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Technique for Channel Equalization in Visible Light Communication Employing Direct Current-Based Optical Filter Bank Multicarrier Modulation

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ABSTRACT

Visible Light Communication (VLC) has gained recognition as a potential technology for high-speed indoor wireless communication and 6-G applications. Filter bank multicarrier (FBMC) is a multi-carrier modulation that provides better spectral efficiency and is regarded as a promising scheme for the next generation of wireless communication and an alternative to orthogonal frequency division modulation (OFDM). However, the use of a multi-light-emitting diode (LED) array in indoor VLC leads to multipath dispersion, causing the issue of intersymbol interference (ISI) that degrades system performance and produces large delays and a high bit-error rate (BER). Therefore, this research proposed a post-equalization technique using an artificial neural network (ANN) equalizer to enhance the system's overall performance and BER. The result shows that channel equalization using (ANN) equalizer upgraded the system performance by 49.9% in high signal-to-noise ratio (SNR), and a lower BER is achieved compared to the conventional VLC-FBMC system without the equalizer.

Keywords:

VLC; Optical FBMC; Neural network equalizer; Bit error rate

1. Introduction

With the increasing need for mobile devices, and wireless services, (VLC) has emerged as a promising technology for indoor wireless access and 6G application and beyond as stated by Ariyanti *et al.,* [1]. This is mainly attributed to its advantages such as high speed, broad bandwidth, and security as discussed by Matheus *et al.,* [2]. FBMC scheme is considered a promising scheme for the next generation in wireless communication and alternative modulation for orthogonal frequency division modulation (OFDM) [3]. FBMC has shown better performance compared to OFDM in terms of spectral efficiency as shown by multiple authors in [3,4]. In an optical system with the intensity modulation direct detection (IM/DD) method, the FBMC signal must be a unipolar signal means real and positive [5]. This is in contrast to the conventional FBMC scheme with bipolar signals used in

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radio frequency communication. There are two primary types of FBMC utilized in generating unipolar signals for VLC systems: flip-FBMC and DC-Biased optical FBMC (DCO-FBMC) as discussed by different researchers in [6,7]. Although DCO-FBMC improves the system's spectral efficiency, it suffers from inefficient BER performance as found by Qasim *et al.,* [8].

Multipath propagation is a significant issue in indoor VLC channels causing degradation in the communication quality due to intersymbol interference (ISI) as stated in the previous study [9]. Gismalla *et al.,* [10] conducted a study that evaluated the BER performance of a VLC system using various modulation schemes and assessed the interference effect on the channel due to multiple transmitters. However, the study does not include suppression of the ISI effect. Channel equalization (CE) techniques employing finite impulse response (FIR) based equalizers [11] are commonly used to tackle the effect of ISI and improve the VLC system [12]. In [13] time domain equalizers using zero force standards are employed in the optical FBMC system, however, it increases the system complexity. This work [14] utilized an LMS linear equalizer (LE) at the receiver in a VLC system with carrier-less amplitude and phase modulation (CAP). It showed that LE is effective in eliminating the linear channel distortion, but not efficient for the dispersion channel. Channel Equalization based on neural networks (NN) is gradually emerging in wireless communication and especially in the VLC field, particularly in nonlinear channels [15]. NN-based equalizers show superior performance in channel equalization compared to conventional FIR equalizers as found by this paper [16]. A performance comparison between a deep neural network (DNN) equalizer and a conventional minimum mean square error equalizer (MMSE) in a wireless communication system with an OFDM scheme is done in [17]. The result showed that the BER performance of a DNN-based equalizer outperforms the conventional equalizer of MMSE. The study in [18] employed an artificial neural network (ANN) equalizer in an optical camera communication system and proved that ANN effectively mitigates the effect of ISI due to channel dispersion and enhances the system speed.

