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Article

Massive Connectivity and Low-Latency for Next-Generation Internet of Things: A Filtered OFDM-based Deep Learning Approach

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Abstract: The Internet of Things (IoT) is one of the numerous services offered by sixth-generation (6G) mobile communications. It is necessary to meet heterogeneous criteria for large connectivity and low latency to serve the various kinds of IoT applications. In order to concurrently provide enormous connectivity and meet the low-latency conditions in the uplink IoT network, we proposed filtered orthogonal frequency division multiplexing (FOFDM) based on a service group adopting the deep learning (DL) technique. The proposed FOFDM-DL platform focuses on two key areas: first, it works for the concurrence of different time-frequency granularity appropriate for distinct service-based grouping, and secondly, it facilitates low latency and massive connectivity to deliver dependable communications. The suggested FOFDM-DL architecture may accommodate the needs of massive machine-type communication referred as mMTC and ultra-reliable and low-latency communications known as uRLLC concurrently for the next-generation communication systems. However, the uRLLC and mMTC requirements can only be supported separately by the new radio (NR)-5G, beyond 5G (or 6G). In comparison to the traditional scheme, simulation results demonstrate that the suggested FOFDM-DL platform works surprisingly well in the next-generation IoT network.

Keywords: Deep learning, internet of things, 6G, orthogonal frequency division multiplexing, massive machine-type communication, ultra-reliable and low-latency communications.

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1. Introduction

By 2025, there will likely be 30 billion linked devices, with IoT connection expected to increase far more quickly than mobile broadband connectivity [1]. As a result, many IoT applications need

high levels of connection, extensive coverage, and affordable hardware. The tactile internet [2] and linked autos [3] are two examples of applications that still call for minimal latency. Huawei introduced the FOFDM system [5], a flexible waveform that can survive with numerous parameter settings, to address the diverse requirements of various service kinds [4]. Additionally, it employs filtering for every sub-band to eliminate side-lobes that are presented in traditional OFDM methods. The bandwidth used by filter is intended for a particular sub-band, and it is a multi-carrier transmission method that provides filtration in the time domain.

The cornerstone of 6G may be machine learning (ML), which has the ability to be native and pervasive enough to make every part of 6G intelligent. Additionally, one of the primary aspects of 6G will be interaction with the environment. By giving people tactile and immersive sensations, it will improve the daily living of human beings. 6G should be seen as a combination of connection and mobility, as opposed to earlier generations of mobile terrestrial systems, which has prioritized the connectivity problems. Recent research achievements in deep learning (DL) were made possible by the availability of a lot of data and improvements in hardware technology. The traditional neural network which employs graph approaches having the transition among neurons to create multi-layered learning techniques is where deep learning has its roots [6]. DL has been effectively used in the area of computer vision, natural-language processing, video, and audio processing, and currently, it is being used in wireless communication. Deep neural networks are increasingly being used in a variety of communication fields, including channel decoding, channel state information estimation, and channel equalization, because of their generalization capabilities. The expansion of applications for DL approaches in wireless systems is made possible by the development of processing resources and the accessibility of vast amounts of data [7].

In order to improve performance, lessen computational complexity and solve the PAPR problem, DL methods have recently been used in OFDM systems. In [8], the DL approach was used in the OFDM received signal to directly recover the broadcast signals and calculate the channel state information indirectly. In this instance, channel statistic data were used to train the DL model offline. Less training pilots were used to acquire the findings, and cyclic prefix (CP) nonlinear clipping noise was left out. The performance was then compared to an estimator using the least mean square error. The layers of a fully connected deep neural network with an index modulation make up the unique DL detector known as DeepIM, which was proposed in [9].

