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Deep Convolutional Spiking Neural Network Optimized with Coyote Chimp Optimization Algorithm for Imperfect Channel Estimation in MIMO-f-OFDM/FQAM Based 5G Network

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Abstract: multiple-input multi-output (MIMO) models need orthogonal frequency division multiplexing (OFDM) to employ in multipath communication efficiently. In channel constraints, the channel estimation (CE) is utilized where time changing features are needed. The previous implemented CE algorithms are highly complex. So, there is a requirement for efficient CE technique to estimate the correctness of received signal. To resolve this difficulty in CE approaches, an innovative CE algorithm called deep convolutional spiking neural network with coyote and chimp optimization algorithm (DCSNN-HCCOA) with the assistance of deep learning (DL) has been proposed. Throughout the estimation period, the proposed MIMO/f-OFDM/FQAM requires the channel consistent, for this purpose the introduced DCSNN is integrated with the hybrid Coyote and Chimp optimization. It provides maximum estimation precision and minimum mean square error (MMSE) and bit error rate (BER). In terms of NMSE, BER, ISI and ICI the obtained results of proposed architecture are better than the other channel estimation systems. The achieved performance measure values are: 0.02, 0.02, 1% and 4% respectively.

Keywords: Deep convolutional spiking neural network with coyote and chimp optimization algorithm, Orthogonal frequency division multiplexing, Multiple-input multi-output.

1. Introduction

In wireless data traffic and reliability communications there is a requirement to handle the fast growth fifth- generation (5G) and wireless communication (WC) has been evolved by combining various disruptive technologies like massive MIMO (mMIMO and mmWave communications [1]. Because of the inevitable achievement of OFDM approach [2]. It has been verified by the contributor in wide-band communication networks. Actually, the effects of frequency selective fading are overcome still by deploying OFDM in 5G systems, hence the multi-path propagation circumstances providing excellent communication quality [3, 4]. When compared with a single-carrier technique, the OFDM method significantly maximizes the spectrum efficiency [5].

Now-a-days, deep learning (DL) approach is implemented in WC like channel state information (CSI), CE and data detection to accomplished very good performance [6]. Here, the fully connected deep neural network (FDNN) is used to evaluate CSI and directly retrieve the output data [7]. The transmitter and receiver must have the knowledge of pilot signals which helps to perform excellent channel estimation [8]. In [9], the receiver is designed with a finite amount of radio frequency chains in mMIMO systems was exploited by denoising based approximate message passing (LDAMP).

The 5G networks depends on various use cases, the pilot symbol's structure is varied in every data frame [10]. However, the least squares (LS) estimation which is one of the traditional channel estimation approach [11]. It gains very minimum computational complexity since; no prior channel statistics is required in LS estimation. But it produces maximum channel estimation errors relatively in various real-time applications. Another way to reduce the channel estimation error and gains better channel estimation quality than other estimation methods is MMSE [12]. But the propagation channel's covariance matrices and the mean value is needed. In several propagation domain, the derivation of statistical information is very difficult or may varies quickly, it makes the implementation of MMSE estimation becomes very challenging [13]. DL gained a better attention in industry as well as academic for many WC's applications like, signal decoding, resource allocation, channel estimation and physical security. For channel estimation, in [14], the underwater channels are estimated efficiently by using deep neural network (DNN) along with pilot signal. The channel estimation for IEEE standard is performed with the aid of DNN model to use the channel correlation in frequency and time regions [15]. Also, the weight parameters of neural networks are optimized with the aid of some optimization algorithms. For example, Pelican Algorithm, Komodo Algorithm, Fixed Step Average and Subtraction Based Optimizer, Puzzle Optimization Algorithm etc. [16-19]

The integration of frequency shift keying (FSK) and quadratic amplitude modulation (QAM) is called as frequency and quadrature amplitude modulation (FQAM). When compared with QAM, the performance of FQAM is enhances significantly so that FQAM is combined with the proposed system implementation.

