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Original Article

Deep Learning for High-Frequency Network

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Abstract - *Recurrent neural networks (RNNs) are neural network that is often employed to process sequential input. RNNs are infamously challenging to train and learn persistent patterns due to the well-known gradient disappearing and explosion difficulties. Long short-term memory (LSTM) and Gated recurrent unit (GRU) was developed to resolve these problems. However, when applied to these devices, the usage of sigmoid action functions and hyperbolic tangents causes gradient degradation across layers. Therefore, constructing a deep trainable network is very challenging. Rectified linear unit (RELU)activation may be used by an IndRNN for non-saturated activation purposes while still being reliably trained. IndRNNs may be layered on top of one another to create a greater network than the current RNNs. Furthermore, in an RNN layer, all the neurons are intertwined, making it difficult to decipher their behavior. In this paper, the base paper technique is deep learning and is compared with other techniques to find out the most optimized, and in the implementation, the bit error rate of the technique is determined.*

Keywords - *Deep Learning, GFDM, Natural language processing, OFDM, and Recurrent neural networks.*

1. Introduction

An RNN node forms a directed or undirected graph along the time axis, making it an example of an artificial neural network (ANN). This allows it to respond in a time-dependent way. Feedforward neural networks can handle variable-length sequences of input because of their internal state (memory) [1][2][3]. Activities such as handwriting recognition that is not segmented or linked are now possible [4], or speech identification [5][6] may be accomplished. It is theoretically possible to run any program on a recurrent neural network, which means it can take inputs in any order and process them [7].

A network with an unending impulse response is called an RNN, while a network with a confined impulse response is referred to as a convolutional neural network (CNN). Dynamic time behavior is found in both types of networks [8].

Finite and infinite recurrent networks have no upper limit on the number of stored states. Additional systems or graphs with time delays or feedback loops can be used to adjust the storage [9]. These controlled conditions are known as gated states or gated memory, and they are present in LSTMs and gated recurrent units. A Feedback Neural Network (FNN) is another name for it.

The IndRNN [10] overcomes the gradient vanishing and explosion problems that plague conventional, completely linked RNNs. To retain short-term memory, the gradient backpropagation algorithm can be used. Cross-neuron data is examined to avoid gradient fading and bursting in the succeeding levels. Non-saturated non-linear functions like ReLU can be used to train IndRNN safely. Skip connections may be used to teach deep networks. Figure 1 shows the IndRNN that unfolded in time [11].

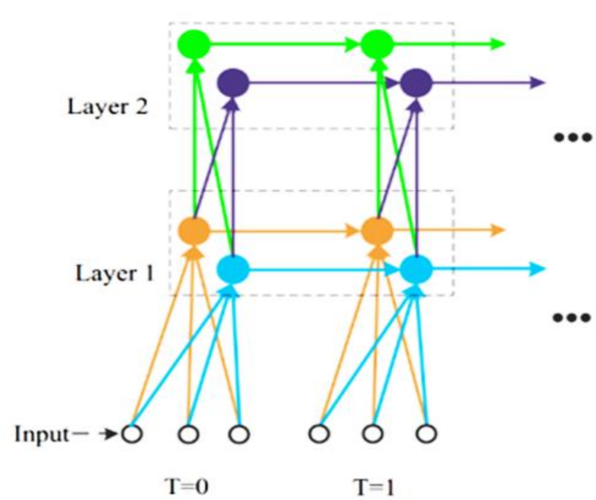


Fig. 1 Basic architecture of IndRNN

Deep learning (DL) has been suggested in the last decade to solve complicated problems in numerous fields, for example, natural language processing (NLP), target identification, and computer visualization, through the advancement of graphics processing units (GPU), neural network design, and optimization algorithms [12]. DL-aided wireless networking is an exciting field that has recently emerged in the direction of next-generation wireless networks [13]. Many experiments have been conducted on both the upper and physical layers (PHY). Still, the latter has received more attention, for example, channel estimation [14], channel coding [15], orthogonal frequency division multiplexing (OFDM) [16], and multiple-input, multiple-output (MIMO) detection include more information on DL-aided wireless contact [17-19]. Natural language processing (NLP) is the technique that deals with understanding human language and makes the computer behave in the same manner [20].

RNN [21] has shown promising results in the classification of challenges like behavior identification [22], scenario classification [23], and expression processing [24]. RNN has the recurrent relationship in which the previous unseen state is feedback to the subsequent state in contrast to feed-forward networks, for example, convolutional neural networks (CNN).

