BMBAD BJESR Mühendislik Bilimleri ve Araştırmaları Dergisi Journal of Engineering Sciences and Researches

Deep Learning Models For Symbol Detection in UFMC Systems

UFMC Sistemlerinde Sembol Tespiti İçin Derin Öğrenme Modelleri

[1]F. Kebire BARDAK , [2]M. Nuri SEYMAN

[1,2]Bandırma Onyedi Eylül Üniversitesi, Mühendislik ve Doğa Bilimleri Fakültesi, Elektrik- Elektronik Mühendisliği Bölümü Bandırma/Balıkesir, Türkiye

[1]kbardak@bandirma.edu.tr, [2]mseyman@bandirma.edu.tr,

Araştırma Makalesi/Research Article

ARTICLE INFO

Article history

Received : 4 August 2024
Accepted : 6 September 2024

Keywords:

UFMC, Symbol detection, LSTM, CNN

ABSTRACT

In wireless communication systems, multi-carrier systems are used to use the limited frequency band in the most efficient way and thus increase spectral efficiency, allowing for high-speed data transmission. In this study, the Universal Filtered Multi-Carrier (UFMC) technique is considered a multi-carrier system that minimizes the intra-channel interference problem by dividing the bandwidth into many sub-bands and filtering only the lower sidebands in addition to high-speed data transmission. In addition, in this study, symbol detection in UFMC systems is carried out by taking advantage of the learning ability of deep learning methods, flexibility to solve non-linear problems, and reducing hardware load by using fewer parameters and parallel processing capabilities. The proposed LSTM and CNN-based deep learning methods provide lower Bit Error Rate (BER) values even at low Signal-to-Noise Ratio (SNR) levels than traditional symbol detection algorithms and significantly increase the system's symbol detection performance under difficult channel conditions. In this way, the spectral efficiency and overall communication performance of UFMC systems are improved.

MAKALE BİLGİSİ

Makale Tarihleri

Gönderim : 4 Ağustos 2024
Kabul : 6 Eylül 2024

Anahtar Kelimeler:

UFMC, Sembol tespiti, LSTM, CNN

ÖZET

Kablosuz haberleşme sistemlerinde, sınırlı frekans bandını en verimli şekilde kullanmak ve böylece spektral verimliliği artırmak, yüksek hızlı veri iletimine olanak sağlamak için çoklu taşıyıcılı sistemler kullanılır. Bu çalışmada, yüksek hızlı veri iletiminin yanı sıra bant genişliğini birçok alt banda bölerek ve yalnızca alt yan bantları filtreleyerek kanal içi girişim sorununu en aza indiren bir çoklu taşıyıcı sistemi olan Evrensel Filtreli Çoklu Taşıyıcı (UFMC) tekniği ele alınmıştır. Ayrıca bu çalışmada, derin öğrenme yöntemlerinin öğrenme yeteneğinden, doğrusal olmayan problemleri çözme esnekliğinden ve daha az parametre ve paralel işleme kabiliyetleri kullanarak donanım yükünü azaltmasından yararlanılarak UFMC sistemlerinde sembol tespiti gerçekleştirilmiştir. Önerilen LSTM ve CNN tabanlı derin öğrenme yöntemleri, düşük Sinyal-Gürültü Oranı (SNR) seviyelerinde bile geleneksel sembol tespit algoritmalarından daha düşük Bit Hata Oranı (BER) değerleri sağlar ve sistemin sembol tespit performansını zorlu kanal koşulları altında önemli ölçüde artırır. Bu şekilde, UFMC sistemlerinin spektral verimliliği ve genel iletişim performansı iyileştirilmiştir.

ORCID ID: [1]0000-0002-9380-2330
[2]0000-0002-8763-7834

1. INTRODUCTION

Recently there has been a significant increase in mobile data traffic. In the future, with the increasing number of intelligent and similar human-centered devices, as well as the widespread use of the Internet of Things technology, mobile internet will become an important part of our lives. This situation is also accelerating the development of next and new-generation communication technologies. In addition to meeting mobile user needs, the integration of Internet of Things (IoT) technology and the seamless provision of communication between objects depend on the development of next-generation wireless communication systems that offer high data rates and spectral efficiency.[1]

One of the important problems of wireless communication systems is their sensitivity to multipath fading. The ability to resist multipath fading and at the same time provide high-speed data transmission makes multicarrier systems preferred for wireless data transmission. In this context, the Orthogonal Frequency Division Multiplexing (OFDM) technique forms the basis of many high-speed communication systems. However, OFDM systems are sensitive to time-frequency shifts and multipath delays, and the Cyclic Prefix (CP) used to alleviate these problems reduces the spectral efficiency of the system. In addition, OFDM's use of square waveforms can lead to the formation of wide sidebands and data corruption when synchronization between subcarriers is not provided [2].

