# Machine-Learning-Based Cognitive Spectrum Assignment for 5G URLLC Applications

Qian Huang, Xianzhong Xie, Hong Tang, Tao Hong, Michel Kadoch, Kim Khoa Nguyen, and Mohamed Cheriet

## Abstract

As one of the main scenarios in 5G mobile networks, ultra-reliable low-latency communication (URLLC) can satisfy the stringent requirements of many emerging applications. To ensure end-to-end secure delivery of critical data, 5G URLLC needs an efficient hybrid access scheme for licensed and unlicensed spectrum in mmWave bands. This article introduces machine learning (ML) and fountain codes into mmWave hybrid access, and proposes an adaptive channel assignment method. The proactively predictive power of ML can reduce the transmission delay, and the rateless characteristic of fountain codes can ensure transmission reliability without retransmission. Finally, through a vehicle-to-everything use case, the proposed method is demonstrated to clearly ensure the URLLC transmission requirements for critical data.

## Introduction

Current fifth generation (5G) mobile networks face an increasingly diversified range of demand drivers, including virtual reality, industrial automation, smart grid, e-health, multimedia, tactile Internet, the Internet of Things (IoT), and the Internet of Vehicles (IoV). According to the latest Cisco White Paper, by 2021, global mobile data traffic will be seven times that of 2016 [1]. With rapid development of various mobile services and related industries, 5G is expected to generate trillions of economic outputs [2]. Thus, 5G must achieve low latency, high reliability, large capacity, full coverage, high mobility, high connection density, low energy, scalability, and other further developments. The Third Generation Partnership Project (3GPP) ratified 5G core standards involving new radio interfaces and new core network architectures in December 2017. According to these standards, a large amount of the innovative research undertaken on 5G requires further exploration to support more scenarios.

The International Telecommunication Union (ITU) defines 5G as an ensemble of evolved mobile vroadband (eMBB), ultra-reliable low-latency communication (URLLC), and massive machine-type communication (mMTC). 3GPP defines URLLC as 1 ms hard delay and 99.999 percent reliability [3]. Many emerging applications of URLLC, such as IoT, vehicle-to-everything (V2X), and tactile Internet, require messages to be securely delivered from the transmitter to the receiver with high reliability and strict delay. Such conditions further intensify the demand for a new hybrid access paradigm of licensed and unlicensed spectrum in 5G.

Due to the licensed spectrum shortage, however, some potential URLLC applications may occupy unlicensed spectrum. Unlicensed spectrum can provide additional transmission capacity for URLLC. Currently, Long Term Evolution-unlicensed (LTE-U), licensed assisted access (LAA), and MulteFire are proposed to share spectrum resources with legacy systems in sub-6 GHz, such as Wi-Fi (IEEE 802.11a/n/ac). LTE-U is an evolutionary technology without listen-before-talk (LBT) proposed by the LTE-U Forum that works with 3GPP Release 10/11/12. The LAA, provided in 3GPP Release 13, is a global unity framework for different requirements. Unlike LTE-U/LAA, MulteFire proposed by Qualcomm is only available for unlicensed spectrum, and does not use LTE carriers as anchors (for link or carrier aggregation).

Millimeter-wave (mmWave) is a promising candidate for providing wireless access to URLLC users due to its abundant spectrum resources, high frequency, short transmission distance, and high directional gain. However, URLLC may incur extremely low spectrum utilization without reasonable control, and even mmWave will suffer from spectrum shortage in the future. Hence, an efficient hybrid access scheme for licensed and unlicensed spectrum in mmWave will be critical for URLLC in 5G. In order to eliminate the inherent defects of mmWave, new technologies must be adopted, such as mini-slot structure, machine learning, fountain codes, and link adaptation [4]. Combined with these technologies, adaptive channel assignment method in mmWave hybrid access can further improve spectrum utilization.

