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GFDM TRANSCEIVER BASED ON ANN CHANNEL ESTIMATION

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ABSTRACT

Generalized frequency division multiplexing (GFDM) is one of the candidate waveforms beyond 5G for wireless communication. Channel estimation is challenging in wireless transmission because of inherent interference. It is based on a pilot signal that uses Least Square (LS) and Normalized Least Mean Square (NLMS) to perform the estimation. This paper used the Artificial Neural Network (ANN) as a channel estimation method, considered a novel estimation process for the GFDM transceiver. The channel estimation based on ANN depends on the data set generated from LS estimation, which considers the proposed method is optimized to LS based on the backpropagation neural network. The ANN algorithm considered a fitness function to estimate the channel. Levenberg-Marquardt backpropagation (LM), Bayesian Regularization backpropagation (BR), and Scaled Conjugate Gradient backpropagation (SCG) training methods training by using the Matlab toolbox used to perform the estimation. BR training method gives the best performance than LS and other training methods at 22 neurons in hidden layers, which at 20dB give BER = 0.0369 that enhanced over LS by 0.08.

KEYWORDS

ANN, GFDM, LS, Transceiver

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1. INTRODUCTION

The requirement of the physical layer beyond 5G concentrates on the enhancement of the application, such as massive connectivity with machine-to-machine (M2M) communication which presents as the internet of things (IoT) (Agiwal 2019). This vision is hoped to be achieved using a flexible communication type called GFDM. GFDM presents an operation method based on shaping its spectrum suitably belonging to efficient sensors (Li 2019). This waveform built on a multicarrier scheme relies on a traditional filter bank structure. The transmitted data for each block is distributed in time and frequency, and a pulse shaping filter adjusts subcarrier pulse shaping. Prototype filters perform circular filtering to remove the brief intervals hence featuring low Out-Of-Band (OOB). These advantages come at the expense of the BER and complexity compared to OFDM (Sameen 2017). The non-orthogonality of the GFDM waveform is a fundamental factor of BER degradation; hence requires complex techniques to improve. GFDM structure used one Cyclic Prefix (CP) for each block. Each block belongs to sub symbols and prototype filtering, improving the bandwidth utilization and low OOB emission (Verdecia 2019). The GFDM nonorthogonal behavior presents a complex and not straightforward channel estimation. The channel estimation is presented based on the pilot symbol, and this method is used in a different type of multicarrier scenario. The pilot is known for the transmitter and receiver, which estimate the channel response using interpolation techniques (Permana 2021). In general, Least Squares (LS) and adaptive filter type Normalized Least Mean Square NLMS training symbols are used for channel estimation. Adaptive filters perform correctly in many applications, such as seismology, biomedical, radar, and communications. In general, it works according to one basic principle: compute the error between the received pilot and desired pilot, which is used to estimate the channel according to the step size value (Rasadia 2012) (Bandari 2017). The ISI is the main challenge of degradation problems of wireless communication channels. The ISI elimination required a robust algorithm to process the fast-changing wireless channel properties (AL-Jaafari 2018). There are different methods used to reduce the ISI. Many researchers offered ways to improve system performance by channel estimation, thus reducing the BER vs. SNR. Some contributions were presented as follows:

The first representation of GFDM was by Gerhard Fettweis with his researchers in 2009 then this group continued in their work to develop the GFDM for wireless communication applications (Fettweis 2009). Ehsanfar et al. (2017) removed the intrinsic interference by using orthogonality conditions and used it on even and odd subcarriers as a new pulse-shaping filter

(Ehsanfar 2017). Valluri and Mani (2018) reduced the BER by using unique words (Valluri 2018). Turhan et al., (2019), presented a deep neural network to enhance the performance of GFDM transceivers (Turhan 2019). Tsai et al., (2021) used the Time Reversal Zero Forcing algorithm to improve the performance and reduce the complexity of the GFDM transceiver (Tsai 2021). Ssimbwa et al., (2022), enhanced by reducing the BER of the GFDM system by using coded GFDM (Ssimbwa 2022).

The transmitted signal suffers from degradation through the channel, and a multi-path frequency selective fading channel is applied to the transmitted signal. The novelty of this paper is to equalize this degradation by using ANN estimation. The ANN was trained by LS's data set and then by three back propagation training methods. The proposed estimation system compares with LS and NLMS methods to prove its superiority.