To eliminate the mentioned drawbacks of the OFDM system, the use of Universal Filtered Multicarrier (UFMC) waveform is recommended in next-generation communication systems. Unlike OFDM, in the UFMC technique, the bandwidth is split into numerous subbands, and the subbands containing multiple carriers are filtered. As a result, instead of filtering the entire band, only the subbands are filtered, reducing distortions even further and eliminating potential inter-carrier interference (ICI). Additionally, since this technique does not require CP unlike OFDM, it provides higher spectral efficiency, enabling faster data transmission [3-5].

In wireless communication systems, estimating the channel state response is critical for the correct reception of transmitted symbols [6-22]. Traditional algorithms used for symbol detection require full knowledge of the channel model and its parameters. However, in some cases, especially when the channel model is quite complex or not well understood, the performance of traditional algorithms decreases. Additionally, channel state information (CSI), which refers to knowing the instantaneous parameters of the channel model, can mitigate the disruptive effects of the channel at the receiver [6-7]. Therefore, traditional techniques based on the channel model require the estimation of instantaneous CSI. However, this process not only brings an additional overhead that reduces the transmission speed, but also significantly degrades the symbol detection performance in case of incorrect CSI estimation [8].

The estimation of channel inpulse response and data detection rely on classic estimation algorithms such as Least Squares (LS), Minimum Mean Square Error (MMSE), Least Square Error (LMS), and Maximum Likelihood (ML). Although the MMSE algorithm used in channel estimation has high performance, its practicality in real-time circuits is limited due to the requirement for statistical channel data, which is challenging to acquire during real-time data transmission. While the use of the LS algorithm is easy, its performance is inadequate in fading channels, which reduces its usefulness [6-7]. Additionally, even though the ML algorithm outperforms the other techniques, its computing increases in direct proportion to the number of antennas in the system when a multiple antenna configuration is employed. Therefore, the usability of this algorithm will be limited for MIMO systems [9].

In recent years, deep learning neural networks have attracted considerably of interest as a potential solution for challenging problems in engineering [6-18]. Deep learning focuses on the ability to learn using mathematical models called artificial neural networks, which essentially attempt to mimic biological neural networks. This technique involves deep learning models, often referred to as multilayered neural networks. These models are capable of learning complex patterns and features on data at a hierarchical level. Deep learning can perform more complex tasks than previous machine learning approaches because these models can be optimized to solve problems by processing large and diverse data sets [23-27].

The deep learning process includes two phases which are the training phase of the model and the inference phase of the model. The training phase involves the feeding of the model with a large number of data instances and weight update; the inference phase involves prediction of new instances that the model has not encountered before [10-27]. Thus, the ability of deep learning neural networks to learn, the ability to process data in parallel, the low hardware requirements and the ability to solve nonlinear problems make these methods applicable in many fields. Besides, deep learning techniques are able to revolutionize the communication technologies by enhancing their intelligence, security and efficiency in tackling wireless communication challenges like symbol detection and channel estimation [10-18].

Deep learning-based communication systems have become the focus of research due to their ability to decipher the relationship between channel inputs and outputs without using an explicit channel model, demonstrating superior performance not only in symbol detection but also in channel estimation. Furthermore, since these techniques are not dependent on the channel model, they can work efficiently even in cases where the model is unknown or the parameters cannot be estimated exactly [10,11]. When we consider to the literature, in [11], the performance of a signal detector designed with convolutional neural networks was compared with succesive interference cancellation (SIC), yielding a better symbol error rate. Studies in [12,13] have shown that deep learning neural networks outperform LS and MMSE methods in terms of bir error rate (BER) performance. In the study in [14], a feedback structure based on the receiver's Signal-to-Noise Ratio (SNR) information was created