Machine learning (ML) can revolutionize measures from reactive to proactive, to support URLLC in the mmWave network. Specifically, ML offers the ability to infer environmental information and predict future trends. It also allows for proactive compensation for additional time overhead, which is caused by the channel variation characteristics of mmWave. In addition, hybrid automatic repeat request (HARQ) cannot satisfy the hard latency requirement of URLLC because of frequent retransmissions. Instead, with the ability to efficiently use conflicting packets to increase throughput, fountain codes can ensure reliable transmission without retransmission [5]. In this article, an adaptive channel assignment based on ML and fountain codes is presented, in a bid to meet URLLC requirements while improving spectrum efficiency.

The remainder of this article is organized as follows. First, the status quo of licensed and unlicensed spectrum access in sub-6 GHz and

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mmWave is introduced. Then an adaptive channel assignment scheme based on ML and fountain codes for mmWave hybrid access is proposed, followed by a V2X use case to justify the performance of the proposed scheme.

## Review of Adaptive Channel Assignment of Licensed and Unlicensed Spectrum

### Hybrid Spectrum Access for Sub-6 GHz

In recent years, unlicensed spectrum technology in LTE has attracted attention as a promising solution for improving spectrum capacity to meet the growing demand for mobile traffic in 5G. Three hybrid access technologies for LTE are presented in Fig. 1.

The LTE-U shares sub-6 GHz bands with other unlicensed networks without LBT. This extension poses a major challenge to the coexistence between LTE-U and Wi-Fi, as the centralized control of LTE conflicts with the distributed channel access of Wi-Fi. Without changing the respective access methods of LTE and Wi-Fi, LTE-U uses carrier sense adaptive transmission (CSAT) protocol [6] to coexist with Wi-Fi.

Like LTE-U, the coexistence of LAA and Wi-Fi in spectrum sharing and traffic management is also a challenging issue [7]. Qualcomm argues that LAA has little interference with Wi-Fi and can enhance overall throughput through spectrum sharing. Conversely, Google believes that LAA will block Wi-Fi users and prioritize LAA users, thus reducing the overall network throughput of Wi-Fi. By employing LBT, LAA can coexist amicably with Wi-Fi on unlicensed spectrum [8]. In addition, LAA performs intermittent transmission of up to 8 ms to increase the priority of Wi-Fi users.

By combining the high performance of LTE with the simplicity of Wi-Fi, MulteFire can offer a more reliable and efficient user experience in traffic-intensive networks. Due to the low transmission power typically applied to unlicensed bands, MulteFire is most appropriately implemented using small cells in areas such as stadiums, shopping malls, airports, and train stations. MulteFire can dynamically detect and select the least commonly used sub-bands to avoid conflicts with other users [9]. In addition, when sub-bands must be shared with users of other access technologies, MulteFire will use LBT to ensure fair coexistence. MulteFire has been designated to comply with global regulatory requirements and is fully compatible with other global deployments.

### Hybrid Spectrum Access for mmWave in 5G

In addition to strict reliability and delay requirements, URLLC must also provide high data rates, spectral efficiency, energy consumption, and better user experience. However, even if the wireless resource dimension is increased, traditional cellular frequencies cannot completely solve the bandwidth limitation problem. MmWave, with bands from 30 GHz to 300 GHz, can effectively alleviate the shortage of traditional cellular frequencies, and is expected to become a key disruptive technology for 5G [10]. However, although the mmWave spectrum provides up to two orders of magnitude more bandwidth than the sub-6 GHz spectrum, it is limited.

In order to prevent the spectrum depletion of mmWave, it can be divided into licensed and unlicensed spectrum as in sub-6 GHz. Considering the spectrum shortage caused by the surge in future mobile traffic, in addition to time-insensitive mobile traffic, some URLLC data will also be implemented on unlicensed spectrum. To the extent of the authors' knowledge, research on mmWave hybrid access in URLLC scenarios is still in its infancy, and most past work has focused on the sub-6 GHz unlicensed spectrum. Although a few researchers have studied LBT in mmWave unlicensed spectrum, as in [11], little research has been undertaken on the adaptive select licensed or unlicensed spectrum in mmWave for URLLC. Hence, the study of a hybrid access model for licensed and unlicensed spectrum in mmWave is significant for URLLC in 5G.