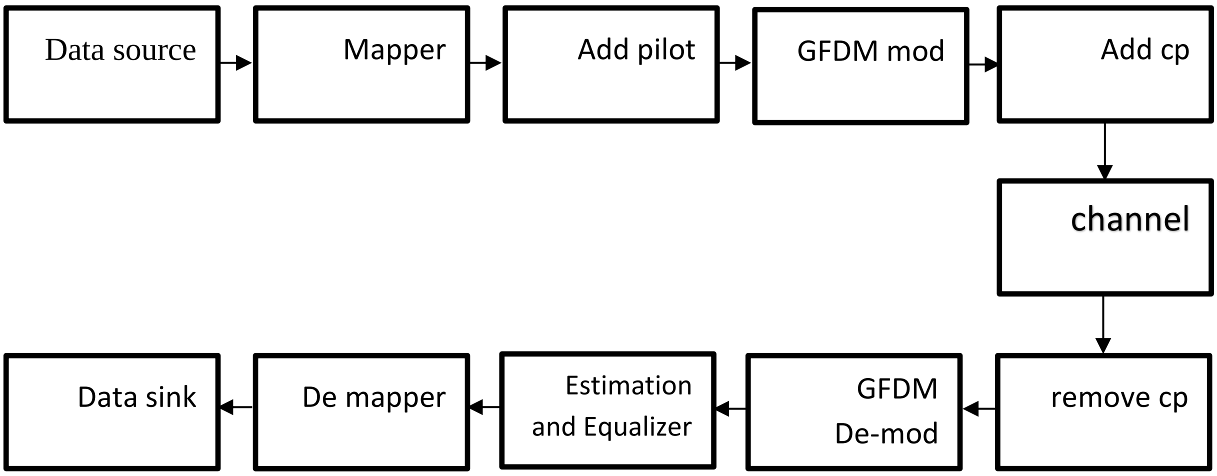

Fig. 1. General block diagram of system transceiver.

2. SYSTEM MODEL

The general block diagram of the system presents in Fig. 1. The first step is to generate a data signal with (Kd× M) length, where Kd is the data subcarrier and M is the sub-symbol, which is included with the pilot signal (Kp× M) where Kp is the pilot subcarrier, with which pilot space equals 5. The signal is modulated based on 16QAM modulation. Then entered into GFDM modulation with (K×M) length where K= Kd+ Kp. The last step before transmitting is to add a cyclic prefix with percentage length =10% of the signal. The transmitted signal is sent and is affected by a multi-path frequency selective Rayleigh fading channel and Additive White Gaussian Noise (AWGN). The same steps are done in the receiving part but vice versa.

The structure of the GFDM system consists of M sub symbols, each corresponding to K subcarriers in a single block. Each block N=KM that required to transmit. QAM modulates the data by 16 order (16 QAM). $d_m = [d_m(0)\cdots d_m(K-1)]^T$ which dm present the data with m^{th} sub symbols. The transmit signal is configured by the superimposition of circularly filter with subcarriers data at each sub symbol represented in below (Ameen 2022):

$$x(n) = \sum_{k=0}^{K-1} \sum_{m=0}^{M-1} d_{k,m} g_{k,m}(n) \tag{1}$$

Where: n is the sample index n =0…N-1. The pulse shaping filter g that length MK and limited by a circularly shifting as given in:

$$g_{k,m}(n) = g\{(n - mK) mod_{MK}\} e^{j\frac{2\pi kn}{K}} \tag{2}$$

3. CHANNEL

The transmitted signal is affected by Multi-Path Frequency Selective Rayleigh Fading Channel with two tap and AWGN as in eq (3) (Vaezi 2019).

$$y(n) = x(n) * h(n) + w(n) \tag{3}$$

Where y(n): is the received signal, x(n) is the transmitted signal, * denotes linear convolution, h(n) is the channel vector has two tap complex random values and w(n) is the AWGN.

3.1. Channel estimation

The channel estimation is an essential factor of the transmission system. the estimation process is done based on inserting pilot symbols at the transmitter, then estimating the channel effect by the received pilot. Hence equalized its effect by different algorithms and methods. This paper presents the channel estimation based on ANN and compares its performance with LS and NLMS algorithms (Akai 2017).

3.2. LS Channel Estimation

LS channel estimation is used to estimate the channel characteristics in a wireless communication system. The channel characteristics refer to how the transmission of a signal is affected by the environment in which it is transmitted. This includes fading, interference, and noise, which can distort or weaken the signal as it travels from the transmitter to the receiver. LS channel estimation involves using a training sequence or pilot symbols transmitted over the channel and used to estimate the channel response. The receiver measures the received training sequence and compares it to the transmitted sequence to determine the channel response. The

LS method involves minimizing the sum of the squares of the differences between the measured and transmitted sequences to find the best estimate of the channel response.

