Smart City Enabled by 5G/6G Networks: An Intelligent Hybrid Random Access Scheme

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Abstract—The Internet of Things (IoT) is the enabler for smart city to achieve the envision of the “Internet of Everything” by intelligently connecting devices without human interventions. The explosive growth of IoT devices makes the amount of business data generated by machine-type communications (MTC) account for a great proportion in all communication services. The fifth-generation (5G) specification for cellular networks defines two types of application scenarios for MTC: One is massive machine type communications (mMTC) requiring massive connections, while the other is ultra-reliable low latency communications (URLLC) requiring high reliability and low latency communications. 6G, as the next generation beyond 5G, will have even stronger scales of mMTC and URLLC. mMTC and URLLC will co-exist in MTC networks for 5G/6G-enabled smart city. To enable massive and reliable LLC access to such heterogeneous MTC networks where mMTC and URLLC co-exist, in this article, we introduce the network architecture of heterogeneous MTC networks, and propose an intelligent hybrid random access scheme for 5G/6G-enabled smart city. Numerical results show that, compared to the benchmark schemes, the proposed scheme significantly improves the successful access probability, and satisfies the diverse quality of services requirements of URLLC and mMTC devices.

Index Terms—Internet of Things, Machine-Type Communications, Random Access, Smart City.

I. Introduction

With the development of technology and urbanization, smart cities have become the development trend of cities and received much attention in recent years. A smart city aims to fully realize intelligence in various social services, such as residents’ lives, government services, security, and education, which makes the city on demand. To realize the smart city, technologies such as the Internet of Things (IoT), cloud computing and mobile technology, are essential. Among these technologies, IoT, as the foundation of the smart city, is attracting increasing attention from both industry and academia due to its promising applications of intelligently connecting devices without human interventions [1].

According to Gartner prediction, more than 30 billion IoT devices will connect to the network by the year 2025 [2]. Thus, the amount of business data generated by machine-type communications (MTC) accounts for a great proportion in all communication services [3]. Due to the extensive coverage, security, reliability and flexibility of communication of the fifth-generation (5G) communication networks, 5G networks have become the main force to support and promote MTC services. The 5G specification has defined two application scenarios for MTC: One is massive machine type communications (mMTC), which aims to provide massive connections; The other is ultra-reliable low latency communications (URLLC), which aims to provide high reliability and low latency communications. mMTC and URLLC will co-exist in MTC network for smart city. For example, driverless and remote surgery require reliable and low latency transmission, while environmental monitoring and smart agriculture need massive access. Recently, 6G cellular communications, as the next generation of beyond 5G, have been speculated [3]. It is envisioned [4] that in 6G, mMTC and URLLC will still exist, despite at even stronger scales; i.e., compared with 5G, 6G will have even more massive MTC and even more reliable LLC.

Random access is the first and critical step of communication between the BS and devices. The random access mechanism in the traditional cellular communication system is mainly designed for human-to-human (H2H) communication with large data packet transmission, few connections, and low energy consumption requirements. In order to support 5G MTC communications with small data packet transmission, sporadic transmission, and diversified Quality of Service (QoS) requirements, it is necessary to design an effective random access scheme. Recently, artificial intelligence (AI)-based approaches have been used to support MTC communications [5], [6]. A reinforcement learning based random access scheme was proposed to learn the optimal access class barring (ACB) factor under the different number of active devices [5]. Gui et al. [7] proposed a long short-term memory (LSTM)-based random access scheme where LSTM deep learning model is utilized to allocate power to each device. However, the above works only studied the case of all devices having the same priority, which are not suitable for heterogeneous MTC network in smart city where URLLC and mMTC devices co-exist [4]. To enable massive and reliable LLC access to such heterogeneous MTC networks, we introduce the architecture of heterogeneous MTC networks, and propose an intelligent hybrid random access (IHRA) scheme for 5G-enabled smart city. Our scheme also applies to 6G-enabled smart city, where mMTC and URLLC will still exist, despite at even stronger scales.
scales. For simplicity, we focus on 5G in the rest of the paper. The features and main contributions of this paper are summarized as follows.