In this manuscript, DCSNN-HCCOA is proposed for efficient channel estimation in MIMO/f-OFDM/FQAM. It undergoes two phases: offline training and online prediction. The major contribution of this proposed algorithm is listed below:

- Initially, introduce a CE network includes convolutional spiking neural network (CSNN) and a hybrid Coyote-Chimp optimization. Here, the SNN is utilized for the interpolation action of frequency domain and time domain channel prediction.
- The derived frequency and time domain joint together to estimate the CSI and time-domain channel prediction.
- Secondly, the combined CCOA is deployed to optimize the error parameters time domain and membrane constant of CSNN to obtain accurate channel estimation for the communication system.
- The f-OFDM classifies the total bands into few sub bands which are filtered with various filters but it suffers due to Inter-Channel Interference which is deals by the FQAM to resolve the interference and gains excellent performance results.

The rest of this paper is provided as follow. Section 2 discuss about some of the literature works that are related to this work. Section 3 discuss the proposed system. Section 4 provides the results and section 5 is the conclusion of this paper.

2. Related works

Some of the state-of-art techniques that are related to CE based on MIMO/f-OFDM/FQAM is discussed as follow:

In 2021, Le et al. [20] had proposed a MIMO-OFDM system based on 5G and beyond channel estimation. Initially, this proposed system is constructed along with the channel profile with the help of third generation partnership project (3GPP). Secondly, the neural networks are used to known the actual channel's features. The deployment of DNN will improve the system performance which is proven by evaluating the degree for fully connected DNN, Bi-long short-term memory (Bi-LSTM) and convolutional neural network (CNN). The effectiveness of the system is shown by means of BER and MSE. But this system is directly trying to evaluate the delay components which degrades the system performance.

In 2022, Ge et al. [21] had proposed an innovative channel prediction framework which combines MIMO-OFDM imperfect CE into deep neural network (DNN). Therefore, interpolation scheme was replaced and accomplishing higher CE accuracy. Still the BER is high in every circumstance.

In 2020, Liao et al. [22] had introduced a DL based MIMO-OFDM CE method in the high mobility platform. The proposed system consists of CNN and Bi-LSTM. Initially, the CNN is utilized to copy the frequency domain's interpolation processes and Bi-LSTM is utilized for time domain channel prediction. Finally, it is trained by a standard time-varying channel method and verified. Here, the ISI is an unfavourable and undesirable constraint which maximizes the BER.

In 2021, Kishore and Rallapalli [23] had implemented hybrid frequency and quadrature amplitude modulation based filtered OFDM (HFQAM-FOFDM). From the experimental scenario, it is clear that the proposed model achieves better BER than other conventional models. The only

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drawback is sophisticated sparse recovery method is needed to unfold the algorithm.

In 2021, Nagarajan and Sophia [24] had suggested multilevel redundant discrete wavelet transform (ML-RDWT) to overcome the effects of down-sampling which degrades the system performance. Further, optimal red deer method (ORDM) is used to optimize the weight to achieve better ICI cancellation. But the ISI is an unfavourable and undesirable constraint which maximizes the BER.

2.1 Problem statement

The problems of the present work are suggested as below:

- The major issue for high-speed data is minimizing the quality of service where the spectrum is insufficient.
- Generally, the channels are multipath fading channels only. Due to this factor, ISI is caused in the received signal, which maximizes the BER.
- To remove ISI perfectly from the signal, robust equalizers are utilized. It helps to achieve low BER and high SNR values. But the conventional algorithms are failed to use strong equalizers.
- The traditional channel estimation models have issues in the channel resources and CSI transmission.
- The existing systems cannot provide better BER and computational complexity in MIMO OFDM models.

From the above-mentioned problem statements, it is clearly show that the traditional methods don’t meet the achievable BER at definite circumstance because of the low convergence rate. So that, MIMO/f-OFDM/FQAM is introduced to overcome the ICI to accomplish better BER performance.

3. Proposed methodology

DCSNN-HCCOA based CE in MIMO-f-OFDM/FQAM architecture is proposed for enhancing the Bit error rate of the communication model. In this, the introduced DCSNN based CE method is classified into two phases: offline training and online prediction. In offline training phase, the learning network is trained with the aid of huge amount of standard time-varying channel model data. In the online prediction phase, the estimated channel matrix is the learning network’s input, and it is feedback of the MIMO/f-OFDM/FQAM WC model. Furthermore, DCSNN is integrated with the optimization algorithms for calculating the optimal parameters for assuring channel estimation. So that, HCCOA is used to optimize the weight parameters of DCSNN. And the performance of the introduced method is analysed with different metrics such as MSE, BER and NMSE are analysed. Workflow of the proposed work is shown in Fig. 1.