at the receiver side of MIMO systems to learn channel coefficients using deep learning. Also in [15], a type of deep learning called long short-time (LSTM) deep learning was proposed for OFDM systems. Investigating NOMA systems is another area where deep learning neural networks have been used for symbol detection [16,17]. However, while most studies on channel estimation in UFMC systems in the literature focus on traditional methods, only a few involve deep learning techniques [18-21]. In [18], pilot tone-assisted channel estimation in UFMC systems was investigated, demonstrating the applicability of classical channel estimation methods in UFMC, while [19] introduced a new channel estimation method for the uplink of multi-user UFMC systems. In another study, traditional channel estimation algorithms in UFMC systems based on comb-type pilot tones were compared, and the optimization problem of pilot signals was formulated in closed form [20].
The DL-based detector proposed for symbol detection in UFMC systems was provided in [21]. The proposed system's performance was evaluated in comparison to that of OFDM systems based on DL and signal detection performed using conventional channel estimation methods. The results of these studies clearly demonstrate that deep learning neural networks are highly successful at detecting symbols in multicarrier systems.
In this paper, deep learning techniques are employed to enhance the capability of UFMC systems in dynamic environments and to address the limitations of conventional symbol detection and channel estimation techniques. Conventional methods assume complete knowledge of the channel model and its parameters, and thus may be less effective in scenarios with complex or unknown channel conditions. In this scenario, deep learning-based methods are advantageous because they can learn the relationships between the channel inputs and outputs in a more robust manner without the need for a channel model. These methods can be adjusted to the changes in channel conditions through artificial neural networks and give a better detection of the symbols. In the case of UFMC systems, deep learning techniques improve the symbol detection and channel estimation that enhances the spectral efficiency thus improving the data transmission rates and offers better performance in various channel environments including the multipath fading channel. In this paper, the focus is on the use of deep learning algorithms in order to improve the performance of UFMC systems that can be used in wireless communication systems in order to transmit reliable and high-quality data.

2. MATERIAL-METHOD

2.1. UFMC System Model

Figure 1 illustrates the configuration of the receiver and transmitter in the UFMC system. When generating UFMC signals, the information bits are initially modulated using quadrature amplitude modulation (QAM). Following this, the complete QAM symbol vector band is subdivided into N_B distinct sub-bands, each of which has a specific dimension and does not overlap. The QAM symbols separated into multiple sub-bands are subjected to the N-point inverse fast Fourier Transform (IFFT). This process yields the expression of the i*th* subband in time-space (Eq.1).

$$x_i(k) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} X_i(n) e^{j2\pi nk/N}, \; 0 \le k \le N-1, \quad 1 \le i \le N_B \tag{1}$$

Here, $X_i(n)$ is defined as the signal in the frequency space on the ith subband. Additionally, n, N, and N_B denote subcarrier indexes, number of subcarriers, and number of subbands, respectively. Subband signals obtained after the IFFT process are filtered using a finite impulse response (FIR) filter. Eventually, the filtered signals are collected and the transmitted UFMC signal is

$$w(k) = \sum_{i=1}^{N_B} w_i(k)\,, \; 0 \le k \le N+L-1 \tag{2}$$

obtained by the formula. Here, $w_i(k)$ indicates the filtered signal in the *i*th subband, while L indicates the filter length. The $w_i(k)$ is obtained after the filtering process is applied:

$$w_i(k) = x_i(k) * f_i(k), \; 0 \le k \le N+L-1, \; 1 \le i \le N_B \tag{3}$$

is found by the convolution process. Here, $f_i(k)$ shows the impulse response of the FIR filter used in the *i*th subband to filter the signal $x_i(k)$.
As depicted in the figure above, the signal processing steps implemented at the receiver end of UFMC system are explained. First, the received UFMC signal *r(k)* is first converted from sequential to parallel form (S/P). At this stage, the length of signal is increased up to 2N this is done in the time domain by a process known as padding. Expanding the signal to 2N is very important in order to get a better and more precise signal processing and representations in frequency domain. This extension leads to the capability of calculating more frequency components during FFT process and thus improves the spectral resolution [20]. Then, a 2N-point FFT process is applied on the extended signal to get the frequency domain signal. The 2N complex signal components are obtained in the form of *R(k)* vector after the application of FFT process. In this vector only the even placed samples are taken and the odd ones are dropped, this is done to get a higher frequency of resolution and better modelling of channel effects. The chosen samples are further processed by a frequency domain equalization in order to remove the channel distortion and to improve the signal to noise ratio. This equalization process carried out in the frequency domain helps in reducing the impairment common with UFMC systems including multipath fading and channel distortion. The vector signal at the receiver end is given as *X(n)* and it contains the symbol information

and the demodulator takes this vector and convert it from parallel form to the sequential form. The QAM demodulator enables the detection of the original data bits. This process is crucial to enhance the signal detection of UFMC systems to improve their performance. Taking the signal to 2N at the receiver end enhances the performance of wireless communication systems in that channel estimation and symbol detection is enhanced. This method enhances the symbol detection efficiency particularly under different channel conditions thus improving the efficiency of UFMC systems [20].