- We propose an IHRA scheme for 5G-enabled smart city. More specifically, to meet latency and reliability access requirements, URLLC devices access the network via a two-step contention-free access procedure, and mMTC devices access the network utilizing a contention-based timing advance (TA)-aided access mechanism to meet the massive access requirement.
- We propose an attention-based LSTM prediction model to predict the number of active URLLC devices. As such, the BS can determine the parameters of multi-user detection dynamically based on the reliability requirement. This further ensures all active URLLC devices to successfully access the network in one shot to meet the latency requirement.
- We present the numerical results, which show that, compared to the benchmark schemes, the proposed scheme significantly improves the successful access probability, and satisfies the diverse QoS requirements of URLLC and mMTC devices.

II. MTC NETWORK ARCHITECTURE BASED ON 5G

Due to the extensive coverage, security, reliability and flexibility of communication of 5G communication network, 5G network has become the main force to support and promote MTC services. In this section, we introduce the MTC network architecture based on 5G, which includes four tiers, including terminals layer, networks layer, platforms layer and applications layer.

- **Terminals layer** includes MTC devices with access ability, which can be divided into two categories: mMTC devices and URLLC devices. mMTC devices mainly include various sensors, such as temperature sensors and humidity sensors, and URLLC devices include medical equipments and industrial equipments, etc.
- **Networks layer** is the 5G cellular network and other access networks interconnected with the 5G network. With powerful cloud technologies, some functions originally performed in the base station (BS) and core networks, including access control, power control, signal processing, and so on, are migrated to the cloud.
- **Platforms layer** refers to the IoT service platform, including cellular network operator platforms, enterprise platforms, government platforms, etc.
- **Applications layer** covers smart industrial, smart manufacturing, autonomous driving, and other services.

III. THE PROPOSED IHRA SCHEME FOR 5G-ENABLED SMART CITY

In this section, we first introduce the traditional contention-based random access scheme in the existing cellular network, and then describe our proposed IHRA scheme for 5G-enabled smart city.

A. Traditional contention-based random access scheme

In the Long Term Evolution-Advanced (LTE-A) cellular network, according to different service triggering events, random access schemes can be divided into two categories: contention-based random access procedure and non-contention based random access procedure. The contention-based random access procedure makes users to select their preambles in a contention manner, and the non-contention based random access procedure is to pre-allocate preambles to some users before random access procedure. Due to the sporadic transmission of devices in MTC communications, the non-contention based random access procedure is infeasible. In the following, we briefly introduce the traditional contention-based random access process.

As shown in Fig.1(a), the contention-based random access process requires the interaction of four messages (i.e., MSG 1, MSG 2, MSG 3, and MSG 4) between the BS and users, which is designed for H2H communications with large data packet transmission, few connections, and low energy consumption requirements. If these four messages can be successfully exchanged, an access request is finally completed. The term “contention” means that multiple users send the same preamble sequence to the BS in the current random access slot to obtain the BS's resource grant, and the BS cannot figure out which users send this preamble. Hence, users need to send a unique message (MSG 3) to the BS, and the BS will transmit a message (MSG 4) to users to confirm which users access the network successfully. In addition, the BS usually broadcasts a system information to inform the available preamble set before the random access procedure.

The details are described as follows:

- **MSG 1: Preamble Transmission**
  
  In the current random access slot, each user randomly selects a preamble from the available preamble set, and sends it to the BS via physical random access channel (PRACH). Since the available preambles are orthogonal, if more than one users select the same preamble in the current random access slot, the BS cannot distinguish them, resulting in the preamble collision.

- **MSG 2: Random Access Response (RAR)**
  
  The BS detects the received preamble signal. Upon preamble collisions, the BS may fail to detect the transmitted preamble. If a preamble is detected successfully, the BS sends a RAR message mainly including the detected preamble confirmation information and the uplink resources used to transmit MSG 3.

- **MSG 3: Connection Request**
  
  If the user receives the RAR information corresponding to its selected preamble within the waiting time, the connection request message is transmitted on the allocated uplink resources. If multiple users leverage the same uplink resource to transmit the connection request message, collisions will occur.

- **MSG 4: Contention Resolution**
  
  If the BS successfully receives the connection request message, it sends a contention resolution message to the user,
indicating that the user has successfully accessed the network. After the user receives this information, the random access process ends. Then, after the user and the BS go through a series of higher-level signaling, the user can transmit data information to the BS.