In order to estimate the channel and detect signals with a requirement of one-bit complicated quantization, a unique DL-based framework with a two-step training approach was developed in [10]. In order to estimate the channel and identify the signal with reduced complexity, enhanced bit error rate performance, and strong resilience, a DL-based OFDM receiver was reported in [11]. To test the real-time restrictions in the deep neural network implementation for communication systems, a hardware description language implementation of an encoder and decoder based on deep neural network [12] was made. Authors in [13] presented a combined channel encoding and PAPR method for polar-coded OFDM systems. Hence, in terms of BER and PAPR, the DL-based FOFDM system can potentially perform better than the traditional OFDM system. Additionally, the 5G-NR can only fulfill the requirements necessary to maintain either mMTC or uRLLC communication. In this paper, service group-based FOFD integrated with DL (FOFDM-DL) is proposed. It facilitates low-latency massive connections to provide a dependable IoT communications environment and allows for the coexistence of different time-frequency granularities suitable for diverse service groups. Additionally, the suggested FOFDM-DL structure can fulfill both the mMTC and uRLLC needs for the next communication systems.

The main contribution of this paper is given below:

- We propose a service group-based FOFDM integrated with DL (FOFDM-DL) to maintain the mMTC and uRLLC requirements;

- For creating suitable diverse service groups, the proposed techniques allow the coexistence of various time-frequency granularities;
- Numerical results show an improvement in the performance of the FOFDM-DL networks compared to the OFDM, and FOFDM.

The rest of this article is structured as follows: The proposed service group-based FOFDM-DL system is explained in detail in Section 2. In Section 3, we describe the simulation findings, and in Section 4, we conclude this paper.

2. Proposed Service Group-Based FOFDM-DL

a) System Model

Baseband OFDM systems are identical to traditional ones. On the transmitter side, the transmitted symbols with pilots are first transformed into a paralleled data stream, and then the signal is transformed from the frequency domain to the time domain. After that, a CP is added to lessen the inter-symbol