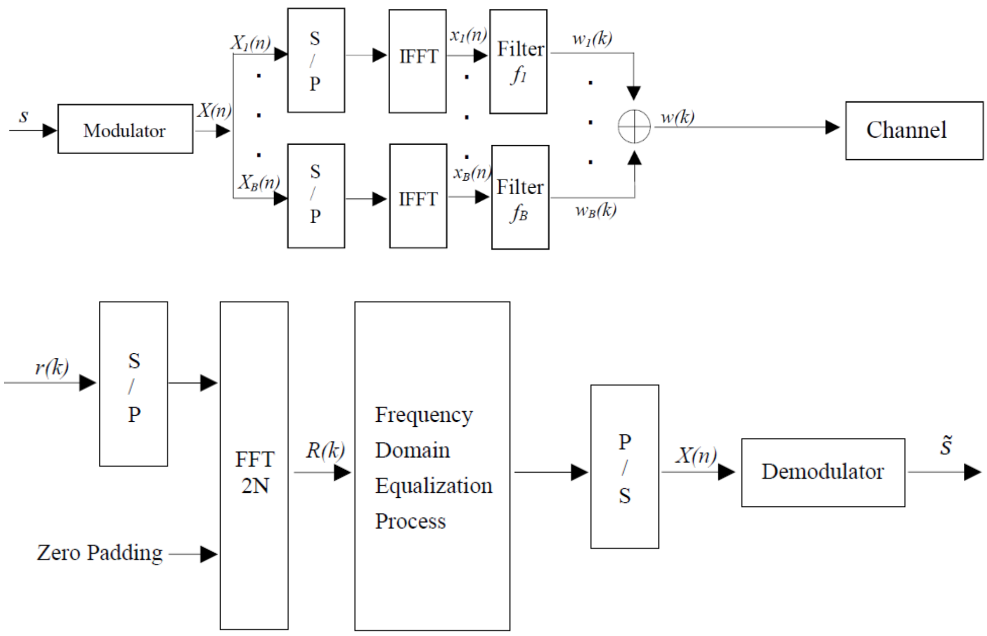

Figure 1. UFMC System Model.

Considering these, the extension of the UFMC signal to 2N at the receiver end and the FFT process are deemed as two important signal processing steps. These processes are intended for ensuring the high level of symbol detection accuracy and the minimizing of channel effects. The employment of the signal extension and the FFT is useful in combating against the effects of spectral leakage and multipath fading which are normal in multi-carrier systems. Nonlinear compensation, frequency domain equalization and QAM demodulation facilitate the removal of distortions that may have occurred during transmission and extraction of the original data bits. Thus, these methods used in UFMC systems are quite effective to enhance the performance of the state-of-the-art wireless communication systems.

2.2. Convolutional Neural Network (CNN)

A deep learning technique known as CNN is designed based on the visual perception mechanisms of biological organisms. It is a feed-forward and multi-layer approach. CNN is extensively utilized in various domains, including pattern recognition, classification, and data prediction. Moreover, it is highly successful in signal detection and channel estimation within wireless communication systems. The CNN algorithm employs a multi-layered approach to analyze images or data, utilizing the complete dataset or its features. The traditional CNN architecture usually contains five primary layers: input layer, convolution layer, pooling layer, normalization layer, and output layer. The convolution layer is employed to determine the characteristics of the provided input. By evaluating the availability of the network in the pooling layer, the network's parameters and computational workload are decreased. Ultimately, the classification procedure is executed within the normalization layer [22, 23].
In each dataset, *n* convolution filters are employed in the convolution and pooling layer of the CNN structure to extract *n* feature vectors. All feature vectors are collected in the X matrix as shown in Eq. (4).

$$X = ReLU(data, A_n) \tag{4}$$

Here, the information received from the input layer involves several image sequences $(A_1, A_2, \dots, A_n)$. ReLU, on the other hand, functions as a non-linear activation function working on neurons. The convolution layer consists of a, $W_z \in R^{dxs}$ filter. Here *s* is the step size of the filter and *d* is the feature vector size *n*. The feature vector created by the filter is obtained as shown in Eq. (5).

$$V = f(conv(X.W_z) + b) \tag{5}$$

Here, *b* is a vector indicating the function's intersection point, which is utilized to carry out the linear classification.