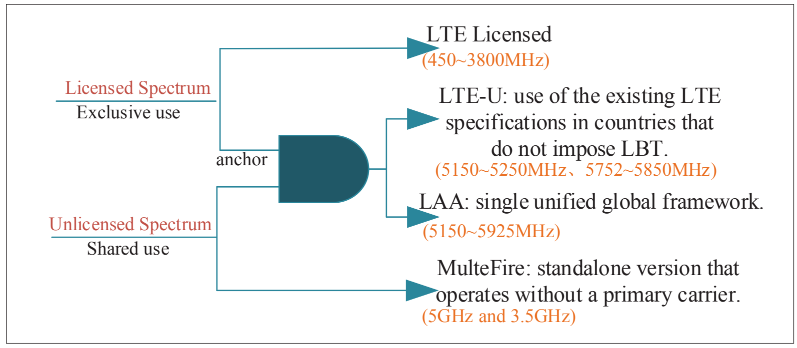


FIGURE 1. Three hybrid access technologies for LTE licensed and unlicensed spectrum (LTE-U, LAA, and MulteFire).

The selection of mmWave spectrum range is subject to the recommendations of standards organizations, such as ITU and 3GPP. Moreover, due to the higher directionality of the beams, the unlicensed spectrum can be selected at high mmWave frequencies (e.g., 80 GHz), and the licensed spectrum can be selected at low mmWave frequencies (e.g., 24 GHz). Unlicensed spectrum in mmWave can be analyzed in two cases:

- When licensing spectrum is sufficient
- When licensing spectrum is scarce

In the former, noncritical data is allowed to access the licensed spectrum without interfering with the transmission of critical data. In the latter scenario, some critical data of URLLC will also use the unlicensed spectrum. This not only ensures the real-time performance and reliability of critical data, but also improves spectral efficiency.

A typical deployment of hybrid access in mmWave small cells is depicted in Fig. 2. As a complement to traditional macrocellular (LTE/5G at sub-6 GHz), mmWave small cells are expected to support URLLC communication from indoor or outdoor hotspots. As shown in Fig. 2, mmWave small cells support real-time cellular access, high-speed backhaul services, ultra-large-scale access, and emerging V2X applications. Due to short wavelength and high path loss, mmWave base stations (BSs) are deployed relatively densely in order to reduce transmission time. The mmWave has very narrow receive/transmit beams, which enhance the directional isolation gain between mobile devices, and also reduce mutual interference, potentially improving data reliability. Furthermore, dividing mmWave bands into licensed and unlicensed spectrum is valuable as it offers additional gains in diversity, capacity, and bandwidth for URLLC.