Focusing on the VLC system with NN equalizers, the study in [19] implemented the DNN post-equalization method in PAM modulation in the VLC system and showed that DNN is effective for nonlinear distortion and improves the signal compensation performance, and minimizes the BER. The research in [20] integrated DNN equalizer in DCO-OFDM-based VLC system for channel estimation. The research output proved that DNN equalizer achieve high BER performance in the VLC system compared to least squares and MMSE equalizers. However, it used the OFDM scheme which is less spectral efficient than FBMC. As per the reviewed literature, no comprehensive research has been done on the utilization of NN-based channel equalization with FBMC-based VLC systems. Therefore, the main contribution of this work is the integration of the high spectral efficiency scheme optical FBMC with the artificial neural network (ANN) based equalizer in the VLC system to mitigate the influence of ISI due to the use of Multiple LED arrays and improve the BER performance.

This paper is organized as follows: Section 2 gives an overview of the FBMC-VLC system model Section 3 covers the basics of the ANN model. Section 4 presents the simulation results. Finally, Section 5 concludes the paper.

2. VLC System Model

Figure 1 shows the design of the VLC system using DCO-FBMC. The figure highlights that the CE is implemented at the receiver side with NN based equalizer. At the transmitter side, the symbols are transmitted over pulses that typically overlap in both time and frequency in multicarrier modulations FBMC scheme, resulting in frequency-selective broadband channels that transform into multiple sub-channels also known as subcarriers. As VLC-FBMC utilizes the IM/DD modulation technique, the signal generated in the time domain needs to be a positive and real signal (unipolar). Hence, the complex signal x(t) produced by the inverse fast Fourier transform (IFFT) is separated into real R(x(t)) and imaginary J(x(t)) parts, and they are placed side by side. This leads to a 2M signal length of the FBMC symbol as [21]:

$$x(t) = \sum_{n=1}^{N} \sum_{l=1}^{2M} a_{l,n} g_{l,n}(t) \quad (1)$$

where M is the number of subcarriers, N is the symbol period, l denotes the subcarrier index; *n* is the n-th symbol, $a_{m,n}$ is the symbol transmitted, and the function g(t) is used in FBMC synthesis to transform $a_{m,n}$ into the signal space. The FBMC real signal is created by splitting the FBMC complex signal into real imaginary components. Then a DC bias part is added to the signal to produce the non-negative (unipolar) FBMC signal $X_{dc}(t)$ and transmit it via the LED.

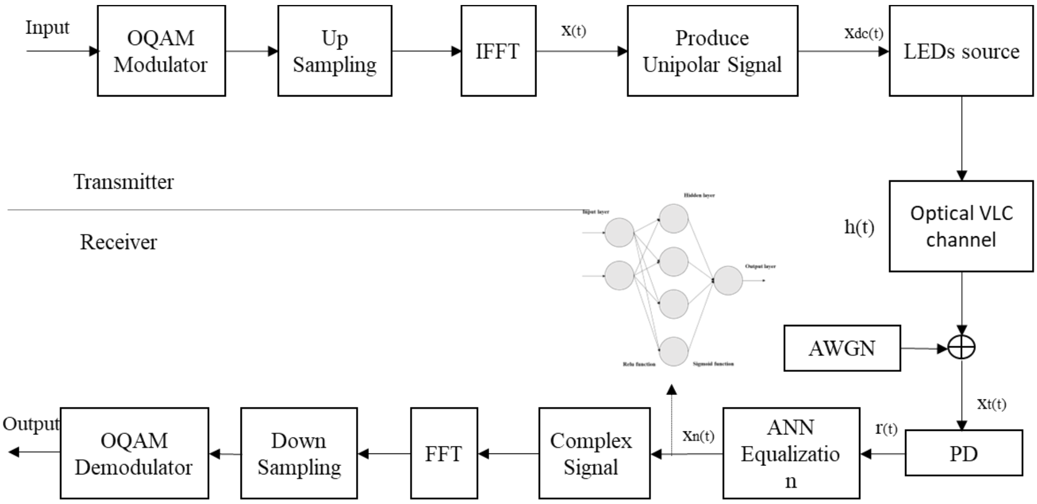


Fig. 1. System model of optical FBMC system with ANN equalizer

VLC consists of two main models, the line of sight (LOS), and the non-line of sight (non-LOS) model. LOS is usually used in indoor VLC due to its ability to achieve a high bit rate and mitigate the effect of ISI. The channel impulse response (CIR) in the LOS optical channel for indoor applications is expressed as:

$$h(t) = L_{los} \delta\,(t - \tau) \quad (2)$$

where τ is the signal propagation delay expressed as (D/c), where c is the speed of light symbol, and L_{los} is the channel attenuation represented in [22] as:

$$L_{los} = \begin{cases} \frac{(m+1)A}{2\pi D^2} \cos^m(\phi) T_s(\psi) g(\psi) \cos(\psi) & 0 \leq \psi \leq \Psi_c \\ 0 & \psi > \Psi_c \end{cases} \quad (3)$$

where m is the Lambertian order emission, A is the photodetector area, the distance between the light source and receiver is denoted by D, $T_s(\psi)$ represent the gain of an optical filter, ψ is the symbol of the angle of incidence. Ψ_c denotes the width of a field of view at a receiver and $g(\psi)$ is the gain of the optical concentrator. Therefore, the transmitter's optical signal $x_t(t)$ becomes:

$$x_t(t) = h(t) * x_{dc}(t) \quad (4)$$

On the receiver side, PD captures the optical signal and converts it into the electrical domain. Hence, the received optical signal $r(t)$ from the VLC channel is expressed by:

$$r(t) = Rx_t(t) + n(t) \quad (5)$$

where $n(t)$ is a symbol for additive white Gaussian noise and R is the PD responsivity. The DC bias is then removed at the receiver before the received signal is translated back into the complex domain. The signal is subsequently processed by the matching filter, FFT operation, and down sampling. The ANN equalizer is then used to conduct the channel equalization operation. The equalized data is then demodulated before being put through the signal de-mapping to recover the original signal. Finally, the FBMC-VLC system's BER performance is examined. Table 1 shows the FBMC model parameters produced for this proposed model.

Table 1
FBMC model simulation parameters

Parameter	FBMC Model
FFT size	1024
No. Symbols	100
Subcarrier (Modulation size)	4-QAM
Overlapping factor	4
Bit rates	7.3, 14.6, and 29.3 Mbit/s
SNR range	0 dB to 10 dB

3. Proposed Neural Network Channel Equalization

This study employs channel equalization using an artificial neural network (ANN) for the FBMC model-based VLC system to enhance performance and minimize the bit error rate (BER). The ANN algorithm equalization has been introduced in VLC systems to tackle the dispersion channel issues. The feedforward artificial neural network equalizer (ANN) is a type of neural network-based equalization and consists of an input layer, a hidden layer, and an output layer. The ANN together with back propagation algorithms is the most common neural network and training algorithm [23]. The ANN layers comprise multiple neurons, and the neurons in the layer are fully connected to the neurons in the adjacent layer with the output implemented by an activation function. The ANN equalization is applied before the demodulation process of an FBMC model, which means that the received distorted FBMC signal becomes an input to the ANN equalizer. The dataset was given by the FBMC signals. The transmitted symbols are set to be the ANN target and the received symbols are the ANN input to be equalized by the proposed ANN equalizer.

3.1 ANN Training Network

The ANN structure is illustrated in Figure 2, comprising a single input layer, one output, and a single hidden layer with 100 neurons with backpropagation in the Levenberg-Marquardt (LMBP) algorithm as a training method to enhance the prediction due to its high accuracy and efficiency [24]. The rectified linear unit (ReLU) and sigmoid function are utilized as activation functions to calculate the output and obtain the best training effect. Both activation functions introduce a nonlinear mapping between the input and output signals which is necessary to compensate for the dispersion of the VLC channel [25]. The dataset produced by the FBMC symbols is divided into training sets and test sets with 5,737 and 1,638 samples respectively. The validation set is used to validate the NN learning with 10% of the total training dataset. The ANN output layer sums the weighted neuron outputs as [26] :