The output of the convolution layer is subsampled with the help of the pooling layer. In pooling, the commonly used technique is applying a maximum operation to the outcomes of each filter. In Eq. (6), the pooling layer output value is obtained.

$$\tilde{X} = (\max\{V\}) \tag{6}$$

Through the utilization of maximum pooling, minimum values are not given to the network and the processing load on the upper layers is reduced. The generated $\tilde{X}$ feature vector is then transmitted to the normalization layer. In conclusion, by preventing breaks or powerful responses that may occur in the feature vector, the normalization layer reduces the error rate during the classification process [24].

2.3. Long Short-Term Memory (LSTM)

LSTM is a special type of Recurrent Neural Network (RNN). LSTM is a distinct variant of Recurrent Neural Network (RNN). LSTM has the capacity to learn long-term dependencies and stores critical information for extended periods. LSTM, which has three types of gate terminals: input gate, forget gate, and output gate, creates a new channel between the input and output and ensures that the error value coming from different layers is kept constant by backpropagation. On the other hand, the entry gate selects information that needs to be stored, while the forget gate selects information that does not need to be stored. The gates which resemble a neuron structure, have a network structure that performs the activation function. Therefore, incoming data contains the capability to be stored or deleted based on a determined weight. These weights are calculated as the network iterates during the learning phase. Through the utilization of this network architecture, the system acquires the ability to receive, store, or delete incoming data [25].

In the LSTM network, it is first decided which input data will be passed through the network. This decision is made by the sigmoid layer called the forget gate. As indicated in Equation (7), the sigmoid layer contains information about how much of each input data will be passed by giving values between 0 and 1 [25].

$$f_t = \sigma(W_f x_t + W_f h_{t-1} + W_f c_{t-1} + b_f) \tag{7}$$

Here, f_t, h_t, and c_t show the forgetting gate, hidden layer output, and memory information at time t, respectively, while x_t gives the number of input features. Additionally, b_f represents the amount of deviation and W_f represents the weight matrix. In the next step, it is decided which new data will be stored. In this step, which is carried out in two stages, firstly, the information about which data will be updated is examined with the sigmoid layer, as shown in Eq. (8), and in the second step, the new values vector is created as in Eq. (9) using the tanh layer. The status update is performed by combining these two statements [26].

$$i_t = \sigma(W_i x_t + W_i h_{t-1} + W_i c_{t-1} + b_i) \tag{8}$$

$$\hat{c}_t = tanh(W_c x_t + W_c h_{t-1} + b_c) \tag{9}$$

The memory update process is shown in Eq. (10).

$$c_t = f c_{t-1} + i_t \hat{c}_t \tag{10}$$

In conclusion, as shown in Eq. (11) and Eq. (12), a sigmoid layer is run again to decide which states of the network will be output, while the decision information given by the tanh layer is obtained as output [26].

$$o_t = \sigma(W_o x_t + W_o h_{t-1} + W_o c_{t-1} + b_o) \tag{11}$$

$$h_t = o_t tanh(c_t) \tag{12}$$

Here, the term o_t refers to the output.

3. SIMULATION RESULTS

In this section, the performances of CNN and LSTM networks, which are deep learning methods, have been compared with classical algorithms LS and LMMSE algorithms used in symbol detection. In order to demonstrate the performance of the proposed deep learning networks in UFCM systems, evaluations have been conducted based on the BER criteria in transmission scenarios of Rican and Rayleigh fading channel models at SNR values ranging from 0 to 30 dB.

Rician and Rayleigh fading channels are channels that are characterised by multipath propagation in wireless communication and present a major challenge to symbol detection. In Rician fading channel, the direct Line-of-Sight (LOS) path is available along with multipath paths. This channel model in general has a better stability because a lot of the signal power is contained in the LoS component. In contrast, Rayleigh fading channel represents an environment where the LoS component is absent and the amplitude and phase of the signals reach the receiver randomly due to the interference of the waves reflected and refracted by the surrounding obstacles; this causes the signal power to be more variable and creates a more complex structure for symbol detection. It has been stated in the literature that Rician channels have a more stable structure than Rayleigh channels due to completely random phase and amplitude changes due to the LoS component [14, 15].

Figure 2 and Figure 3 compare the performances of various symbol detection algorithms (LS, LMMSE, CNN and LSTM) under these two different channel conditions. In Figure 2, under Rician fading channel conditions, the LSTM algorithm exhibits superior performance by providing lower BER compared to traditional methods (LS and LMMSE) and the CNN algorithm. It can be observed that the conventional techniques LS and LMMSE algorithms have high BER values in low SNR conditions and are unsuitable for such difficult channel conditions. The LS algorithm has the highest BER values, and the performance is poor particularly at low SNR level. Although the LMMSE algorithm is better than LS algorithm, it does not offer satisfactory performance under Rician channel conditions. On the other hand, CNN and LSTM based techniques offer lower BER results in every SNR level indicating a better performance under challenging and dynamic environment including Rician fading channels.