After performing the GFDM demodulation for each sub-symbol, perform the LS estimation steps. The received pilot signal Y_p extracted from demodulated signal Y. LS_{es} Estimation compound in (4) by a received pilot Y_p over the transmitted pilot x_p. They were then applied to interpolate to get the channel estimation H_{LS} as in (5). The transmitted data can be recovered by dividing the received signal over channel estimation H_{LS} as in (6) (Vilaipornsawai 2014).

$$LS_{es} = \frac{Y_p}{x_p} \tag{4}$$

$$H_{LS} = \text{interpolate } (LS_{es}) \tag{5}$$

$$Y_{es} = \frac{\mathrm{Y}}{H_{LS}} \tag{6}$$

3.3. NLMS Channel Estimation

The NLMS estimation is based on the adaptive filter principal present in Fig. 2. Signal. w_{NLMS} is the output of the NLMS filter. Y_p is the received pilot signal to NLMS. The principal objective of the NLMS filter is to minimize the error signal e_{NLMS} between the w_{NLMS} and Y_p by adjusting the adaptive filter coefficients value until arrived the error to zero. The NLMS filter presents a linear coefficient to give the best fit for an unknown environment. The adaptive filter is connected in parallel with the received signal (Ghauri 2013). Equations (7) to (11) present a mathematical model of the NLMS algorithm.

$$w_{NLMS} = h_{NLMS} * x_p \tag{7}$$

$$e_{NLMS} = Y_p - w_{NLMS} \tag{8}$$

$$h_{NLMS} = h_{NLMS} + \frac{2 * e_{NLMS} * x_p}{{x_p}^T * x_p} \tag{9}$$

$$H_{NLMS} = \text{interpolate } (h_{NLMS}) \tag{10}$$

$$Y_{NLMS} = \frac{\mathrm{Y}}{H_{NLMS}} \tag{11}$$

Where: w_{NLMS} is the output of filters, h_{NLMS} is channel pilot estimation coefficient, x_p is the transmitted pilot, e_{NLMS} is the error, Y_p is the received pilot, H_{NLMS} is the channel estimation, Y_{NLMS} is the received estimation.

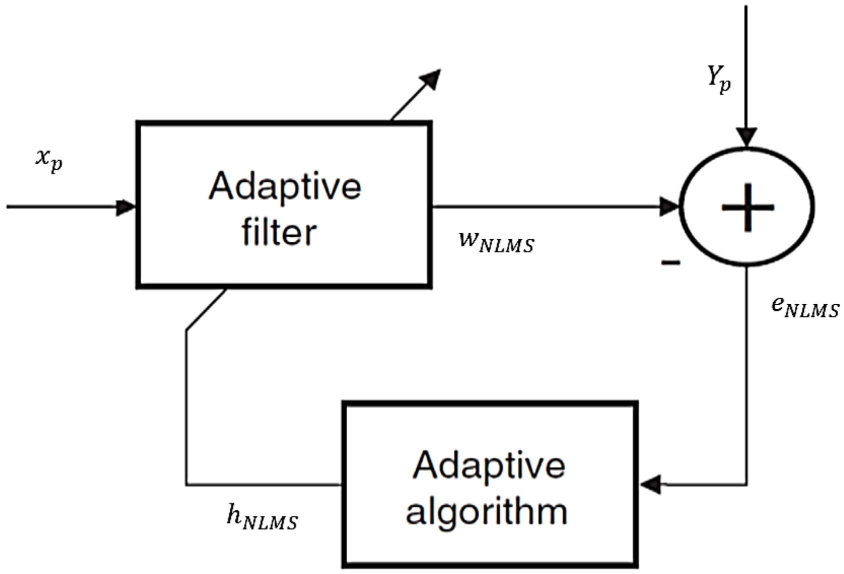

Fig. 2. block diagram of the NLMS algorithm.

3.4. ANN Channel Estimation

ANN is a computational processing network that efficiently solves complex adaptive decisions and self-correction (Alrubei 2020). Supervised learning is a practical algorithm for system identification and channel estimation and other applications (Farsad 2018) (Ali 2020). ANN's structure contains input, output, and hidden layers and can adjust its size depending on the training data and application (Ali 2015). The hidden layer is responsible for the nonlinear computation and reduces errors between the desired and actual output. At the same time, the output layer is responsible for producing the fitted value or classification label of the testing sample. Neurons are the central processing elements of ANN architecture and are simple and highly interconnected (Al-Rikabi 2020). At first the data set generated at desired state then training the network by generated data set to get the ANN. The data trained by three different training algorithm methods: Levenberg–Marquardt (LM), Bayesian Regularization (BR) and Scaled Conjugate Gradient (SCG). The performance considered based on Mean Square Error.