The aforementioned random access procedure is proposed for H2H communications. There are several challenges when it is utilized for the MTC communications:

- Compared with the small data packet transmitted by the MTC devices, the above random access procedure will introduce heavy signaling overhead, thereby reducing the efficiency of data transmission.
- Massive device accessing the network will cause serious preamble collision. This further increases the number of retransmission devices, thereby increasing delay and power consumption.
- The above random access procedure does not take the different QoS requirements into consideration, which is not suitable for the heterogeneous MTC network where URLLC and mMTC devices co-exist.

The combination of deep learning and wireless communication is the key technology to realize the “smart connection” in 5G-enabled smart city. Therefore, to tackle the above problems, we propose an IHRA scheme by utilizing LSTM and attention models.

B. The proposed IHRA scheme

Fig. 1(b) illustrates the proposed IHRA scheme, which aims to satisfy the diverse QoS requirements by utilizing deep learning technology. In addition, the cell is divided into multiple annulus with quantized distance \( d = 16T_s \times c \) from the center to the edge of the cell with radius \( R \), where \( T_s \) is the basic unit in the communication system and \( c \) is the speed of light [9]. Devices in the same annulus have the same TA index, and the number of annulus in the cell is \( \zeta = \left\lceil \frac{R}{d} \right\rceil \). We assume that each mMTC device knows its distance to the BS by utilizing distance measuring technologies, and thus it knows its TA index. This assumption is reasonable since most mMTC devices’ locations are fixed [9]. The details of the proposed IHRA scheme are described as follows.

MSG 1: Preamble Transmission

Each active mMTC device randomly selects a preamble sequence from the available \( \tau_p \) preambles, and mMTC device in the \( i^{th} \) annulus regards the \( \lceil \frac{2\zeta - \zeta}{i} + i \rceil^{th} \) subcarrier as the starting position to place their selected preambles [9].

Let \( \rho_{r,i} \) denote the received preamble \( r \) from the \( i^{th} \) annulus, and \( n(r,i) \) denote the number of devices selecting preamble \( r \) in the \( i^{th} \) annulus. Then, the received preamble signal can be written as \( Y = \sum_{r=1}^{\tau_p} \sum_{i=1}^{\zeta} n(r,i) \rho_{r,i} + N \), where \( N \) represents additive white Gaussian noise with mean zero and variance \( \sigma^2 \).

MSG 2: RAR Transmission and Muti-User Detection Parameters Broadcasting

The BS can obtain the value of \( n(r,i), (r = 1, \ldots, \tau_p, i = 1, \ldots, \zeta) \), based on the cross-correlation value of \( Y \) and preamble \( r \) [9], which is discussed in [9] in detail. Then, the BS generates a RAR corresponding to preamble \( r \) with \( n(r,i) = 1 \), including preamble identification, TA index, and resource block. Note that, \( n(r,i) = 1 \) means that only one device selects preamble \( r \) in the \( i^{th} \) annulus. Thus, there are multiple RARs corresponding to preamble \( r \), resulting in preamble \( r \) corresponding to multiple resource blocks.

In addition, by utilizing our proposed attention-based LSTM prediction model, the BS predicts the number of active URLLC devices. Thus, based on the reliable transmission requirement, the BS determines and broadcasts the parameters of multi-user detection (including the resource block, modulation and code schemes) to all active URLLC devices.

MSG 3: Uplink Message Transmission

Each mMTC device finds RARs including its preamble identification, and matches the TA indexes in these RARs with its own. If the TA index of one RAR is the same as its own, it transmits its uplink message with the highest transmit power level via the resource block indicated by this RAR. Otherwise, this mMTC device randomly selects a resource block from resource blocks allocated to its selected preamble, and transmits its uplink message with a randomly selected transmit power level.

Based on the broadcasted parameters, active URLLC devices modulate and code their payload data to obtain their uplink messages, and transmit to the BS via the same resource block.

MSG 4: Contention Resolution

For each resource block carrying the uplink message of mMTC devices, the BS utilizes the successive interference canceller (SIC) algorithm to detect the received uplink message [10]. The SIC algorithm decodes the uplink message of devices from the highest to the lowest power level. More specifically, the mMTC devices with the highest power level will be decoded first. If it can be successfully detected, the interference of the data information of this device is eliminated, and then the data information of the device with the second highest power level is detected until the data information of the device cannot be successfully detected. The following two events ensures that device selecting power level \( l \) can be successfully decoded: 1) this device is free from power level collision and devices with power levels larger than \( l \) are successfully decoded; 2) this device is free from power collision and the number of devices with power levels larger than \( l \) is zero. If this device can be decoded successfully, the interference of the uplink message of this device is cancelled from the received uplink message.