Specifically, the BER performance of LSTM algorithm is the best among all the algorithms considered in this paper. Here, when the BER is 10^{-1}, the SNR gain offered by the LSTM algorithm is 14 dB more than the LS algorithm and is 2 dB more than the CNN algorithm which is the next best performing. At BER value of 10^{-2}, the LSTM algorithm has a 7. It can be seen that the proposed algorithm achieves 5 dB better SNR gain than the LMMSE algorithm and a 2. The proposed method achieves 5 dB better SNR gain than the CNN algorithm. Also, when SNR value is 20 dB, it is seen that the BER difference between LSTM and LS algorithms is higher than the 10^{-1} ratio. From these results, it can be seen that LSTM has the ability to capture the dependencies in the time series data and the changes in the channel characteristics. On the same note, the CNN model offers accurate symbol detection despite the low SNR due to the model's capacity to learn the spatial features of the signal.

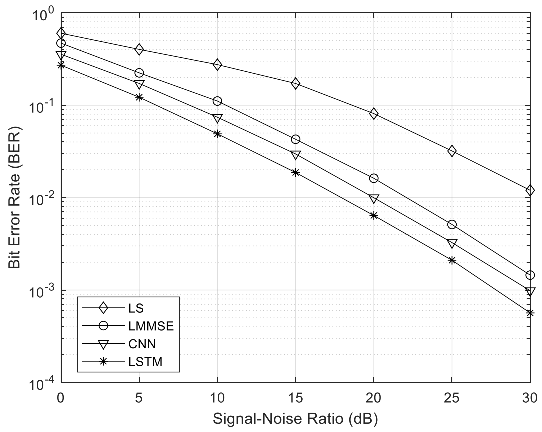

Figure 2. BER-SNR values of the estimators over Rician Fading Channels.

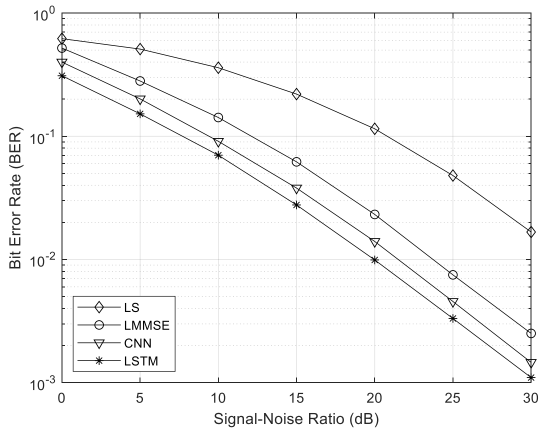

Figure 3. BER-SNR values of the estimators over Rayleigh Fading Channels.

To illustrate the performance of the symbol detectors under poor channel conditions, the transmission scenarios in Rayleigh channel conditions were depicted in Figure 3. The conventional schemes LS and LMMSE depicted in the figure do not yield good results when the channel is severe with high BER and low SNR. LS reduction has the highest BER values and proves that the system performance is poor at low SNR values. Although LMMSE program is better than LS, still it is not very efficient in Rayleigh channel conditions. On the other hand, the deep learning based models CNN and LSTM offer better BER performance for the complex and variable, as in the case of Rayleigh fading channel, with the provision of lower BER in all SNR bands.

Of all the proposed results, the LSTM programs especially give the minimum BER values and give the highest probability of symbol detection. From the Figure 3, it can be seen that there is no decline in the performance of LSTM even when the channel is noisy. This is because LSTM transition is able to learn the distortions in the data flow in the time series and the channel characteristics and thus in most cases including the difficult ones such as Rayleigh fading channels, it produces better results than the other channels. For instance, when the BER value is 10^{-2}, LSTM boosting has a 2 dB better SNR gain than CNN, 4 dB better than LMMSE, and 12 dB better than LS illumination. This proves that the use of LSTM technology is more effective in terms of BER than the conventional techniques and the CNN technology. This comparison shows that random changes in the signal's amplitude and phase make it harder to find symbols in Rayleigh fading channels. The LSTM algorithm, on the other hand, has lower BER values than both CNN and traditional algorithms under both channel types. These gains can be attributed to the LSTM algorithm's capacity to learn the dependencies in time series data and its ability to adapt to changes in channel properties effectively.