An RNN is characterized by at least one feedback link, which enables activations to circulate in a loop. This helps the networks to do progressive analysis and sequence learning, such as series reproduction /recognition or sequential organization/projection. RNN architectures come in a variety of shapes and sizes. A regular MLP (Multi-Layer Perceptron) with additional loops is one typical form [24]. These would be taken advantage of the Multi-Layer Perceptron's strong non-linear mapping capability and have some memory. Others have more standardized systems, with every neuron theoretically linked to every other neuron and stochastic activation mechanisms. Learning could be accomplished by applying identical gradient descent processes to those contributing to the backpropagation method with feed-forward systems for uncomplicated architectures and deterministic activation functions [24]. Simulated annealing methods could be more suitable when the activations are stochastic. A few of recurrent networks' most significant forms and functions will be discussed in the following sections. Furthermore, in (1), all established Recurrent neural network models have the same portion.

$$(Wxt + Uht1 + b) \quad (1)$$

Where recurrent connection intertwines all of the neurons, while a simplified representation of the outputs of neurons [24] makes it difficult to determine the work of one neuron without contemplating the others, it is difficult to perceive and appreciate the functions of the qualified neurons. The field of Natural Language Processing (NLP) has emerged as a potentially useful framework for addressing problems of this nature [25].

1.1. OFDM

OFDM is a rapidly evolving technology for the wireless local area and ad hoc networks. OFDM may be utilized in mobile ad hoc networks (MANET) to enhance energy efficiency and speed. Mobile nodes of a MANET communicate immediately over the radio frequency range and wireless connectivity. Peer-to-peer or solitary ad hoc networking is the term for this kind of networking. When the end mobile node is out of reach, additional nodes among the destination and source act as a router, transporting data among the two. Multi-hop ad hoc networks are what they are called. Multi-hop and Single-hop ad hoc networks are shown in Figure 2 [26].

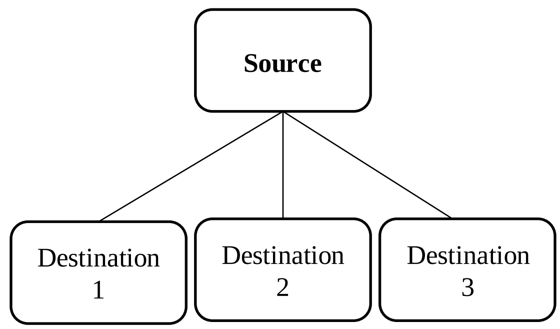


Fig. 2 Single hop ad hoc network [25]

The OFDM transmitter and receiver's decoder and encoder function as channel encoders and decoders, respectively, converting the source signals into a collection of binary data [26]. Fast Fourier Transformation (FFT) is one of the main methods for implementing OFDM on the transmitter and receiver sides for effective communication. FFT is a technique for changing time-domain signals to frequency domain signals and vice versa [27]. Figure 3 indicates the construction of an OFDM transmitter and receiver.

Convolutional encoders are often used as channel encoders in wireless transmission methods. The convolutional encoder's operating concept convolutes the input stream with the impulse response. Channel encoding goes into further detail on the convolutional encoder method. Following the channel encoder, the serial to the parallel unit transforms serial data into parallel data so that all of the inputs to the inverse Fast Fourier Transformation (IFFT) unit may be accessed simultaneously. The time-domain signals are transformed into frequency domain signals utilizing IFFT [28]. With the assistance of the serial to parallel block, the parallel data from the IFFT processor has transformed into serial information once again.