$$x_n = f(\sum_{\mathrm{n}} \mathrm{w_n} r_{\mathrm{n}}) \quad (6)$$

where w_n and r_n are the coefficients of the n^{th} weight and input vector and $f(.)$, is the activation function which is the ReLu function to map the hidden layer as:

$$\varphi_{Relu}(x) = \max(0, x) \quad (7)$$

And the sigmoid function to map the neurons in the output layer between 0 and 1 as [18]:

$$\varphi_{Sig}(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (8)$$

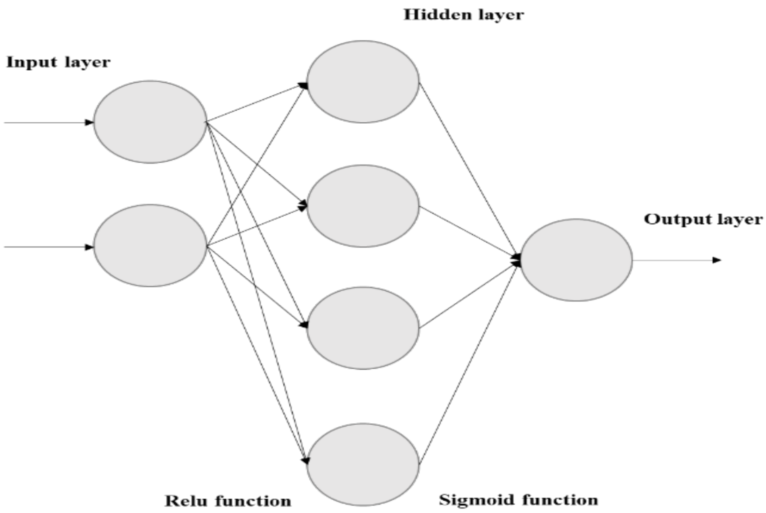


Fig. 2. Proposed ANN equalizer network structure

During the training process, the LMBP adjusts the ANN weights parameter based on the input to minimize the error-cost function E_n (the difference between the predicted transmitted symbol x_n and the actual transmitted data $\mathrm{x(t)}$) as given by:

$$E_n = \|x_n - \mathrm{x(t)}\|^2 = \|f(\mathrm{w_n} x_n) - \mathrm{x(t)}\|^2 \quad (9)$$

The ANN training process is implemented in MATLAB software version 2021. Table 2 shows the ANN equalizer parameters used in the proposed model. Batch normalization is applied to the fully connected hidden layer to prevent overfitting and we employed the Adam optimizer with a learning rate of 1×10^{-3} and batch size of 64, to help in faster convergence and enhance the performance of the ANN equalizer.

Table 2
The ANN equalizer parameters

Parameter	FBMC Model
No. hidden layer	1
No. neuron in the hidden layer	100
Activation function	Tan-sig, ReLu
Algorithm	LMBP
No. hidden layer	1
Optimizer	Adam
Regularization	Batch normalization
Learning Rate	1x10-3

4. Result and Discussion

The simulation output of the optical FBMC model employing ANN equalizer and the evaluation of the BER performance are discussed here. In this model, we have employed a method for determining the number of layers required and the optimal number of neurons in the hidden layer. This determination is based on achieving the best output performance, which is assessed through mean-square error (MSE) values, as demonstrated in Figure 3 and Figure 4. Interestingly, the optimal number of hidden layers that achieved the best performance for the proposed ANN is the single hidden layer as shown in Figure 3.

Moreover, our investigation reveals that the optimal MSE, which stands at an impressive $4.3\text{x}10^{-5}$, is achieved at the fifth epoch of the training process as demonstrated in Figure 3. This outcome signifies the point at which the ANN equalizer's performance reaches its peak in terms of minimizing error and enhancing the overall robustness of the optical FBMC system.