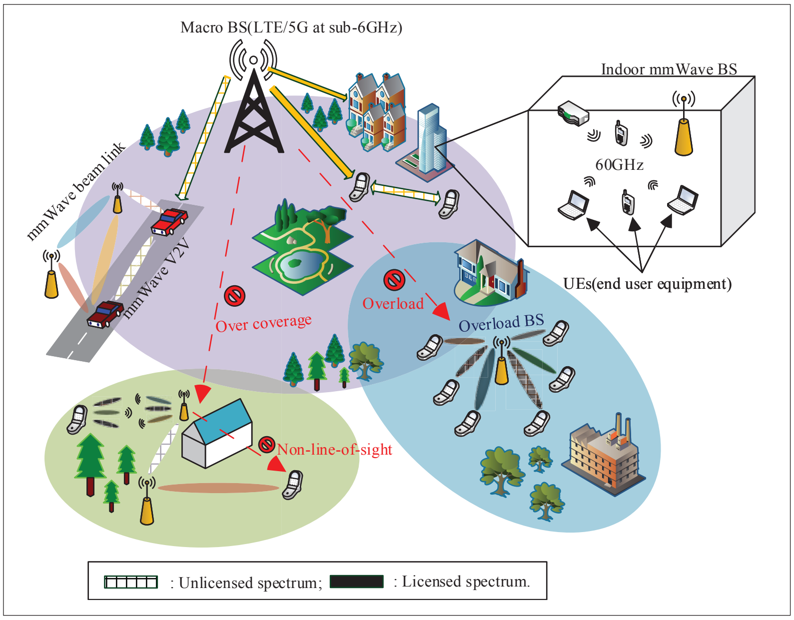


FIGURE 2. Hybrid spectrum access in mmWave small cells

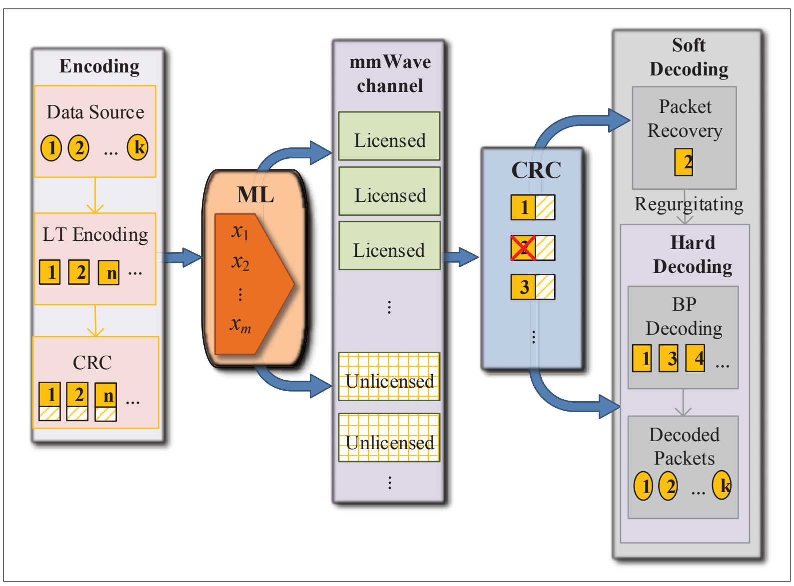


FIGURE 3. Adaptive channel assignment based on ML and LT code.

## Fountain Coded MmWave Adaptive Channel Assignment in 5G URLLC

### Adaptive Channel Assignment Based on ML and Fountain Codes

Over the next decade, a large amount of URLLC applications will affect daily life in a visible or invisible way. Such applications include V2X, pilotless automobiles, underground mine gas monitoring, and remote collaborative surgery. URLLC focuses on ultra-reliable critical data communications that require haptic interactions. 3GPP defines URLLC as 1 ms latency and 99.999 percent reliability, as well as zero movement interruption. Obviously, these requirements cannot be met in LTE.

New technology drivers such as mmWave, mini-slot structure, ML, fountain codes, massive multiple-input multiple-output (MIMO), beamforming, and link adaptation must therefore be adopted. To satisfy URLLC requirements and improve spectral efficiency, Fig. 3 demonstrates an adaptive channel assignment method based on ML and fountain codes for mmWave hybrid access. The goal in this research is to use fountain codes to reduce latency and improve reliability through a low-complexity ML-based adaptive channel assignment method.

At the transmitter side, the data source is first encoded with Luby Transform (LT) code, which is a classic fountain code. As there is no retransmission during data transmission, the transmission delay can be reduced. However, LT code alone cannot effectively mitigate the effects of fading and noise on the wireless channels; thus, cyclic redundancy check (CRC) code is used next. The time-varying channel is converted to a packet-erased channel after CRC encoding, and LT code is an effective way to correct packet erasure.