3.4.1 Levenberg–Marquardt

LM algorithm is a combined algorithm between steepest descent and Gauss-Newton methods. When the solution is remote from the correct one, the algorithm operates like a gradient descent method, slow but guaranteed to converge. When the solution matches the correct solution, it operates like a Gauss-Newton method. The LM algorithm uses this approximation to the Hessian matrix mathematical model of LM present in (12) (Bogdan 2011):

$$w_{t+1} = w_t - [J^T J + \zeta I]^{-1} J^T e \tag{12}$$

where:

w_{t+1}: The new weight vector. J: The Jacobian matrix. ζ: Combination coefficient. e: A vector of network errors between the desired and actual output.

3.4.2 Scaled Conjugate Gradient

SCG is modification of steepest descent algorithm. In conjugate gradient perform conjugate direction to generate faster convergence, faster than at steepest decent, while saving a low error rate obtained in the previous steps. In each iteration, the step size adjusted. The initial direction is negative of the gradient as in eq (13). The weight is update as in eq (14). The direction of next step performs as in eq (15)(16) (Parmar 2017).

$$p_0 = -g_0 \tag{13}$$

$$w_{k+1} = w_k + \alpha_k g_k \tag{14}$$

$$\beta_K = \frac{(|g_{K+1}|^2 - g_{K+1}{}^T)}{g_K{}^T g_K} \tag{15}$$

$$P_{K+1} = -g_{K+1} + \beta_K P_K \tag{16}$$

Where: p is search direction vector and g is gradient direction vector, w is the weight. α is the step size.

3.4.3 Bayesian Regularization

The training of BR is according to the LM training methods. It minimizes the weight and squared errors (17) (18) to build network that generalizes well. The network weight present as training objective function F(w) as present in (19).

$$E_w = \sum_{i=1}^{n} w_i{}^2 \tag{17}$$

$$E_D = \sum_{K=1}^{n} e_k{}^2 \tag{18}$$

$$F(w) = \alpha E_w + \beta E_D \tag{19}$$

Where: E_w is the sum of squared weights and E_D is the sum of errors. α and β are the parameters of objective function. At began, the network weight is distributed as random variables then distributed as gaussian distribution (Gouravaraju 2021).

4. RESULTS AND DISCUSSIONS

The performance of the channel estimation methods is illustrated and discussed in this section. LS, NLMS, and three methods for ANN estimate the GFDM transceiver with a random channel model. The parameters considered in the simulation are shown in Table 1. the simulation results approved that the performance of LS and NLMS are identical, as shown in Fig. 3. The performance at LS was tested under a different number of tapes, as shown in Fig. 4, which gives degradation when the number of tapes increased, then the 2-tapes are approved in this work. The performance of NLMS is ignored when compared with ANN methods. LM, SCG and BR are training based on data set generated from the GFDM transceiver at infinity SNR with values of observations. The ANN methods operate as channel estimation and use the transmitter and receiver pilot as data training, in which input to the network is the received pilot. The transmitter pilot is the target. Based on the transmitter and receiver pilot perform the estimation of the channel. The training operation is based on 64 features for input and 32 features for output. The value of observations is 16000. The performance of ANN methods was measured based on a comparison with LS for each case.

The LM, SCG, and BR training methods compare with LS at different values of neurons. The performance of channel estimators under different methods is presented based on different values of neurons in the hidden layer. Figs. 5-10 present the performance of LS with ANN methods (BR, LM, SCG) at the number of neurons =10,15,17,20,22 and 35. Fig. 5 presents the advancement of LS over BR, LM, and SCG at the number of neurons equal to ten, which the ANN by few numbers of neurons cannot predict the channel and perform the excellent estimation. However, at 15 neurons in the hidden layer, as in Fig. 6, the ANN training by BR methods gives better performance than LS and other ANN methods, which BER is 0.026376, 0.028183, 0.044401 and 0.029489 for BR, LM, SCG, and LS respectively. Fig. 7 presents the advanced LM over LS, BR, and SCG at 17 neurons when the number of neurons equals 20,22, and 35 BR back to be the best, as in Figs. 8-10. The minimum BER gets at 22 neurons with BR training methods. The structure of the BR neural network with 22 neurons in the hidden layer, training progress, and summary model are shown in Figs. 11-13, respectively. The Table 2. Present comparison at 20 dB between the proposed system and literature, which the best result at BS with 22 neurons.