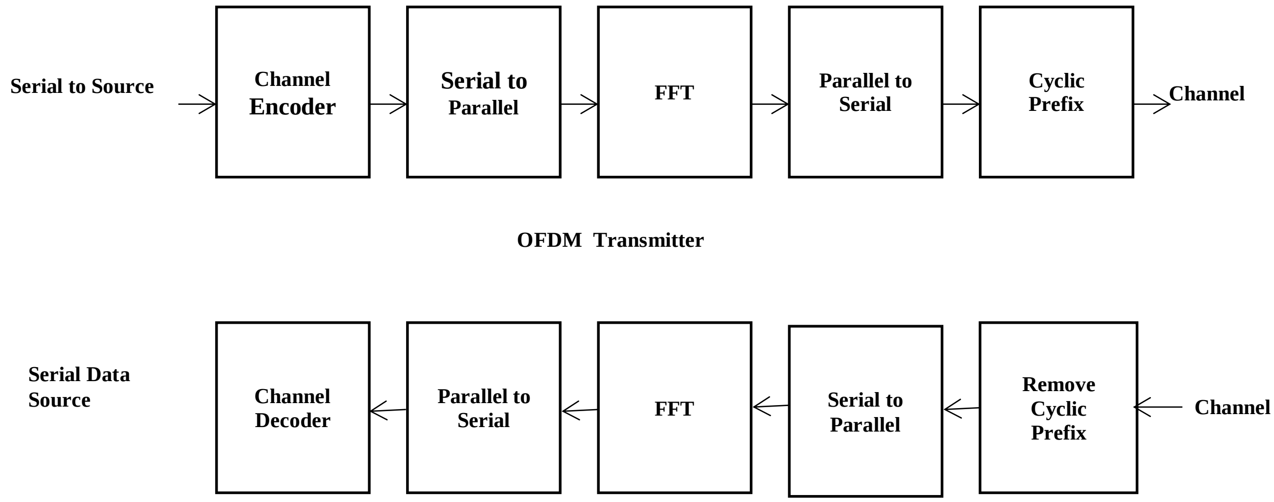


Fig. 3 OFDM System architecture [25]

The reverse operation is performed on the receiver side of the OFDM system to recover the original data signals. The approximate signal is transmitted to FFT for demodulation, and a cyclic prefix (CP) was eliminated on the receiver's end of OFDM. OFDM is a potential contender for next-generation wide-band network systems because of its multipath fading channel and capacity for pipelined/parallel signal processing [29]. The IFFT and FFT transformation techniques may be used to effectively implement the demodulation and modulation of an OFDM system [30]. The performance of OFDM-based communication systems must be excellent in terms of both power consumption and throughput [31].

1.2. Generalized frequency division multiplexing (GFDM)

The GFDM waveform has a low potential, low out-of-band (OOB) emission, low adjacent channel leakage ratio (ACLR), low peak-to-average ratio (PAPR), and flexible timing and frequency constraints, is a possible waveform for the future generation of wireless telecommunications. Because of its adaptable transceiver topology, GFDM allows for a wide range of transmitter and receiver configurations.

As a result, GFDM may be used in a wide range of situations, and its parameters can be tweaked to suit the needs of services. Furthermore, many low-complexity implementations of GFDM transceivers are available, making them economically viable. Different algorithms may be utilized in the GFDM receiver to decrease difficulty further while retaining acceptable performance [32].

1.3. GFDM Derivation

GFDM packet design differs from OFDM because just one CP is required to handle the transient channel response. Furthermore, each subcarrier's data symbols are purified via a well-localized passband filter, restricting intercarrier interference (ICI) to neighboring subcarriers. As in OFDM, the data symbols are distributed over time and frequency. The data stream in each subcarrier, on the other hand, is regulated by a filter that limits the frequency response to a certain bandwidth. Data symbols are broadcast at an interval T, similar to OFDM, and the subcarrier spacing is set at F = 1/T [16].

It is divided into four sections and the first is an introduction to the article, followed by two sections containing related works by various authors. The research methodology and implementation outcomes are presented in the third section, and the conclusion and future scope are presented in the fourth and final sections, respectively.

2. Literature Review

Following are references to papers on GFDM and OFDM written by various authors:

Chen et al. [33] stated that an OFDM-centred generalized optical quadrature spatial modulation (GOQSM) method for MIMO optical wireless communication systems was developed. Authors suggest a DNN facilitated recognition for OFDM-centred GOQSM systems, contemplating the noise amplification and error propagation impacts when using "maximum likelihood and maximum ratio combining (ML-MRC)-based detection."

Jiang et al. [34] stated that the increasing popularity of the Internet of Underwater Things (IoUT) had increased the demand for underwater acoustic (UWA) transmission solutions. On the other hand, traditional OFDM technology falls short in terms of Symbol Time Offset (STO) and flexibility to varied application scenarios. UWA's communications have been improved by incorporating the newly developed universal filtered multi-carrier (UFMC) technology.

Fong et al. [35] recommended an approach named group of optimized and multi-source selection that combines five classes of forecasting approaches. Orthodox time-series forecasting techniques, with machine learning methods, are utilized, with limited usable databases being moved from bottom to top via optimization processes. This would formulate the best winning templates for the panel segment with fewer mistakes.