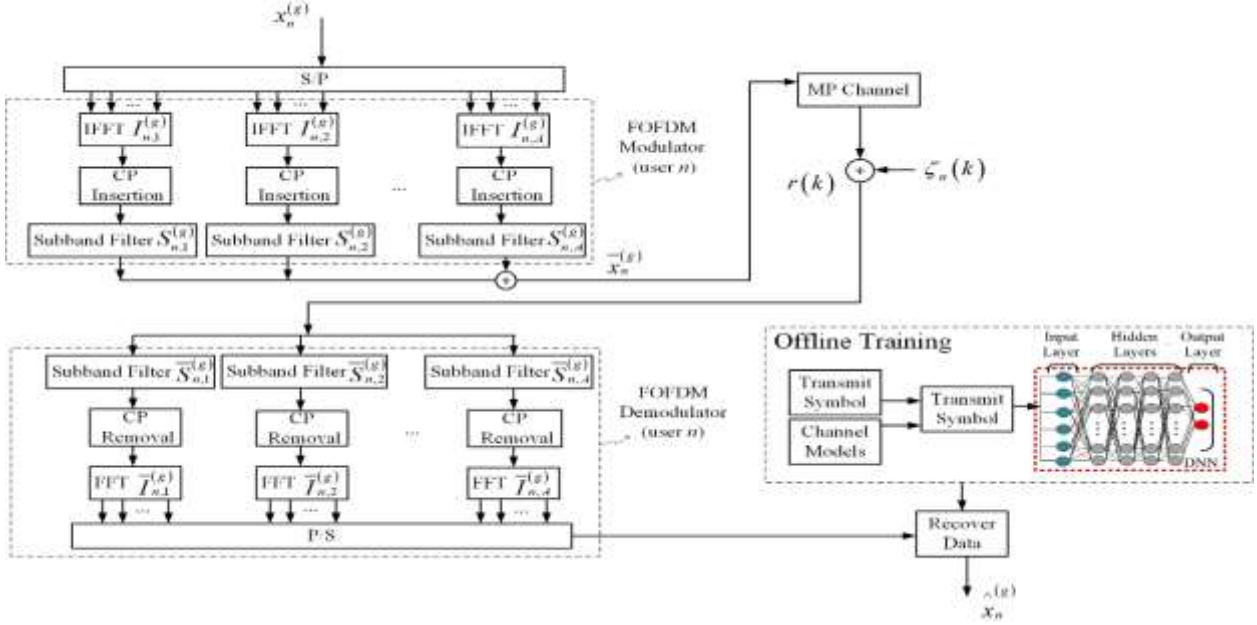


Figure. 1 Block diagram of the FOFDM-DL transceiver based on service grouping

interference. The CP must not be any shorter than the channel's maximum delay profile. We investigate a multi-path channel with sample spacing that is characterized by complicated random variables $\{h(k)\}_{k=0}^{K-1}$. Therefore, the signal received $y(k)$ is expressed as

$$y(k) = x(k) * h(k) + n(k) \tag{1}$$

Here, $n(k)$ represents the additive white Gaussian noise (AWGN). The received signal that is in a frequency domain is processed after DFT after the CP has been removed.

$$Y(m) = X(m) * H(m) + N(m) \tag{2}$$

Where the Fourier transform of *y(k)*, *x(k)*, *h(k)* and *n(k)*, are *Y(m)*, *X(m)*, *H(m)*, and *n(m)* respectively. We suppose that the first OFDM block contains the pilot symbols and the subsequent OFDM blocks contain the transmitted data. They come together to make a frame. Over the pilot frame

and data blocks, the channel can be thought of as constant, yet it changes from first frame to the next. In our initial investigation, the received data consisted of one pilot block and one data block. The DL model uses this input to recover the sent data end-to-end.

b) Service Grouping in FOFDM

The FOFDM platform based on service groups is shown for *N* user in service group *g*. To accommodate the diverse needs of IoT applications, a different FOFDM waveform is used in communication systems, using scalable numerologies, such as different transmission time intervals (TTI), and subcarrier spacing. Additionally, this system may overcome common OFDM weak spots such as high PAPR and strong side lobe in the frequency domain by the use of a sub-band filter [14].

The signal transmitted is denoted by:

$$\overline{x}_n^{(g)} = \sum_{a=1}^{A} x_{n,a}^{(g)} * I_{n,a}^{(g)} * S_{n,a}^{(g)} \tag{3}$$

Where for *n* user and *g* group, $x_{n,a}^{(g)}$, $I_{n,a}^{(g)}$, $S_{n,a}^{(g)}$ are modulated symbol, Fourier transform matrix, and a^{th} sub-band filter with total A sub-bands. After that, we express the received signal as below:

$$y(k) = \overline{x}_n^{(g)}(k) * h_n(k) * \zeta_n(k) \tag{4}$$

Where ζ is the distortion that is represented as: $\zeta_n = L + n$, where *L* is the interference from other users. Given that users must be serviced in the uplink, the functional process for the service group-based FOFDM method may be characterized in the following phases.

Step 1: Service Grouping of Users: For grouping the *N* UEs to be served in G_{tot} that is donated by $G^{(g)}$, that is $g \le G_{tot}$, where G_{tot} is the total number of service grouping.

Step ***2:*** Parameter Configuration Assignment: Give user *N* the preconfigured parameter configuration $G^{(g)}$, appropriate for the g^{th} service group, for utilization.

c) FOFDM DL Training

Two phases are used to create an efficient DL method for combined channel estimation and symbol detection that is the offline training and online training. During the offline training step, the model is trained using the received OFDM data, which are produced with diverse data sequences and facing different channel circumstances with specific statistical attributes, such as a hilly terrain or typical urban delay profile. The DL model creates the result that restores the transmitted data during the online deployment phase without explicitly predicting the wireless channel.