3.1 System model

Consider a MIMO-f-OFDM/FQAM model with transmit and receive antennas as M_t and $M_r$respectively. Also, consider Msubcarriers and Lf-OFDM/FQAM symbols in a subframe. The symbol vector $p$of f-OFDM/FQAM is transmitted with the aid of i th antenna is mathematically given as, $f_i z_{i,p} = \left[z_{i,p}(1), \cdots, y_{i,p}(M)\right]^L$, where $i \in M_t \equiv \{1, \dots, M_t\}$, $t \in \ell \equiv \{1, \dots, L\}$ and for the m_{th} subcarrier $f_i z_{i,p}(m), m \in M \equiv \{1, \dots, M\}$ represents the transmitted signal in the p th f-OFDM/FQAM symbol. Therefore, on the receive antenna $j \in M_r \equiv \{1, \dots, M_r\}$, the received f-OFDM/FQAM symbol vector can be written as,

$$x_{j,p} = \sum_{i=1}^{M_t} \left(F^K f_i(-m) z_{i,p}\right) \otimes Q_{i,j,p}, 1 \le i \le M_t, \quad 1 \le j \le M_r \quad (1)$$

where, in the time-domain, the received sequence is denoted as $\boldsymbol{x}_{i,p} = \left[x_{i,p}(0), \cdots, x_{i,p}(0)(M)\right]^L$.

In the transmitter side, the FQAM modulation method is used to map the input data into symbols. After that, the Inverse Fast Fourier Transform (IFFT) function is carry out, it converts the FQAM symbols into OFDM signals. Hence, add the cyclic prefix in the next phase and at last, the outcoming signal $z(m)$ passes via a f-OFDM which can be given in the Eq. (2).

$$h(m) = z(m) * f_i(m) \quad (2)$$

The $h(m)$ be the modulated signal which is forwarded via the noisy channel. In the receiver side, the filter called $f_i^*(-m)$ is used via this filter the received signal is passed. Finally, the actual input data is received at the receiver side as the output data by utilizing the FQAM demodulation operation.

$$r(m) = h(m) * s(n) * f_i^*(-m) \quad (3)$$

In the frequency domain, the received signal can be mathematically defined in Eq. (4),

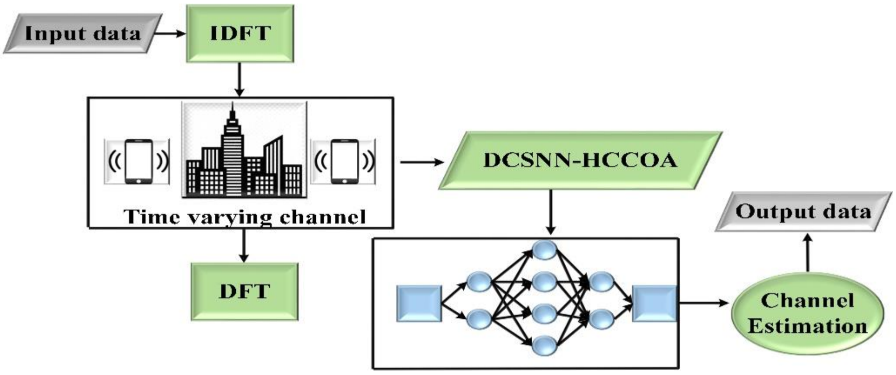


Figure. 1 Workflow of proposed work

$$\tilde{\boldsymbol{x}}_{j,p}(m) = \sum_{i=1}^{M_t}\big(D_{i,j,p}(m,m)f_i^* z_{i,t}(m) + \sum_{l=1,l\neq m}^{M} D_{i,j,p}(m,l)f_i^* z_{i,t}(l)\big) \quad (4)$$

where f-OFDM outcome of $\boldsymbol{x}_{j,p}$ and $\boldsymbol{s}_{j,p}$ can be denoted as $\tilde{\boldsymbol{x}}_{j,p}$and $\tilde{\boldsymbol{s}}_{j,p}$correspondingly. The Channel Frequency Response's (CFR) matrix is represented as $D_{i,j,p}$. The major objective of the channel estimation approach is, to obtain the channel matrix in the receiver side via the known $\boldsymbol{x}_{j,p}$and $\boldsymbol{s}_{j,p}$. Fig. 2 illustrates the system model.