The BS decodes the uplink messages of URLLC devices by utilizing the multi-user detection algorithm, which is not the focus of our paper and interested readers can refer to [11] and references therein.

A. Attention-based LSTM prediction model

The proposed random access scheme predicts the number of active URLLC devices by utilizing a proposed attention-based LSTM prediction model, and configures the parameters of multi-user detection to these URLLC devices, to guarantee
the reliability and latency requirements of URLLC devices. The proposed prediction model includes two LSTM layers, one attention layer and one fully connected layer, as shown in Fig. 1(c). The data set travels from the first LSTM layer to the attention layer, then feeds into the second LSTM layer, and finally connects to a fully connected layer to predict the number of active URLLC devices. We describe the details of each layer of this prediction model as follows.

1) LSTM layer:
LSTM is a special kind of recurrent neural network (RNN) [12]. In the original RNN, as the increase of training time and the number of network layers, the problem of gradient explosion or gradient disappearance is prone to occur, which makes it impossible to process long sequence data, and thus cannot obtain information about long-distance data. LSTM is designed to let neural networks remember long-term information. The application areas of LSTM mainly includes text generation, machine translation, speech recognition, image description generation and video tagging, etc.

Each LSTM layer consists of multiple LSTM cell. Each LSTM cell includes input gate, output gate, and forget gate. The input data of the LSTM is denoted by $X = [X^{(1)}, X^{(2)}, \cdots, X^{(q)}]$, where $q$ is the length of the time steps. The process of building these gates during the $t^{th}$ time step is [13]

$$
\begin{align*}
\Gamma_f^{(t)} &= \delta(W_f^{(f)}[h^{(t-1)}, X^{(t)}] + b^{(f)}) \\
\Gamma_i^{(t)} &= \delta(W_i^{(u)}[h^{(t-1)}, X^{(t)}] + b^{(u)}) \\
\tilde{C}^{(t)} &= \tanh(W_c^{(c)}[h^{(t-1)}, X^{(t)}] + b^{(c)}) \\
C^{(t)} &= \Gamma_f^{(t)} \times C^{(t-1)} + \Gamma_i^{(t)} \times \tilde{C}^{(t)} \\
\Gamma_o^{(t)} &= \delta(W_o^{(o)}[h^{(t-1)}, X^{(t)}] + b^{(o)}) \\
h^{(t)} &= \Gamma_o^{(t)} \times \tanh(C^{(t)}) 
\end{align*}
$$

where $\Gamma_f^{(t)}$, $C^{(t)}$ and $h^{(t)}$ are the forget gate, the input gate, and the output gate, respectively. $W$ and $b$ represent the weight and the bias, respectively. Furthermore, $\delta$ and $\tanh$ stand for $sigmoid$ activation function and hyperbolic tangent function, respectively.

2) Attention layer:
Attention model (AM) was first introduced from the machine translation task and has now become a mainstream neural network concept [14]. Attention can integrate related information and allow the model to provide dynamic attention...
to some useful input information, which has been utilized as a useful tool for improving the performance of LSTM network.

Denote the output of the $t^{th}$ time step of the first layer by $h_1^{(t)} = f(x_1^{(t)}, h_1^{(t-1)}, C_1^{(t-1)})$ where $f(\cdot)$ stands for the LSTM process calculated by 1. Then, the output of the attention layer during the $i^{th}$ time step is $z^{(i)} = \sum_i a^{(i)} h_1^{(i)}$, where $a^{(i)}$ is the attention weight, which is computed by $a^{(i)} = \frac{\exp(e^{(i)})}{\sum_{j=1}^{q} \exp(e^{(j)})}$, where $\exp$ stands for the exponential function, and $e^{(i)}$ is the aggregation state computed via the Bahdanau-attention method [12]: $e^{(i)} = V^T \tanh(W_u s + W_h h_1^{(i-1)})$, where $V, W_u$ and $W_h$ are the input weights, and $s = [h_1^{(1)}, \ldots, h_1^{(q)}]$ is the output of LSTM during these $q$ time steps.