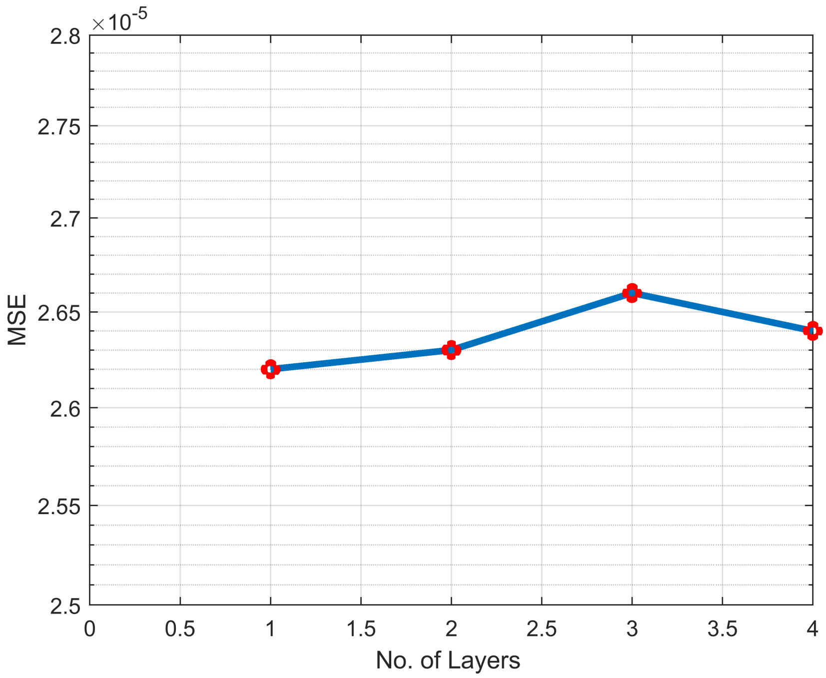


Fig. 3. The effect of the number of layers on MSE performance

The performance evaluation of the proposed CE, employing ANN training, was conducted within the FBMC-VLC channel system, using the specified parameters outlined above. In Figure 4, we present a comprehensive depiction of the system's improvement after the integration of the ANN equalizer, focusing on BER performance and SNR requirements across three distinct bit rates. Figures 5(a) and 5(b) clearly illustrate the marked enhancement in BER performance for bit rates of 7.3 Mbit/s and 14.6 Mbit/s following the implementation of the ANN channel equalizer. This improvement is particularly pronounced at higher SNR values.