3.2 Proposed DCSNN for CE

The introduced DCSNN based CE is classified as, offline training and online prediction. Initially, the input signal is forwarded to the introduced learning network which produces the predicted CSI. The step by step procedure is given as below:

3.2.1. Input data

In this paper, the DCSNN is used, therefore the CSI of 4×4channel matrix is considered as an input data and it can be given as $D_{i,j} \in C^{L\times M}, i \in M_t, j \in M_r$, the obtained values of CSI at data symbols and pilot symbols are set as 0. So, CSI data is gained among whole pairs of antennas as $\boldsymbol{D} \in C^{M_t\times M_r\times L\times M}$. To see the data transformation process among every f-OFDM/FQAM symbol in the introduced CE network. It can be given as follow,

$$\boldsymbol{D} = [D_1, \dots, D_t, \dots, D_L] \quad (5)$$

3.2.2. Convolution layer performs interpolation of frequency-domain

The pre-processed input signal is directed to the convolutional layer. This layer is mainly utilized to interpolate in the frequency region. It carryout an independent convolutional function over D_t' with$V_{i,p}$ convolutional filters of size $i'' \times j''$at $p$time step. The result of this convolution layer can be mentioned in the Eq. (6),

$$D_t'' = o\big(V_{2,p} * o\big(V_{1,p} * D_t' + a_{1,p}\big) + a_{2,p}\big) \quad (6)$$

where the offset is denoted as $a_{i,p}$and the activation operation is represented as $o(\cdot)$. The convolution operation is mentioned as *. Here, the activation operation called tanh.

3.2.3. Max pooling layer

The non-linear down-sampling is achieved in this max pooling layer. After that, this function classifies the pre-processed data into numerous domains of non-overlapping channel. All the channel domain generates the result more accurate. The mathematical formula can be considered as,

$$O_{i,j,l} = max\left\{r'_{i',j',l}: i' \leq i'' < i + q', j' \leq j'' < j' + q'\right\} \quad (7)$$

where, the input and the output matrix are represented as $r'$and $o$respectively. The padding is denoted by the parameter q'.

3.2.4. Dropout

The dropout units of visible and hidden layers are available in this dropout layer which is randomly visualized as a regularization approach to remove the overfitting issues. It also minimizes the difficult co-adaptations between the neurons.

3.2.5. Spike encoding scheme for time-domain channel prediction

The spike train is stated by the conversion of filtered convolution signals. To transform the signal maps into signal vectors, there is need for pulling down the input signal. These vectors are considered