Shuai et al. [36] stated that gestures are an essential part of human-computer interaction since they are a frequent method of human communication interface (HCI). Based on the IndRNN, the author presented a novel method for skeleton-based hand gesture detection. Initially, a bidirectional IndRNN is created to provide the capacity to process data in both directions. Then, the deep Bi-IndRNN network is built for gesture recognition, with the temporal dislocation of each joint being utilized to improve the input characteristics in add-on to the joint coordinates.

Merve et al. [37] stated that there had been a proposal for DL-assisted information recognition of spatial multiplexing (SMX) MIMO transmission with IM. The suggested approach learns transmission properties in the frequency and spatial domains by applying the major benefits of DL methods. Furthermore, Deep-SMX-IM is a simple technique that ultimately shows decreased complexity due to IM's subblock-based detection. For various system configurations, Deep-SMX-IM was proven to have substantial error performance improvements over zero-forcing (ZF) detectors without increasing computational complexity.

Li et al. [38] stated that due to gradient vanishing and explosion issues, RNNs are notoriously tricky to train, making it difficult to learn long-term patterns and build deep networks. To solve these issues, this article presents an IndRNN, which is a novel kind of RNN with the recurrent connection defined as a Hadamard product, where neurons within the same layer operate independently of one another but are connected within layers. IndRNN with regulated recurrent weights efficiently solves gradient disappearing and explosion issues due to better-behaved gradient backpropagation, allowing long-term dependencies to be learned. Furthermore, an IndRNN may be trained using non-saturated activation functions like ReLU.

Mehran et al. [39] stated that a DL technique for channel approximation is used in communication systems. The author examines the time-frequency response of a fast-fading transmission channel using a 2D diagram. The aim is to use certain known values at the pilot sites to discover the unknown values of the channel reaction. To achieve this goal, a generic pipeline based on deep image processing methods, image super-resolution (SR), and image restoration (IR) are suggested.

Turhan et al. [40] stated that using a DNN for symbol identification and demodulation in GFDM is explored. To enhance the system's error routine, a novel receiver model is suggested that includes both conventional linear detector-based coarse detection and deep neural network-based fine detection. It has been shown that the suggested DNN-based detection and demodulation method outperforms conventional linear detectors in terms of bit error rate (BER).

Shi et al. [41] stated that Graph convolutional networks (GCNs), which represent skeletons of the human body as spatiotemporal graphs, have shown exceptional accomplishment in skeleton-centered action identification. The graph's topology is established physically in current GCN-based techniques, and it is stable across the entire layers and input samples. This might not be optimum for the hierarchical GCN and varied samples in action recognition tasks. Furthermore, current techniques seldom examine the second-order (bone lengths and orientations) of skeleton data, which is inherently more useful and discriminatory for activity identification.

Öztürk et al. [42] stated that in a novel manner, GFDM is coupled with IM, using the block-centered structure of GFDM. Using an improved distance spectrum and GFDM's flexible IM numerology, this method is designed to reduce "out-of-band (OOB)" emission while simultaneously giving a novel multilayer model scheme. The above research is summarised in Table 1.

Table 1. Summary of the Literature Review

S.No	Author and Year	Technique	Results
1	Chen et al., (2021) [33]	DNN	The author used DNN to facilitate recognition for OFDM-based GOQSM systems, contemplating the error propagation and noise amplification impacts.
2	Jiang et al., (2021) [34]	OFDM	The traditional OFDM technology falls short of addressing different flaws.

3	Fong et al., (2020) [35]	Orthodox time-series forecasting	This technique formulates the best winning templates for the panel segment with the least mistakes.
4	Shuai et al., (2020) [36]	HCI	The author utilized the technique to improve the input characteristics in add-on to the joint coordinates.
5	Merve et al., (2019) [37]	DL	This technique was proven to have substantial error performance improvements over the ZF detector without increasing computational complexity.
6	Li et al., (2019) [38]	RNN	Compared to the widely used LSTM, this approach reduces calculation time at each step and may be up to ten times faster.
7	Mehran et al., (2019) [39]	DL	The goal is to use certain known values at the pilot sites to discover the unknown values of the channel reaction.
8	Turhan et al., (2019) [40]	DNN	DNN-based detection and demodulation method outperform conventional linear detectors in terms of bit error rate (BER).
9	Shi et al., (2019) [41]	GCN	With this technique, the hierarchical GCN and a wide range of samples may not be ideal for action recognition tasks.
10	Öztürk et al., (2018) [42]	GFDM	It provides a new multilayer system model to use IM's improved distance spectrum.