The systems are trained by treating the wireless channels and OFDM modulation as if they were black boxes. In the past, researchers have created a variety of CSI channel models that, in regards of channel statistics, accurately represent the real channels. The training data for these channel models may be obtained through simulation. In each simulation, the transmitted symbols are first generated at random, and the pilot symbols that make up the corresponding OFDM frame are then added. The channel models are used to replicate the present random channel

state. Based on the OFDM frames subjected to the current channel deformation, and including channel noise, the received OFDM waveform is derived. The original broadcast data and the received signal are gathered as the training datasets. The model is trained to reduce the discrepancy between the transmitted data and the neural network's output. There are various methods to represent the difference.

d) Parameter Configuration and Structure of Frame

Specific configurations are made for the FOFDM system and a frame structure specifically intended for the IoT context. Longer TTIs are needed for IoT applications to offer huge connection and broad coverage, as well as improved spectral efficiency. The support of a portion of UEs with a greater demand for low latency, however, still necessitates a lower TTI for a smaller round-trip latency and lower latency for effectively sending tiny packets. For two service kinds in the IoT context, a flexible frame structure is therefore suggested. Additionally, it should be noted that the FOFDM platform supports different TTI and waveform numbering systems because sub-band-based filtration is used. Accordingly, system parameters are designed for the FOFDM framework by dividing IoT systems into two categories such as, with the low-latency and massive connectivity requirements.

Machine-to-machine transmissions are constrained to a tiny portion of the channel capacity that is orthogonal to the broadband UEs since long-term evolution is used to allocate capacity for machine-type communications. With a longer TTI and CP than 10micro-s, the new random access technique for 5G is referred to as parameter configuration for massive communication. In contrast, very small packets should be used for low-latency service to allow one-way physical layer communication within 100micro-s; as a result, each packet cannot last longer than 33micro-s because of the structural supplementary latency, along with the encoding process at the transmitter and the diagnosis and decoding process at the receiver. Therefore, the specified symbol duration is 30 seconds. The inverse of symbol duration is then used to calculate the amount of subcarrier spacing. Additionally, the overhead of the CP length setup is taken into account; for low-latency applications, this overhead should be quite little. Block diagram of the FOFDM-DL transceiver based on service grouping is shown in Figure 1.

3. Simulation Results and Discussions

Each UE uses a convolutional coding with a 1/2 coding rate preceded by a length-8 extending sequence after configuring the settings for the waveform. The simulation has used typical urban (ETU) scenario with speed of 1 km/h and excellent channel estimation in a multi-path fading channel. There are ten sub-carriers assigned to each sub-band. In order to illustrate the effectiveness of DL techniques for combined channel estimation and symbol identification in FOFDM wireless communication networks, we have carried out a number of experiments. In DL, a deep neural network A model is trained using simulation data, and its bit-error rates are compared to those of older approaches at various signal-to-noise ratios. Under the trials that follow, it is shown that the DL-based technique is more reliable than least square and minimum mean square error in conditions when there is non-linear clipped noise, there are fewer training pilots utilized, or the CP is not present. In our tests, a 16-length CP and an OFDM network with 64 sub-carriers are taken into consideration. Three of the five layers in the DL model that we employ are hidden layers. Each layer has 16, 120, 250, 500, 256 neurons. The input number is equal to the quantity of actual and fictitious sections in two OFDM blocks, which respectively comprise the transmitted symbols and the pilots. A single model that was separately trained is used to group and forecast approximately 16 bits of the data transmitted. The predictions are then concatenated to produce the output. With the exception of the last layer, where we used the Sigmoid function for mapping the outcome to the interval [0,1], all layers employ the Relu function as the activation function.

