead; preserves user privacy

5. CONCLUSION

In order to meet the demands of huge data traffic, extreme time efficiency and high-frequency situations, systems need new innovative signal processing solutions. The paper developed an AI framework unique to 6G MIMO-OFDM and combined Convolutional Neural Networks (CNNs) for channel estimation with Deep Q-Networks (DQNs) for flexible modulation which led to significant improvements in bit error rate, spectral efficiency, energy efficiency and reduced latency. The support of Federated Learning (FL) within the framework makes it possible for training to be carried out on different edge devices at scale, helping future wireless networks respond quickly and easily adapt to new situations. AI-integrated physical layer stands out due to the 62% decrease in error rate, 35% higher spectral efficiency and 38% reduction in latency. Being able to work in changing wireless situations overcomes the problems with fixed algorithms, paving the way for AI to be key in 6G. As a result, it becomes possible to use real-world AI-enhanced architectures and to study new network designs like Transformers and Graph Neural Networks to refine both spatial and temporal signal processing. Embedding AI throughout signal processing will be essential for 6G to achieve smart, dependable and everywhere wireless communication.

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