Finally, we combine the attention model output $z^{(i)}$ and the LSTM output $h_1^{(i-1)}$, and regards the combination signal as the input data for the current time slot, i.e. $X_1^{(i)} = \text{concat}(z^{(i)}, h_1^{(i-1)})$ where $\text{concat}$ is the concatenating function.

3) Output layer:

The extracted features in the last LSTM layer connect to a fully connected layer to obtain the output $X^{(q+1)}$. After rounding the output $X^{(q+1)}$, we get the predicted number of active URLLC devices.

IV. NUMERICAL RESULTS

We first present the prediction performance of our attention-based LSTM prediction model. Then, we make a comparison between our proposed IHRA scheme and the traditional contention-based random access scheme (termed ‘TARA’ in our result figures), in terms of the number of successful access devices. Note that, our proposed IHRA scheme allocates the highest transmit power level to devices whose TA indexes are the same as those in RARs corresponding to their selected preambles. To show the advantage of this allocation strategy, we also include a scheme where all devices select their uplink transmit powers randomly and uniformly as our baseline. This scheme is termed ‘IHRA-random’ in our result figures. Furthermore, we set the quantized unit to $2d = 32T_m c = 150m$ where $T_m = 3.072 \times 10^{-7}s$ and $c = 3 \times 10^8 m/s$ stand for the basic time unit and the speed of light, respectively [9]. For our proposed attention-based LSTM prediction model, the learning rate is 0.001, and the loss function is the root-mean square function. The number of active URLLC devices in each time slot follows a distribution of Poisson with mean $\lambda = 5$.

Note that, if the predicted number of active URLLC devices is lower than the real one, our proposed IHRA scheme cannot ensure all active URLLC devices access the network successfully in one shot. To tackle this problem, we take the maximum number of active URLLC devices from $t$ to $t + 4$ time slots as the value in the $t^{th}$ time slot. Fig. 2 compares the proposed attention-based LSTM and LSTM prediction models. In this figure, ‘real peak value’ stands for the maximum number of active URLLC devices from $t$ to $t + 4$ time slots, and ‘real value’ denotes the actual number of active URLLC devices in the $t^{th}$ time slot. Fig. 2(b) shows that our proposed attention-based LSTM prediction model predicts more accurately than the LSTM prediction model, and the predicted value is larger than or equal to the real value in the $t^{th}$ time slot. This means that the allocated parameters can ensure reliable communication for URLLC devices, so that all active URLLC devices during time slot $t$ can access the network successfully.

![Fig. 2. The comparison between the proposed attention-based LSTM and LSTM prediction models.](image)

![Fig. 3. The number of successful mMTC devices versus the number of preambles.](image)
Fig. 3 shows how the number of successful mMTC devices varies with the number of preambles for $R = 1200, 800$. We set the number of active mMTC devices to $N_a = 80$, and the number of power levels to $L = 4$. We can see from Fig. 3 that, with the increase of the number of preambles, the number of successful mMTC devices increases and is significantly higher than the baselines. This indicates that the transmit power level allocation strategy is efficient to improve the number of successful devices. Furthermore, with the increase of the size of the cell, the number of successful mMTC devices increases.

The reason is that, with the increase of the size of the cell, the number of different TA values increases, and then the BS can distinguish more mMTC devices.

Fig. 4 shows how the number of successful devices changes with the number of active devices for $R = 1200, 800$. We set the number of preambles to 40, the number of active URLLC devices to 3. We can see from Fig. 4 that, with the increase of the number of active devices, the number of successful devices decreases slowly for the TARA scheme and increase linearly for other schemes. We can also note that the number of successful devices of our proposed IHRA scheme is significantly higher than the baselines. Furthermore, with the increase of the size of the cell, the number of successful mMTC devices increases. The reason is the same as we described for Fig. 3.

V. CONCLUSION AND FUTURE DIRECTIONS

IoT is the enabler for smart city to interconnect devices, which makes MTC account for a great proportion in all communication services. mMTC and URLLC will co-exist in MTC network. mMTC requires massive connections, while URLLC requires high reliability and low latency communications. In this article, we introduce the architecture of heterogeneous MTC network, and then propose an IHRA scheme for 5G-enabled smart city. Numerical results show that, compared to the benchmark schemes, the proposed scheme significantly improves the successful access probability, and satisfies the diverse QoS requirements of URLLC and mMTC devices.

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