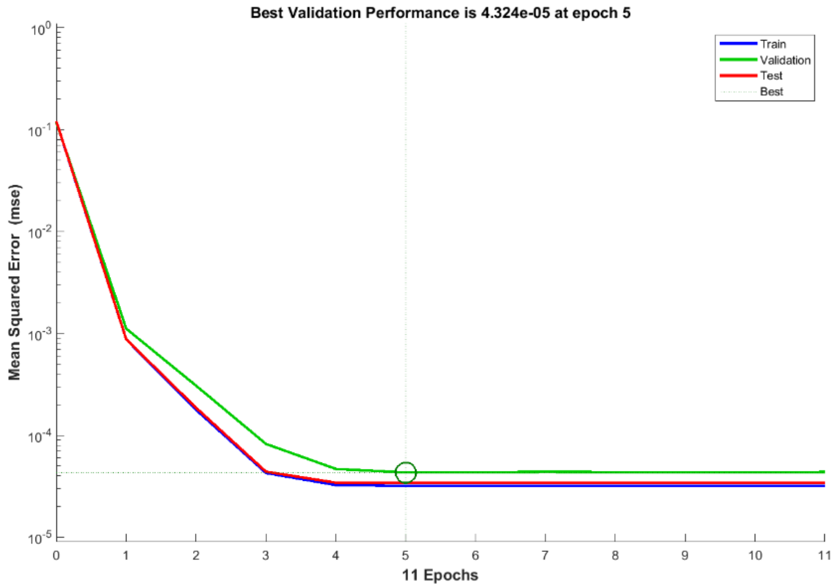
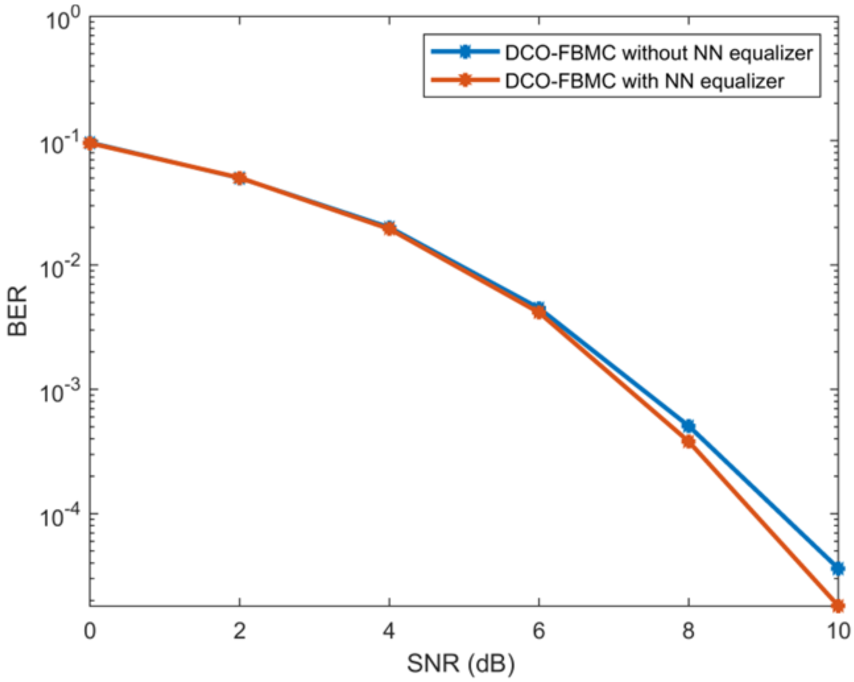
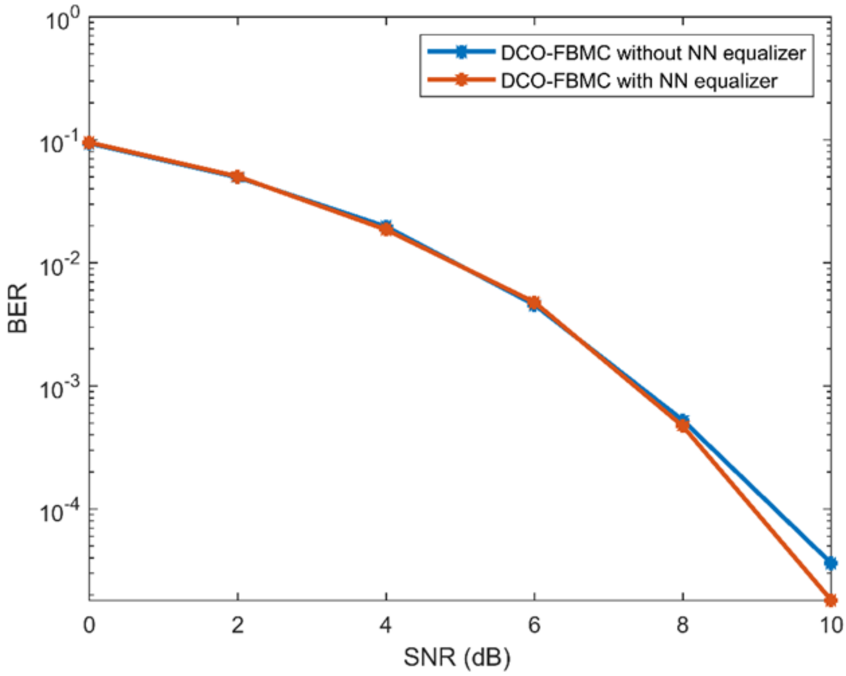


Fig. 4. The CE-ANN training performance (MSE)