It can be observed from the both figures that deep learning techniques and especially LSTM outperform classical techniques for the Rician and Rayleigh fading channels. This scenario demonstrates the potency and the need to apply deep learning-based algorithms in enhancing the symbol detection efficiency. The effectiveness of deep learning methods stems from the fact that these methods are able to learn from the data representations that are not easily discernable to the human eye. As for LSTM, for instance, it has the ability of capturing long term dependencies in time series data, which makes it produce a good performance even in the presence of channel variability. The repetitive structure of LSTM enhances the model's capability to cope with changes in the channel conditions and thus improve the symbol detection. Moreover, the deep learning methods do not necessarily require the knowledge of the channel model as is the case with traditional algorithms and this makes the deep learning methods to be quite useful even under unknown or complicated channel conditions. Therefore, the results of this study indicate that deep learning techniques can enhance the overall performance of wireless communication systems by enhancing the reliability and precision of symbol detection, particularly in conditions of multipath fading or in situations where spectral efficiency is of paramount importance.

4. CONCLUSIONS

In this study, the suitability of LSTM and CNN deep learning architectures to enhance symbol detection in UFMC systems was compared and discussed in details. The numerical results derived indicate that both deep learning methods deliver better performance than conventional methods. In particular, the BER of the LSTM model was the lowest and even in the complex channel conditions and variable SNR, it was 30-50% lower than the BER of the traditional LS and LMMSE algorithms. This can be attributed to LSTM's ability to learn data dependencies and channel features for a certain period of time. Therefore, the adaptive nature of LSTM makes it very ideal for the dynamic and fading environments.

On the other hand, the proposed CNN model was able to learn the spatial features from the given images for symbol detection and showed relatively better results than all the other models for low SNR levels. Based on the results of the study, the CNN method showed a BER improvement of 20-40% over conventional methods which enhanced the detection of the signal and the minimisation of the channel interference. Both models enhance the performance of symbol detection in various channel conditions thereby enhancing the spectral efficiency and data transmission rate of UFMC systems. The numerical results from this work reveal that LSTM and CNN are viable and efficient tools for the detection of symbols in UFMC systems.

These results confirm that deep learning-based methods, especially LSTM and CNN, are powerful tools to improve the performance of symbol detection under variable channel conditions. LSTM's capacity to learn dependencies and channel variations in time series data and CNN's ability to model the spatial properties of the signal make both methods superior in difficult channel conditions. Therefore, deep learning methods are expected to be more widely used in future wireless communication systems.

Author's Contributions

All authors contributed equally.

Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

Funding Statement

This work was supported by the Scientific Research Projects Coordination Unit of Bandirma Onyedi Eylül University Project Number: BAP-22-1004-011

REFERENCES

[1] A.A. Laghari, K. Wu, R.A. Laghari et al., "Retracted Article: A Review and State of Art of Internet of Things (IoT)," Arch Computat Methods Eng vol. 29, pp. 1395–1413 2022.

[2] L.J. Cimini Jr., "Analysis and simulation of digital mobile channel using orthogonal frequency division multiplexing," IEEE Trans. Commun., vol. 33, no. 7, pp. 665–675, 1985.

[3] V. Vakilian, T. Wild, F. Schaich, S.T. Brink, and J. F. Frigon, "Universal-filtered multi-carrier technique for wireless systems beyond LTE," in Proc. IEEE Globecom Workshops, Atlanta, GA, USA, pp. 223–228, Dec. 2013.

[4] P.N. Rani and C.S. Rani, "UFMC: The 5G modulation technique," in 2016 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), Chennai, India, 2016, pp. 1-3.

[5] G. Bochechka, V. Tikhvinskiy, I. Vorozhishchev, A. Aitmagambetov, and B. Nurgozhin, "Comparative analysis of UFMC technology in 5G networks," in 2017 International Siberian Conference on Control and Communications (SIBCON), Astana, Kazakhstan, 2017, pp. 1-6.

[6] M.N. Seyman, "Convolutional fuzzy neural network based symbol detection in MIMO NOMA systems," Journal of Electrical Engineering, vol. 74, no. 1, pp. 60-64, 2023.

[7] M.N. Seyman and N. Taşpınar, "Channel estimation based on neural network in space time block coded MIMO–OFDM system," Digital Signal Processing, vol. 23, no. 1, pp. 275-280, 2013.

[8] N. Farsad, N. Shlezinger, A.J. Goldsmith, and Y.C. Eldar, "Data-driven symbol detection via model-based machine learning," in 2021 IEEE Statistical Signal Processing Workshop (SSP), Rio de Janeiro, Brazil, 2021, pp. 571-575.