As mmWave has wide spectrum resources and strong directivity, mmWave spectrum assignment is more diverse. An emerging concern is to improve the spectrum efficiency while ensuring URLLC during channel selection, and a low-complexity ML-based adaptive channel allocation method is adopted to do this. More appropriate channels can be selected for current services by using ML to predict channel status and mobile terminal behavioral trends. Specifically, when there are only a few access users, noncritical data access can be given to licensed spectrum without interfering with the transmission of critical data. Conversely, when there are too many access users, some critical data will also use the unlicensed spectrum.

At the receiver side, packet CRC check is first required. Packets that pass the CRC check are transmitted to hard decoding, while the remaining ones are transmitted to soft decoding. The LT code employs the Belief Propagation (BP) algorithm to simplify the hard decoding of packets received over packet-erased channels. For corrupted packets that do not pass the CRC, soft decoding based on the sum product algorithm [12] can attempt to recover them. The recovered packets are then regurgitated to the BP decoding module. Soft decoding can effectively reduce the decoding delay caused by the failure to receive corrupted data for a long time.

### Machine Learning for Channel Condition Prediction

As forward-looking scientific research, artificial intelligence (AI) is increasingly applied in computer-related fields such as robotics, IoT, IoV, control systems, and simulation systems. Certain tasks can be performed more effectively by AI than the human brain as it is immune to emotions and fatigue. In recent years, after a long period of exploration and development, AI is becoming more efficient and sophisticated.

The ML algorithm in AI is a series of potential game rules supporting powerful data analysis. The adaptive system is one ML application that adjusts behavior based on past experience and develops rules based on this. In unlicensed wireless systems, the primary focus is to quickly discover idle sub-bands and use them efficiently to minimize interference to critical data. Therefore, the objective is to comprehensively analyze the characteristics of currently used spectrum and user behaviors, then accurately and quickly sense and switch the idle spectrum.

This research aims to improve reliability and reduce latency by combining fountain codes with a simple but effective ML-based adaptive channel allocation method. This method allows multiple licensed and unlicensed sub-band combinations, and the combinations can be updated before each packet transmission. Undoubtedly, this channel allocation method relies on seeking a simple and efficient ML algorithm.

The ML algorithm [13] can be used to balance the load of each licensed and unlicensed spectrum after calculating the network load. It then works by switching the critical data to the licensed spectrum with the best channel conditions and the noncritical data to the least congested unlicensed spectrum. The proposed method consists of four main operations. First, the collected channel conditions are learned by each smart node (BS or mobile device with computational analysis capability) using a low-complexity ML algorithm. Then the licensed and unlicensed sub-bands are adaptively activated or deactivated after learning the number of users, user data types (critical or non-critical), and user locations in the network. This is followed by optimal channel allocation for the licensed spectrum, performed to minimize the total latency for all critical data. Finally, the best unlicensed spectrum is allocated to the remaining non-critical data. In this way, all spectrums can be utilized to the maximum while ensuring reliable and secure transmission of critical data in real time.

### Reliability Through Fountain Codes

Due to the high latency caused by frequent retransmissions, HARQ is unable to satisfy the hard latency requirement of URLLC. Increasing the radio resources by multi-dimensionality can reduce the transmission delay, but this can lead to low spectrum utilization and system throughput.

Digital fountain codes are rateless codes and also erasure codes. Rateless codes mean that the transmitter can generate any number of encoded packets from $k$ original packets, and the receiver can recover the original data by any $(1 + \varepsilon)k$ coded packets obtained. A well designed fountain code not only has a small decoding overhead $\varepsilon$, but also has a simple coding and decoding process, and little coding complexity. In wireless communication systems using multiple access transmission techniques, fountain codes can effectively use conflicting packets to increase the system throughput.