3. Background Study

DL has been projected in the last decade to solve complicated problems in various areas, for example, NLP, target recognition, and computer vision, through the advancement of graphics processing units (GPU), neural network design, and optimization algorithms. Recent research and accomplishments in DL are discussed. Aside from these findings, DL-aided wireless networking is an exciting field that has recently emerged in the direction of next-generation wireless networks. Many experiments have been performed on both the upper and physical layers (PHY). Still, the latter has gained more publicity, for example, channel estimation, channel coding, and MIMO detection. In addition, a CNN is used to manage complicated signals, such as Quadrature Amplitude Modulation (QAM) signals, through a fully convolutional neural network (FCNN). A new GFDM receiver scheme has been suggested, built using a linear detector and a neural network. The suggested scheme's BER efficiency was compared to a classical linear detector in Rayleigh multipath fading channels [43].

4. Problem Formulation

The input signal influences the total reflection at the output point. Modulators (also known as balanced modulators, doubly balanced modulators, or high-level mixers) are sign-changers used for the input signal. In practice, the contribution of an effectively trainable deep network is difficult to quantify.

A labeled sample of a problem space can never be created for a deep learning algorithm. Consequently, to characterize the results, it would have to interpolate or generalize among earlier samples. In this research, the Hilbert transform is used for signal preprocessing, and the Ind RNN is used to choose the demodulator filter.

- Ind RNN can be simply controlled to avoid the vanishing problems, and gradient exploding but permit the network to acquire enduring dependencies.
- Ind RNN can also be trained by non-saturated activation functions, including (relu).
- Stacking several Ind RNNs would provide a deeper network than the current Recurrent neural networks.
- Ind RNN improves the performance as contrasted among the traditional RNN and LSTM.

5. Research Objective

- To study the analysis of InRNN behavior by verifying the processing of long sequences.
- To supervise the InRNN to avoid gradient exploding and disappearing problems.
- To determine the bit error to get the best optimum technique.
- To obtain IndRNN robustly by non-saturated activation functions, including (relu).
- To improve the performance of the RNN and LSTM.

6. Research Methodology

This section contains the proposed methodology, which is explained below in detail:

6.1. *Inter Symbol Interference (ISI)*

ISI is a signal change in which one or more symbols interfere with each other, resulting in noise or poor performance [44].

6.2. *Causes of ISI [44]*
- Non-linear frequency in channels
- Multipath Propagation

6.3. *Correlative Coding*
Inter Symbol Interference is an undesirable trend that reduces the signal. However, if the same ISI is applied carefully, it is conceivable to obtain the bit rate of the 2W bits per second in the channel with a bandwidth of W Hertz. This system is known as Correlative Coding or Partial Answer Signaling [43].

6.4. *Duo-binary Signaling*
So far, ISI is an undesirable trend that destroys the signal. However, if a similar ISI is used carefully and 2W bits per second may be achieved on a W Hertz bandwidth channel. This form of arrangement is recognized as Partial Answer Signaling or Correlative Coding.

Given that the sum of Inter Symbol Interference is understood, it is simple to build the receiver to prevent the impact of ISI on the signal. Find an example of Duo-binary Signaling to understand the underlying principle of correlative coding [43].

6.5. *Eye Pattern*
The Eye Pattern is an effective technique for analyzing ISI findings. Binary waves were given Eye patterns because of their closeness to the human eye. The eye-opening pattern is the inner portion of the eye pattern [44].

6.6. *Pulse Shaping Filter*
The alteration of a waveform of emitted pulses improves the suitability of a transmitted signal to its intended purpose or communication medium, usually by restricting the transmission for an effective bandwidth. The inter-symbol interruption induced by the channel can be held under control by filtering transmitted pulses in this manner. The following filters are usually used in contact systems [44]:

- Gaussian filter
- Sinc Filter
- Raised- Cosine Filter

6.7. *Matched Filter*
The matched filter may be as relevant as the pulse-shaping filter. While the pulse shaping filter is responsible for producing signals so that every single symbol cycle does not coincide, the matched filter is responsible for filtering out any signal reflections that happen throughout the communication phase. Since a direct-path signal enters the receiver before a mirrored signal, the reflected signal can coincide with a corresponding symbol time [44].

Advanced pulse shaping filters are established in the GFDM modulator and Matched filters to filter out signal reflections in this suggested work. The contrast would be analyzed using symbol error rate analysis applying the QAM transmission technique across various channels. Applying lightweight Pulse forming filters can achieve lower out-of-band emission and lower ISI while maintaining high SER performance. The block diagram displayed in Figure 4 is a GFDM-based transceiver [44].