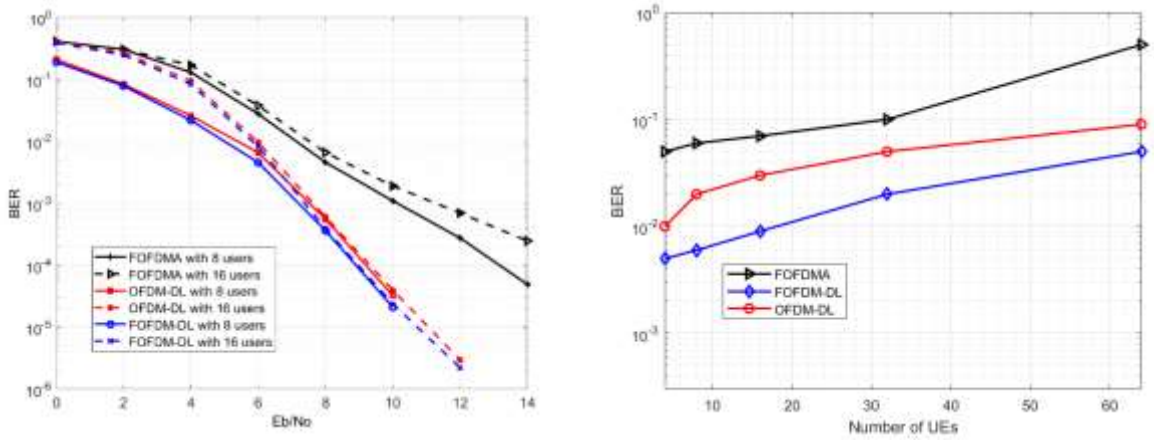
Investigation of the bit error rate of the three techniques, OFDM-DL with parameter configuration, and the proposed FOFDM-DL in terms of SNR (Eb/No) viewpoint includes two service groups with massive connectivity and Low Latency parameter settings. The resource is perceptively shared by

between eight and sixteen UEs. For the FOFDM-DL platform, we assume a relatively small number of UEs with greater low-latency requirements, i.e., two UEs for Low Latency and six UEs for massive connectivity when eight UEs are taken into account. When 16 UEs are taken into account, there are also 4 UEs for low-latency and 12 UEs for massive connectivity. Figure 2(a) compares the BER performances of the three methods.

Figure 2 demonstrates that standard OFDM-DL provides higher bit error rate performance than FOFDMA, that has the lowest performance, by around 2.2 dB at the desired BER of 10−3. This is because DL has the ability to utilise accurately predict since each user receives error free data. With a gain of 0.3 dB over traditional OFDM-DL at the target BER of 10−3, our proposed service group-based FOFDM-DL platform performs at the highest level thanks to the sub-band filter of the FOFDM that shields neighbouring UEs from interference. Additionally, it concurrently satisfies the service needs of UEs belonging to various service groups, offering appropriateness with adjustable parameters. Figure 2(b) illustrates the further investigation on the BER performance of the proposed FOFDMDL, OFDM-DL, and FOFDMA schemes with varied numbers of UEs where (Eb/No) is equal to 9. Figure 3 demonstrates how the BER performance degrades when more UEs are enabled. The bit error rate of FOFDMA, OFDM-DL, and FOFDM-DL are 0.5, 7.02x102, and 5.1x102 correspondingly when (Eb/No) is equal to 9 and the total number of UEs utilised are fixed to 64. The best performance comes from FOFDM-DL, while the lowest comes from FOFDMA. It demonstrates how much more suited waves with DL are used for supporting huge connection.

4. Conclusion

In this article, FOFDM-DL is presented as a reliable communication system for the Internet of Things that can enable enormous connections and meet low-latency requirements. Additionally, a special structural system for the IoT infrastructure is proposed, and the FOFDM platform is set with certain specifications. Additionally, the proposed FOFDM-DL structure can accommodate both the mMTC and uRLLC needs for the next-generation communication systems. Therefore, the 6G communication system can only serve the mMTC and uRLLC needs independently. The suggested system exhibits a 0.3 dB SNR increase over traditional OFDM-DL, according to simulation findings, at the desired BER of 10−3. The proposed FOFDM-DL system also adopts for the coexistence of different time-frequency granularities that are appropriate for various service groups.



(**a**) (**b**)

Figure 2 Performance comparison: (a) BER Vs Eb/No of FOFDM-DL, OFDMDL, and OFDMA schemes; (b) BER Vs Number of UEs of FOFDMA, OFDM-DL, and FOFDM-DL schemes.

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