As shown in Fig. 4, in the entire fountain coding process, only the amount of water required for each container at the receiving end is focused on, and water droplets falling outside the container are irrelevant. Suppose the source information consists of $k$ original packets. First, the fountain encoder forms as many coded packets as possible. Then the ML algorithm is performed on the channel, based on data such as channel state information (CSI) and queue state information (QSI), and the coded packets are adaptively transmitted. At the receiving end, if the received packets are correct, they are placed in the container; otherwise, the packets will be discarded. When the receiver recovers $k$ correct linear independent packet combinations, it can stop receiving coded packets. Finally, the source information is obtained by solving a system of linear equations consisting of $k$ equations. There are always $k$ linearly independent groupings of packets that can be used for successful decoding. Thus, the transmitter does not need to retransmit the error or lost packets.

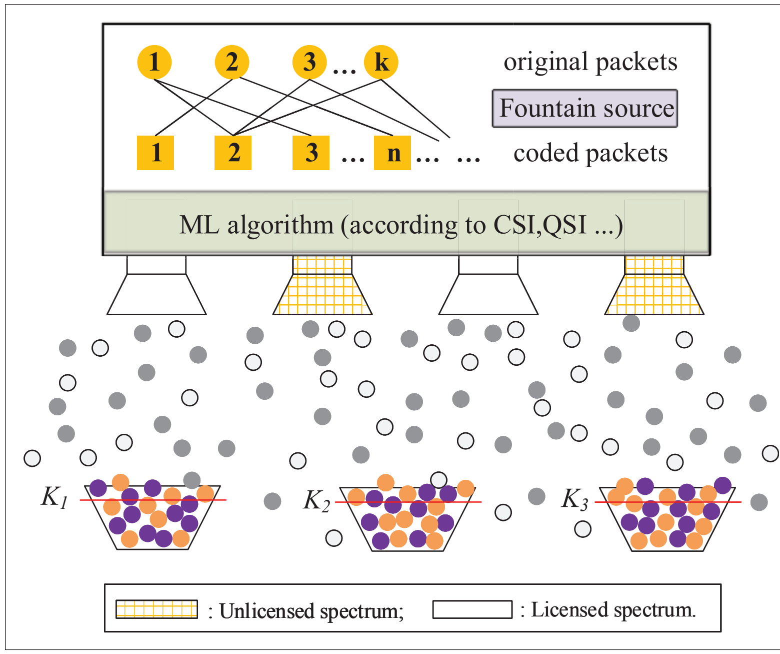


FIGURE 4. Fountain coding/decoding schematics.

In addition, the rateless characteristic of fountain codes can adaptively adjust the transmission rate according to the instantaneous channel quality and achieve high throughput with near zero outage probability. Such codes are optimal for any erasure channel because source information can be decoded with high probability as long as enough symbols are received. Overall, the fountain codes have many benefits. Not only is the precise CSI not required as a fixed rate code, but in error-prone channels, the transmission power does not need to be increased to ensure the receiver is successfully obtained because it can adaptively adjust the rate according to channel quality.

## Case Study of V2X

As the number of vehicles grows rapidly, applications targeting a variety of road safety and traffic efficiency operations are becoming increasingly important. By 2020, the number of vehicles supporting built-in connectivity will increase by 80 percent in the entire automotive market [14]. With the development of mobile multimedia technologies, the demand for high traffic and high rate services in the IoV has also increased dramatically. However, as the IoV is traffic-intensive, especially in dense urban areas, the amount of vehicular data transmission has increased dramatically. The limited IoV dedicated sub-6 GHz spectrum struggles to meet the transmission requirement of vehicular users. Further, it is difficult to implement URLLC communication for critical road safety applications.