The binary data source is responsible for generating the binary data stream b, which is then encoded and mapped using a suitable digital modulation technique (BPSK, QPSK, or QAM) to obtain encoded symbols bc. The encoded symbols belong to a set of 2μ - complex constellation points where μ signifies the number of bits per symbol, also known as an order of modulation.

The resulting symbols bc are arranged as an input data vector, having K elements at a time, where "K = MN, i.e., the product of two integers. The K elements can be visualized as disintegrated into N subcarriers with M symbols in each GFDM data block.

In a GFDM data block, M symbols intersect in time. Hence M is the GFDM system overlapping factor. The NM×1 column vector includes the complicated data symbols of one GFDM block, where the M×1 data vector di = [di (0) ………. di (M-1)] T denotes the data symbols to be transferred on the subcarrier".

The data symbols are sent in the form of blocks in GFDM. Each data block is divided into K sub-carriers, with each sub-carrier containing M sub-symbols. The used subcarriers aren't orthogonal to one another. Filters transferred in both time and frequency realms are used to form the pulses of sub-carriers.

After serial to parallel conversion, a pulse-shaping filter is necessary for the modulator process (the mapped data is decomposed into n number subcarriers having m sub symbols). Improved Nyquist filter efficiency in ISI reduction is still a work in progress. On the other side, Pulse forming filters must have a low ISI, but they must also inhibit out-of-band emission by eliminating neighboring channel intrusion.

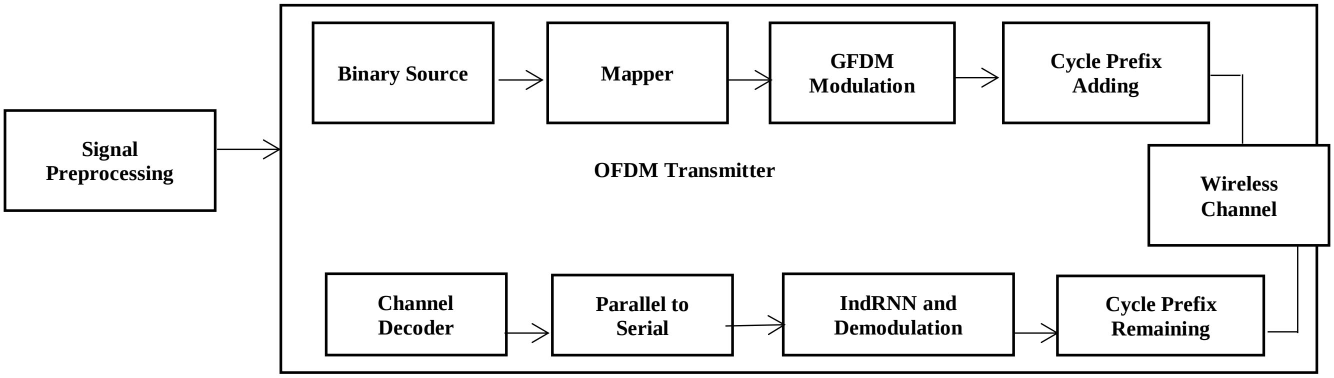
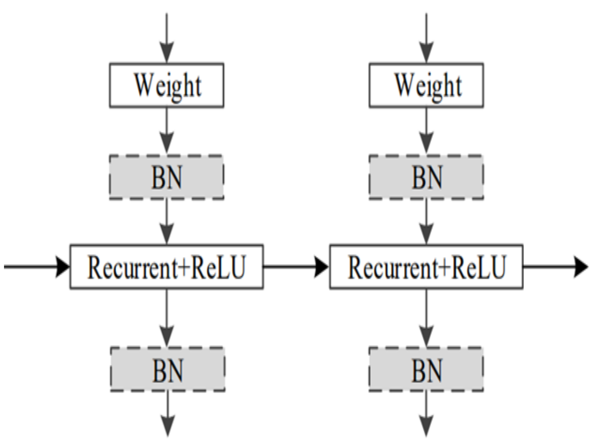