[9] M.N. Seyman, "Symbol detection based on backtracking search algorithm in MIMO-NOMA systems," Computer Systems Science & Engineering, vol. 40, no. 2, pp. 795-804, 2022.

[10] R. Jiang, Z. Fei, S. Cao, C. Xue, M. Zeng, and Q. Tang, “Deep learning-aided signal detection for two-stage index modulated universal filtered multi-carrier systems,” IEEE Transactions on Cognitive Communications and Networking, vol. 8, no. 1, 2022.

[11] C. Lin and Q. Chang, “A deep learning approach for MIMO-NOMA downlink signal detection,” Sensors, no. 19, pp. 1-22, 2019.

[12] N. Thompson and J. Thompson, “Deep learning for signal detection in non-orthogonal multiple access wireless systems,” in 2019 UK/China Emerging Technologies (UCET), Glasgow, United Kingdom, 2019, pp. 1-4.

[13] H. Ye, G. Y. Li, and B. H. Juang, “Power of deep learning for channel estimation and signal detection in OFDM systems,” IEEE Wireless Communication Letters, vol. 7, no. 1, pp. 114-1147, 2018.

[14] J.-M. Kang, C.-J. Chun, and I.-M. J. I. A. Kim, “Deep learning based channel estimation for MIMO systems with received SNR feedback,” IEEE Access, vol. 8, pp. 121162-121181, 2020.

[15] M. H. Essai Ali, “Deep learning-based pilot-assisted channel state estimator for OFDM systems,” IET Communications, vol. 15, no. 2, pp. 257-264, Jan. 2021.

[16] N. Thompson and J. Thompson, “Deep learning for signal detection in non-orthogonal multiple access wireless systems,” in 2019 UK/China Emerging Technologies (UCET), Glasgow, United Kingdom, 2019, pp. 1-4.

[17] C. He, Y. Hu, Y. Chen, and B. Zeng, “Joint power allocation and channel assignment for NOMA with deep reinforcement learning,” IEEE Journal on Selected Areas in Communications, vol. 37, no. 10, pp. 2200-2210, 2019.

[18] X. Wang, T. Wild, F. Schaich, and S. ten Brink, "Pilot-aided channel estimation for universal filtered multi-carrier," in 2015 IEEE 82nd Vehicular Technology Conference (VTC2015-Fall), Boston, MA, USA, 2015, pp. 1-5.

[19] Y. Xu, H. Chu, and X. Wang, "Joint timing offset and channel estimation for multi-user UFMC uplink," IEEE Wireless Communications Letters, vol. 9, no. 2, pp. 236-239, Feb. 2020.

[20] L. Zhang, C. He, J. Mao, A. Ijaz, and P. Xiao, "Channel estimation and optimal pilot signals for universal filtered multi-carrier (UFMC) systems," in 2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC), Montreal, QC, Canada, 2017, pp. 1-6.

[21] Md. F. Ahammed, A.A. Molla, R. Kadir, M.I. Kadir, “Deep bidirectional LSTM for the signal detection of universal filtered multicarrier systems”, Machine Learning with Applications, vol. 10, 2022.

[22] Y. Luan and S. Lin, "Research on Text Classification Based on CNN and LSTM," 2019 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA), Dalian, China, pp. 352-355, 2019.

[23] J. Gu, Z. Wang, J. Kuen, L. Ma, A. Shahroudy, B.Shuai, T. Liu, X. Wang, G. Wang, J. Cai, T. Chen, “Recent advances in convolutional neural networks,” Pattern Recognition, vol. 77, pp.354-377, 2018.

[24] F. Stoican, Y. He, Y. Liu et al., “Application of CNN-LSTM in Gradual Changing Fault Diagnosis of Rod Pumping System”, Hindawi, Mathematical Problems in Engineering, p. 9, 2019.

[25] P. Görgel ve E. Kavlak, "Uzun Kısa Süreli Hafıza ve Evrişimsel Sinir Ağları ile Rüzgar Enerjisi Üretim Tahmini", Dicle Üniversitesi Mühendislik Fakültesi Mühendislik Dergisi, vol. 11, no. 1, pp. 69-80, Mar. 2020.

[26] M.M. Eid et al., “Meta-Heuristic Optimization of LSTM-Based Deep Network for Boosting the Prediction of Monkeypox Cases,” Mathematics, vol. 10, no. 20, p. 3845, Oct. 2022, doi: 10.3390/math10203845. [Online].