Table 1. System Parameters.

Description	symbol	Value
Number of samples per sub-symbol	K	80
Number of sub-symbols	M	16
Block Length	M×K	1280
Percentage of cyclic prefix	CP	10%
Roll off factor of the pulse shaping filter	a	0.1
Modulation order of the QAM symbol	mu	4
Spacing pilot	Cp	4
Number of neurons in hidden layer	ne	10,15,17, 20,22,35

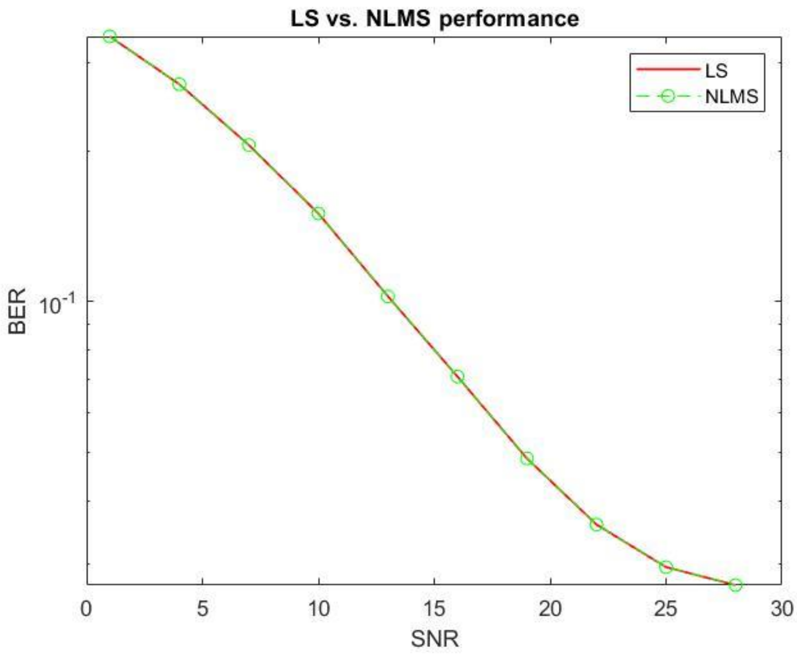

Fig. 3. Pperformance of LS and NLMS.

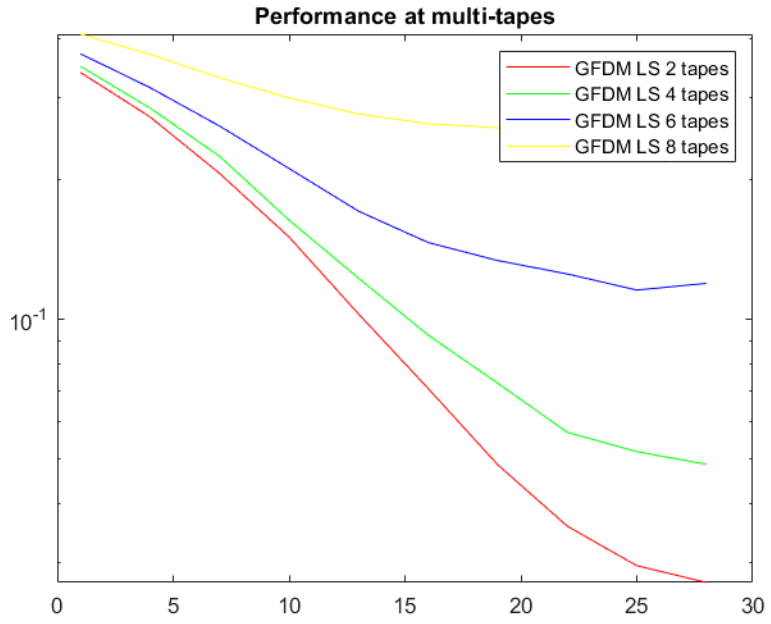

Fig. 4. Performance at multi-tapes.