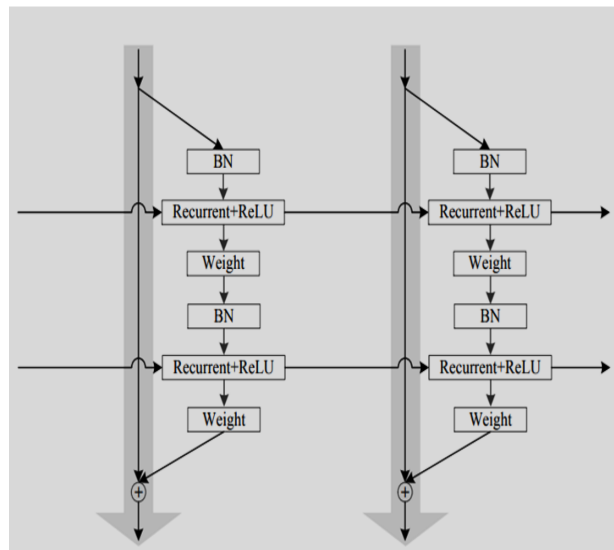
Fig. 4 The block figure of the GFDM transceiver.

The simple Ind-RNN architecture is depicted in Figure 5 (a), where "weight" and "Recurrent+ReLU" signify the recurrent and input processing at every level, respectively, through the rectified linear unit as the activation mechanism.

A deep Ind-RNN can be developed by assembling this simple architecture. Also, batch normalization, signified as "BN," may be applied before or after the activation function in the independently recurrent neural network, as seen in Figure 4 (a). Since the input is processed by the weight layer (Wxt + b), it is only logical to expand it to several layers to expand the administering.



(a)



(b)

Fig. 5 Description of (a) the fundamental independently recurrent neural architecture and (b) the residual independently recurrent neural network architecture [38].

IndRNNs may be packed in the form of enduring connections in add-on to merely stacking them for processing the input.

The example of a residual IndRNN in Figure 4 (b) is focused on a pre-activation form of the residual layers in [44]. The gradient could be immediately transmitted to the other layer through identity mapping at each time point. Since an independently recurrent neural network solves the gradient bursting and disappearing challenges across time, the gradient can be transmitted easily across various time measures.

As a result, the network would be both larger and more retentive. Like other networks, the longer and deeper independently recurrent neural network may be educated end-to-end.

7. Implementation and Results

The implementation that was done making use of the suggested approach can be found in this section of the paper, and the tools that were utilized for the implementation can be found below:

7.1. *Tools Used*

7.1.1 MATLAB

MATLAB (matrix laboratory) is an interactive environment and a high-level programming language for numerical computing, programming, and visualization in the fourth generation. In addition to the MATLAB programming language, MathWorks offers an array of software tools for numerical computation and analysis. Analysis and visualization of functions and data may be done with MATLAB. It can also connect with programs developed in other languages [45].

The work that was done to support the intended effort is as follows.

7.2. *Results*

7.2.1. Results 1

Figure 6 below shows the subcarrier index used to convey information to the receiver.

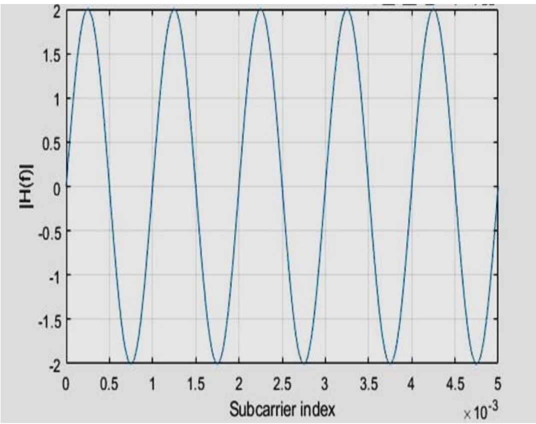


Fig. 6 Subcarrier Index

It is a second modulated signal frequency-modulated into the primary carrier frequency to create an extra transmission channel. It allows for a single transmission to carry more than one separate signal.

7.2.2. Results 2

Figure 7 depicts the transmit (TX) and received (RX) signals, where the signal at the receive antenna is the convolution of the send signal and the channel reply. In addition, insert some noise into the signal based on the signal-noise ratio (SNR) value.

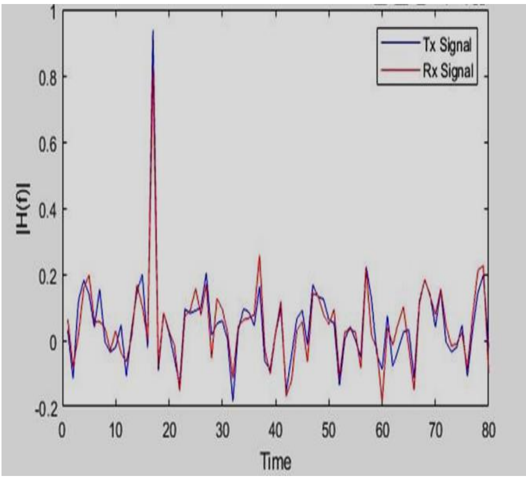


Fig. 7 Tx and Rx signal

7.2.3. Results 3

Figure 8 depicts the channel equalizer, which employs a straightforward zero-forcing channel estimate observed by a straightforward interpolation. The channel values among the pilot carriers are interpolated to approximate the channel in the data carriers.