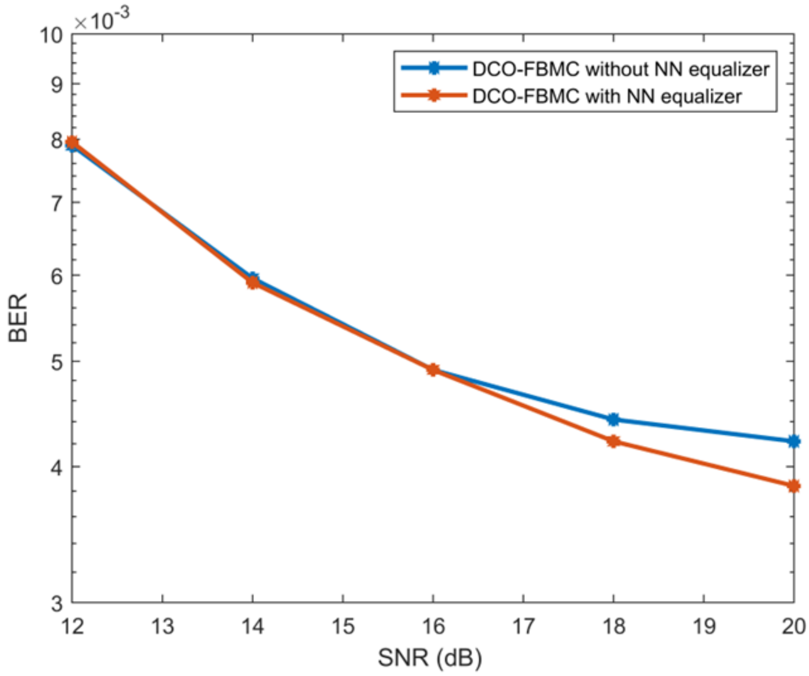
For instance, at an SNR of 10 dB, the BER is reduced to $1.8\text{x}10^{-5}$ with the ANN equalizer, compared to $3.6\text{x}10^{-5}$ for the conventional FBMC without an equalizer, as depicted in the Figure 5. This is about a 49% improvement in the BER performance. However, at a substantially higher bit rate of 29.3 Mbit/s (as depicted in Figure 5(c)), the impact of the ANN equalizer on BER performance is improved at the cost of high SNR values compared to the lower bit rate. The communication reached BER of $3.8\text{x}10^{-3}$ at SNR of 20 dB in contrast to BER of $4.2\text{x}10^{-3}$ without ANN equalizer at the same SNR value. This outcome can be attributed to the limitations associated with 4-QAM, which has an extended FFT length constraint when transmitting high bit rates. Additionally, the smaller constellation size in 4-QAM results in each symbol representing only 2 bits of data, in contrast to higher QAM formats. In summary, the integration of the ANN equalizer yields substantial BER performance improvements, especially at lower to moderate bit rates. However, for exceptionally high bit rates, inherent limitations of the 4-QAM modulation scheme become evident, contributing to communication challenges even with the ANN equalizer in place.


DCO-FBMC without NN equalizer
DCO-FBMC with NN equalizer
BER
SNR (dB)

(a)


DCO-FBMC without NN equalizer
DCO-FBMC with NN equalizer
BER
SNR (dB)

(b)



(c)

Fig. 5. Optical FBMC performance with ANN equalizer at a bit rate of (a) 7.3 Mbit/s, (b) 14.6 Mbit/s, (c) 29.3 Mbit/s

5. Conclusions

This paper presents an artificial neural network (ANN) model that utilizes artificial intelligence (AI) technology for channel post-equalization in the DCO-FBMC-based visible light communication system, to improve the model BER performance. The ANN employed fully connected neurons in the layer with one hidden layer and the LMBP algorithm as a training method. The simulation result showed that the ANN equalization scheme has improved the FBMC-VLC system performance by 49.9% and effectively suppressed the influence of ISI due to the channel delay and the use of multiple LED arrays. A lower BER of 1.8×10^{-5} is achieved compared to the conventional FBMC without the ANN equalizer. Future work of this study will focus on high QAM format and bit rates and a deep neural network will be carried out to ensure success outcome.

Acknowledgement

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