Figure 5 illustrates the deployment scenario of V2X in 5G, which is one of the most prominent URLLC use cases. As shown, V2X refers to an integrated system of IoV, which includes vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), vehicle-to-network (V2N), and vehicle-to-pedestrian (V2P) networks. The system must provide traffic efficiency and infotainment support services, while ensuring active road safety. However, road safety

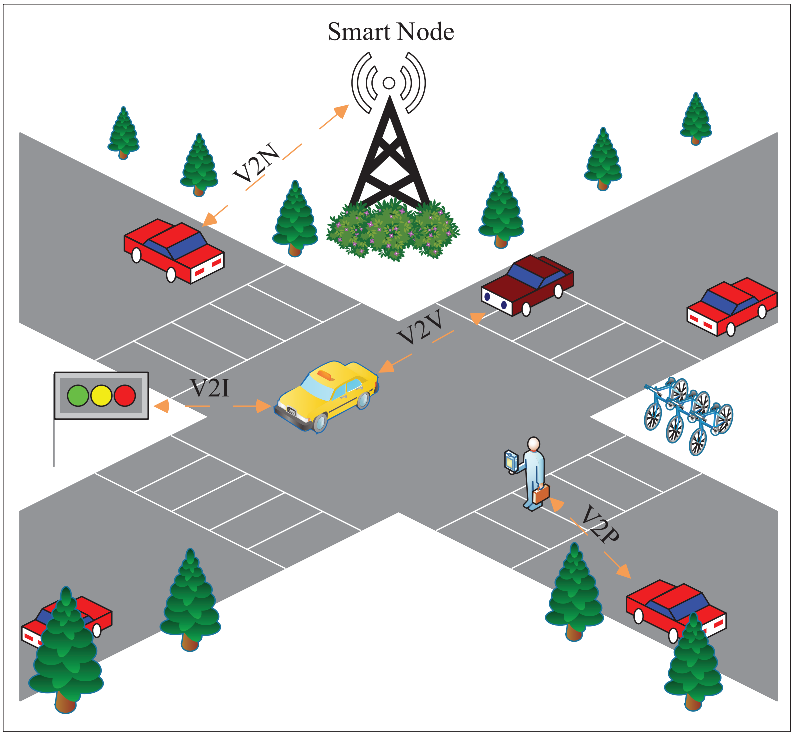


FIGURE 5. Typical deployment scenario of V2X.

requirements and vehicular entertainment services are contradictory because of bandwidth limitations in traditional LTE. In particular, the consequent data congestion in dense scenes makes the stringently URLLC requirements in V2X unsatisfactory. Maximizing spectrum resources and making effective use of these resources are thus prerequisites for achieving URLLC communication in V2X.

As mentioned above, mmWave can be considered a potential solution to provide high reliability, low latency, high data rates, and high capacity. However, when mmWave signal is occluded, the propagation conditions become unpredictable due to high frequency characteristics. As the speed of vehicles increases, this can lead to frequent interruptions and cell handovers. The critical issue in V2X is to accurately and quickly predict the next move of vehicles and pedestrians. Therefore, the introduction of ML, fountain codes, mobile edge computing (MEC), and cloud computing is necessary.

Cloud computing is a computing resource sharing model that supports ubiquitous, on-demand distribution. Introducing cloud computing in V2X can reduce the computing load on mobile devices and accelerate ML with a powerful cloud platform. However, the location of the cloud is fixed and remote, which is not suitable for the low latency requirement of V2X. In MEC, cloud services are combined with edge nodes (smart nodes) located near the user's geographic location. By spreading cloud services to the edge of the network, MEC reduces the latency of service requests while unloading pressure form the core network. The advantages of MEC are mentioned in [15], and include reducing latency, use of contextual information, and proximity services.

The mmWave spectrum is limited, especially in intensive traffic environments. To solve this problem, this article considers an adaptive channel-assignment-based hybrid access model for mmWave licensed and unlicensed spectrum. First, mmWave is divided into licensed and unlicensed spectrum to support V2X users. Then mmWave hybrid access works together with ML, fountain codes, MEC, and cloud computing. As illustrated in Fig. 6, vehicles, pedestrians, and smart nodes (BSs with MEC) are deployed on the roads, and exchange road safety and infotainment data with each other by mmWave beams. Additionally, they can also share storage and processing capacity. Dividing the mmWave spectrum into licensed and unlicensed can increase the personalized support for different services, and provide additional capacity and bandwidth in V2X.