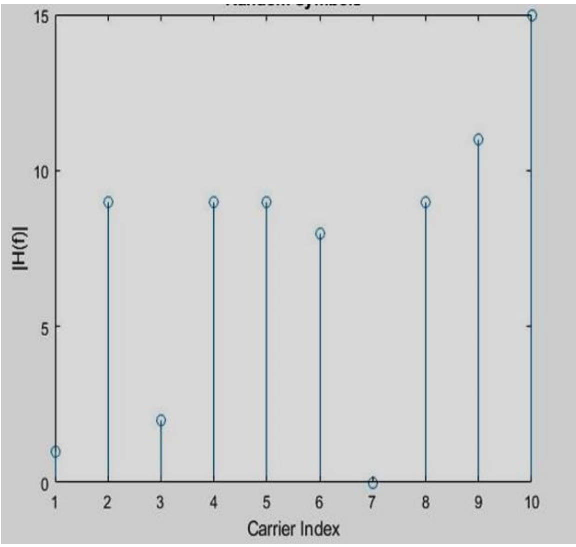


Fig 8. Channel Equalizer

Figure 9 below shows the comparison in error among the techniques used in the base paper with the other four. These three techniques are compared, namely the technique used in the base paper [46], i.e., point completion network (PCN), maximum a posteriori (MAP), CNN, and FCN technique. Table 2 illustrates the values of techniques found in the comparison graph.

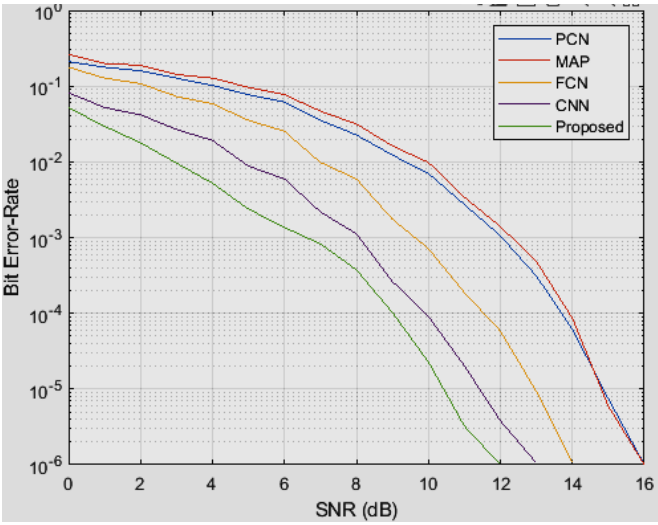


Fig. 9 Comparison graph

Table 2. Comparison of the proposed methodology with previous methodologies

Techniques	Bit Error Rate	SNR dB
PCN	$10^{-0.6}$	16
MAP	$10^{-0.63}$	16
FCN	$10^{-0.65}$	14
CNN	$10^{-1.1}$	13
Proposed	$10^{-1.3}$	12

8. Conclusion and Future Work

Researchers have discovered that when an IndRNN develops a new recurrent connection, it creates neurons in a layer that is not connected. It addresses the gradient explosion and then vanishing issues by controlling the recurrent weights, allowing it to handle extremely lengthy sequences efficiently. IndRNN's gradient enhancement can build non-saturated activation functions such as ReLU, which can be successfully used. In addition, given that every neuron in the layer can function independently of the others, it is possible to enhance one neuron without affecting the others. The experimental findings indicate that the suggested system outperforms the conventional linear detector in Rayleigh multipath fading channels in terms of BER. More specifically, at the SNR value of 10 dB, the proposed technique achieves a BER value of $10^{-1.3}$. The proposed technique exhibits significantly better BERs than the others. It has been shown that the suggested system outperforms conventional linear detectors in terms of BER. In the implementation, the bit error rate is calculated and compared with the base paper techniques to determine the best optimum solution, which gives more efficient outcomes among all techniques. In the future scope, the DL-assisted joint detection and demodulation (JDD)-based GFDM scheme is a viable approach for wireless networks beyond 5G.

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