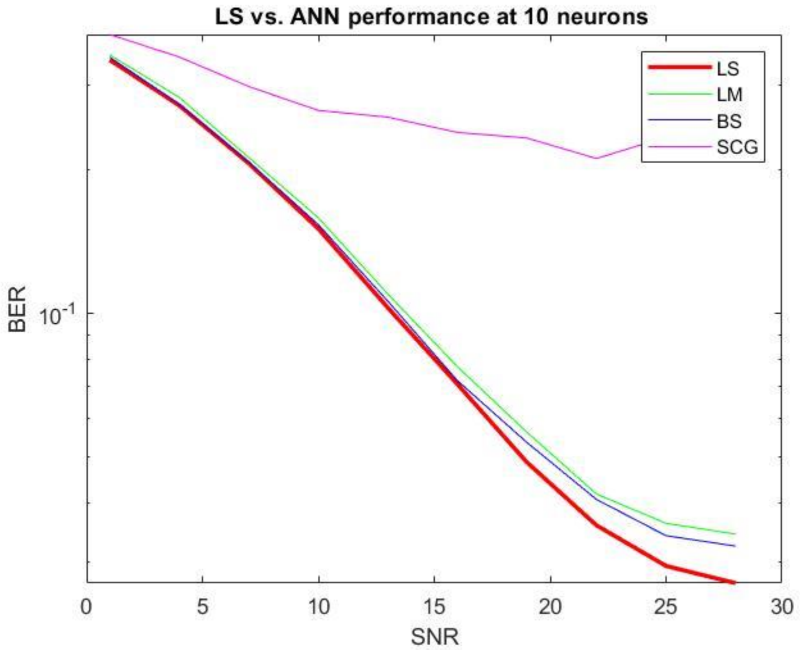

Fig. 5. LS vs. ANN performance at 10 neurons.

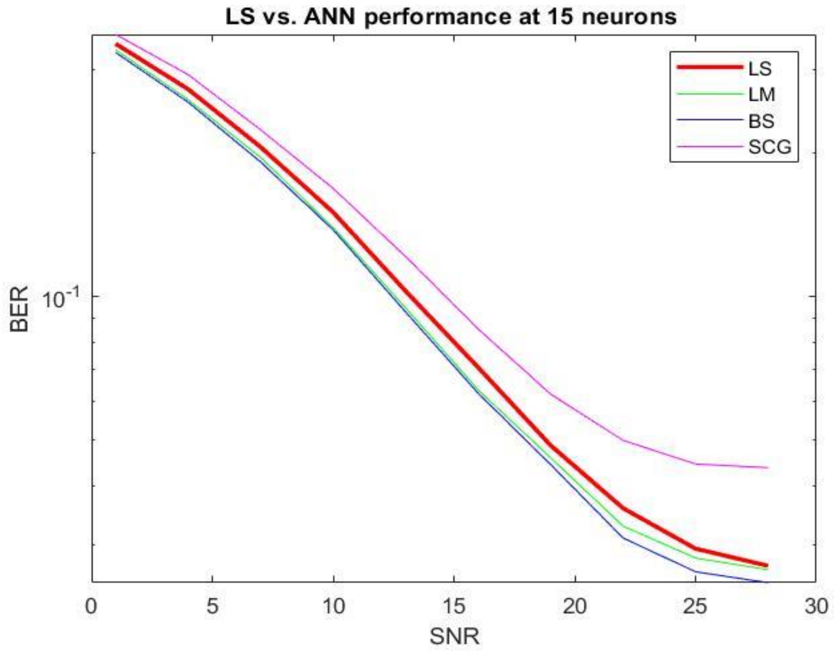

Fig. 6. LS vs. ANN performance at 15 neurons.