To ensure security of V2X, critical data such as road safety and traffic efficiency must be preferentially assigned to the mmWave licensed spectrum. Then, according to the ML results based on the channel states and behavior trends of vehicles and pedestrians, it is determined if there is any remaining licensed spectrum in the next period of time. Non-critical data such as infotainment can also occupy licensed spectrum if there is excess licensed spectrum; otherwise, the unlicensed spectrum is used. MEC deployed on the smart nodes performs a low-complexity ML algorithm in V2X. Finally, the use of fountain codes at the transmitter side can further enhance the reliability of critical data.

According to the classical laws of physics, in the case of the same transmission power, the shorter the wavelength, the shorter the propagation distance. According to the idealized free space propagation loss formula, the propagation loss $Los = 92.4 + 20 \lg f + 20 \operatorname{ld} d$, where $f$ is the frequency in GHz, $d$ is the distance in km, and the unit of $Los$ is dB. A 30 GHz mmWave has a loss of 101.9 dB after propagating 100 m. Under non-ideal propagation conditions, the propagation loss is much larger due to the complex and harsh environmental factors.

As an extremely high frequency (EHF), mmWave's large propagation loss causes its single-hop communication distance to be short. However, in outdoor communication scenarios such as V2X, mmWave must be able to communicate over long distances in complex environments. Therefore, mmWave developers can compensate for such large propagation losses by methods including relaying, hybrid beamforming, increasing transmit power, increasing antenna gain, and improving receive sensitivity.

## Conclusions

This article develops an adaptive channel assignment scheme based on machine learning and fountain codes, in a bid to cope with the scarcity of existing cellular spectrum and the stringent requirements of URLLC. Supported by analysis, the proposed scheme can satisfy the delivery of massive information, while ensuring the real-time reliable transmission of critical data. However, in the specific design and implementation process of the solution, high hardware cost, high computational complexity, and short transmission distance may be encountered. These problems can be solved by evolving hardware technology and emerging technologies such as hybrid beamforming, cloud computing, and MEC. Therefore, the proposed adaptive channel assignment scheme can be applied to many emerging URLLC scenarios such as V2X. This method is an excellent candidate for future 5G licensed and unlicensed spectrum scheduling for critical data transmission.


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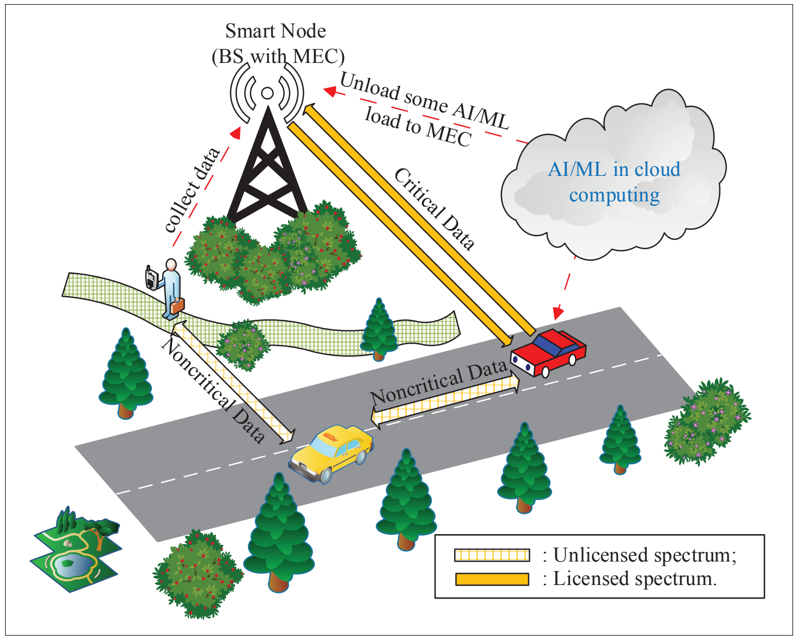


**FIGURE 6.** Adaptive channel assignment in V2X.


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