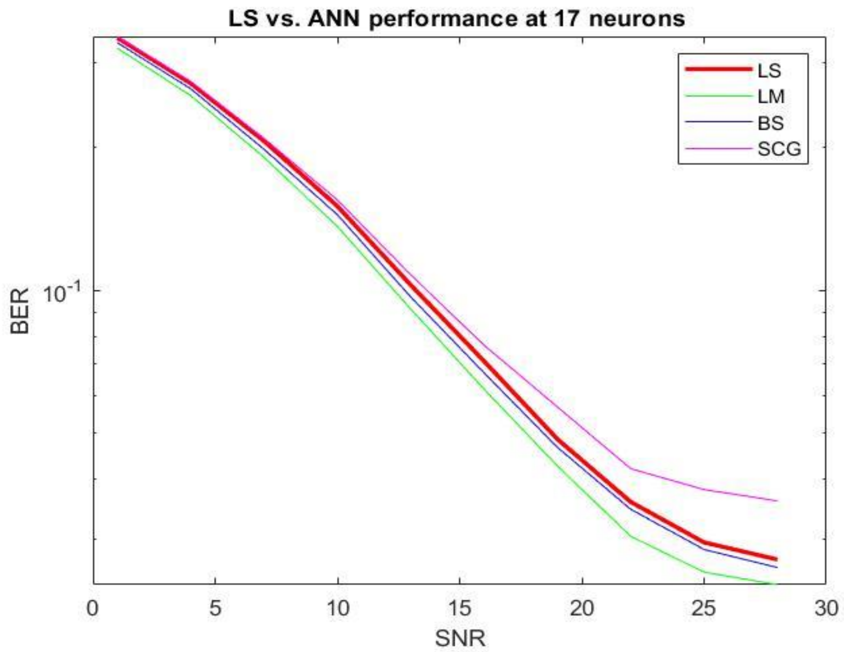

Fig. 7. LS vs. ANN performance at 17 neurons.

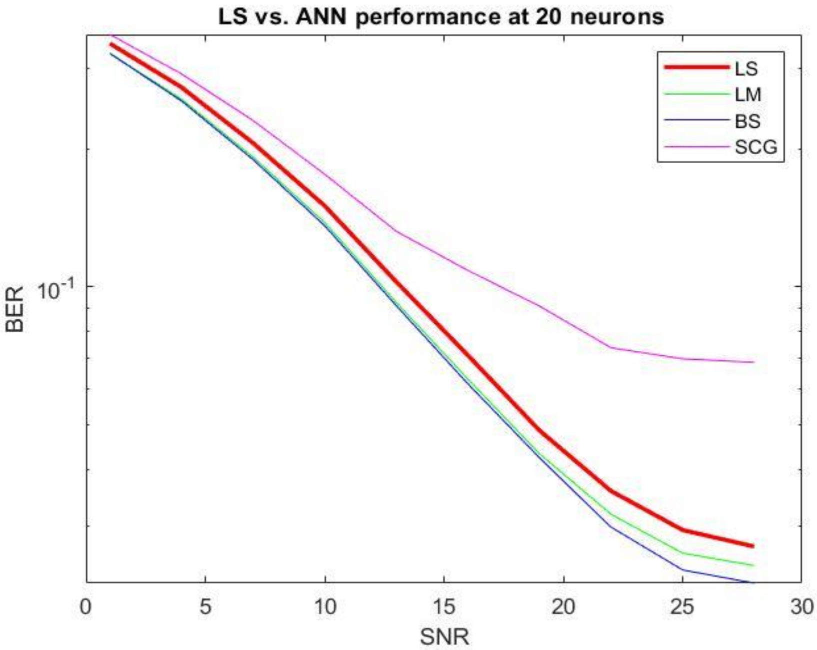

Fig. 8. LS vs. ANN performance at 20 neurons.

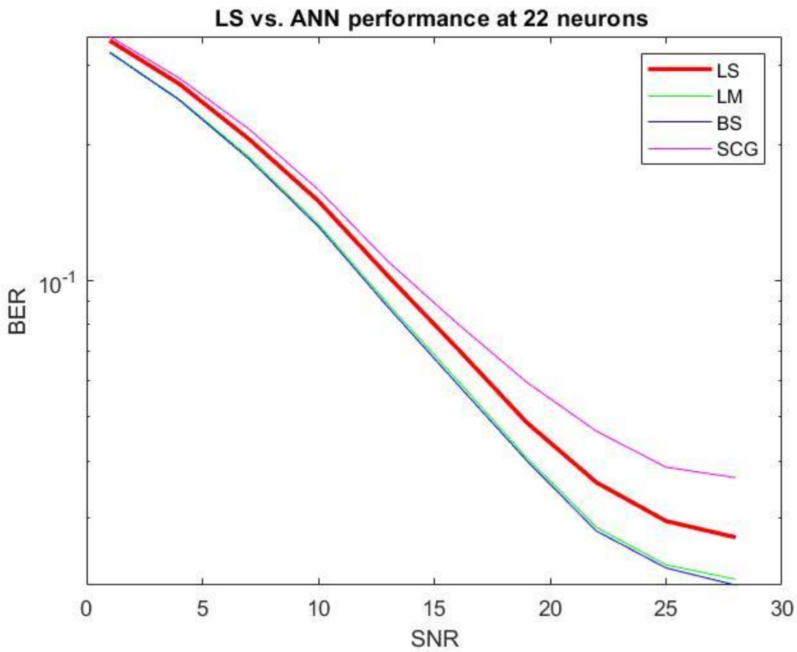

Fig. 9. LS vs. ANN performance at 22 neurons.

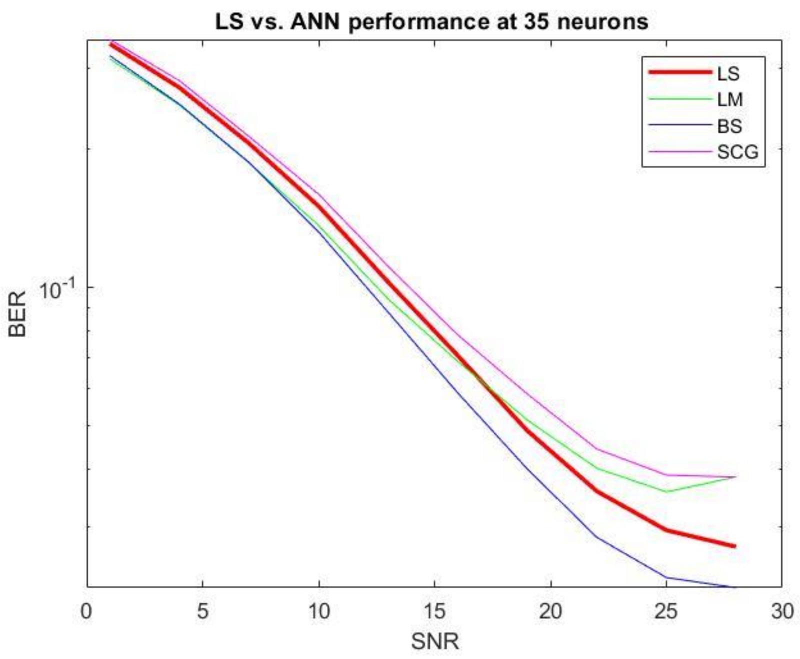

Fig. 10. LS vs. ANN performance at 35 neurons.

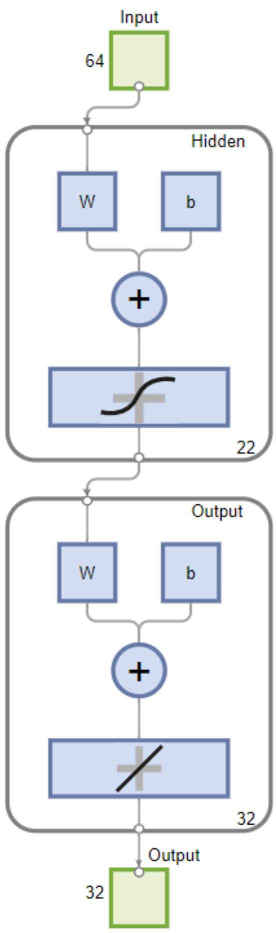

Fig. 11. ANN structure.

Model Summary

Train a neural network to map predictors to continuous responses.

Data
Predictors: in - [64x16000 double]
Responses: out - [32x16000 double]

in: double array of 16000 observations with 64 features.
out: double array of 16000 observations with 32 features.

Algorithm
Data division: Random
Training algorithm: Bayesian regularization
Performance: Mean squared error

Training Results
Training start time: 28-Dec-2022 22:08:55
Layer size: 22

	Observations	MSE	R
Training	13600	0.0367	0.9857
Validation	0	NaN	NaN
Test	2400	0.0370	0.9855

Fig. 12. Model summery.

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	1000	1000
Elapsed Time	-	15:42:54	-
Performance	71.6	0.0367	0
Gradient	31.4	0.00268	1e-07
Mu	0.005	0.5	1e+10
Effective # Param	1.81e+03	1.8e+03	0
Sum Squared Param	309	789	0

Fig. 13. Training progress.

Table 2. Performance comparison.

Ref	BER Improvement
(Ehsanfar 2017)	8×10^{-3}
(Valluri 2018)	0.03×10^{-3}
(Turhan 2019)	0.2×10^{-3}
(Tsai 2021)	0.08
(Ssimbwa 2022)	0.009
Proposed	0.008

5. CONCLUSION

The multicarrier scheme structure of GFDM and the high degree of flexibility in assigning the subcarrier and sub-symbol values with other significant features made it suitable for the next generation. The increase in the BER as a result of noise and interference is one of the substantial problems in wireless communication systems, and work is continuing to improve performance using different methods. Neural network that training by backpropagated feed-forward methods as an improvement for LS and NLMS methods. BR methods give BER enhancement than LS at 22 number of neurons.

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