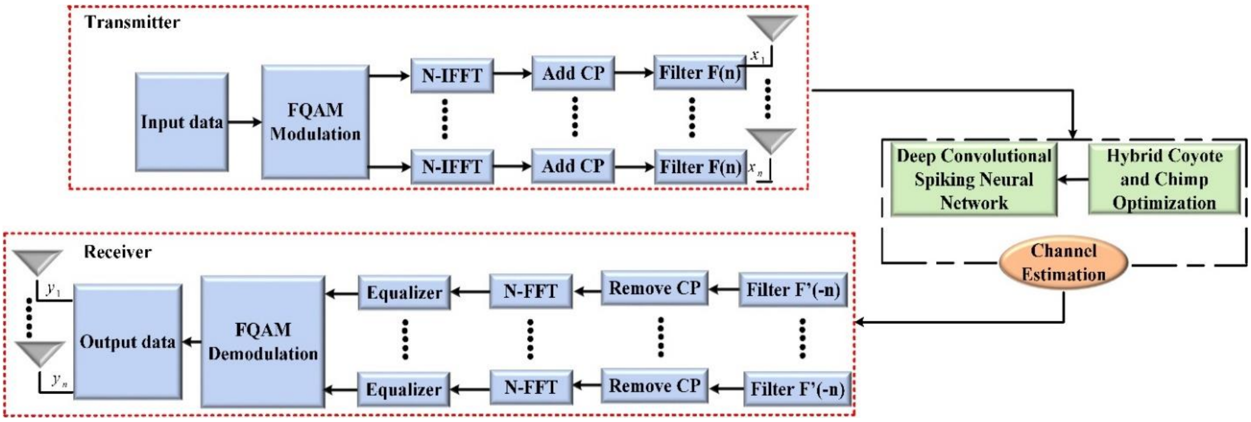


Figure. 2 System model

to be an input of the next layer. The spike encoding of the input signal is performed by the model called soft-leaky integrate and fire system (SLI-FS). It is further classified as two types such as, potential behaviour of membrane and spike rest procedure. The dynamics of SLI-FS neuron membrane potential for the input signal $I_s'(t)$ is $p_{LIFM}^{'}(t)$ and its differential expression is mentioned in the Eq. (8),

$$\frac{dp'_{LIFM}(t)}{dt} = -\frac{1}{C'} LIFM\left(p'(t)H_{t-1}, D_t^{''}, \Phi\right) + \frac{I'_s(t)}{MC'}, t \geq 0, \quad (8)$$

where, the membrane capacitance is denoted as C', the membrane time constant is represented as $MC^{'}$.

Here, $H_t$signifies the variable quantity of hidden layer and Φrepresents the transformation function. The neuron rate response along with refractory's period of normalized LI-FM is mathematically given in the Eq. (9),

$$l^{'} = \frac{1}{\chi_{time} - \gamma_{MC'} log\left(1 - \frac{1}{I'_s}\right)} \quad (9)$$

Consider $l^{'} = 0$and $I_s^{'} = 1$, therefore, the Eq. (10) becomes,

$$l^{'}(I'_s) = \left[\chi_{time} - \gamma_{MC'} log\left(1 + \frac{1}{\beta(I'_s - 1)}\right)\right]^{-1} \quad (10)$$

where χ_{time} signifies the time domain and $\gamma_{MC'}$represents the membrane constant. However, the outcome of steady state firing rate can be given as,

$$l(I_s) = \begin{cases} \left[\chi_{time} + \gamma_{MC} log\left(1 + \frac{1}{\rho(I'_s - 1)}\right]^{-1}, & if I'_s \geq 1 \\ 0, & otherwise \end{cases} \quad (11)$$

The final layer of the CSNN is utilized to reduce the dimension of the result. Then it is reshaped as $M_t \times M_r \times M$ and gain the final result as $\widehat{\boldsymbol{D}} = \left[\widehat{D}_1, \cdots, \widehat{D}_L\right]$.

Atlast, the introduced DCSNN estimates the channel. But the parameters of DCSNN must be optimized with the aid hybrid Coyote Chimp optimization algorithm which is obtained from the LI-FM i.e. $\chi_{time}$and γ_{MC}.

3.3 Hybrid coyote chimp optimization algorithm (HCCOA)

In this research work, HCCOA has been proposed for optimizing the parameters of DCSNN. Furthermore, hybrid optimization procedure minimizes the complexity, bit error rate and computational period.

3.3.1. Coyote optimization algorithm (COA)

COA is one of the nature-inspired meta-heuristic approach, its mimic nature highly solves the optimization issues. This algorithm is works depends the adaptation behaviour of the coyote as well as the experience of coyote is exchanging. It is an excellent method to achieve a balance among exploration and exploitation.

3.2.2. Chimp optimization algorithm (CHOA)

CHOA is a new group intelligence-based approach influenced by the chimp hunting strategy. There are four communal chimp's type are present in this algorithm such as chaser, attackers, driver and barrier. Each and every member of a chimp colony has various capabilities which are needed for the efficient hunting process.

Step 1: Initialization

In the search space, few random cayotes are produced as the candidate solutions. The below mention Eqs. (12) and (13) demonstrates the modelling of process. In the hunting group, the driver and the chaser behaviour are formulated as,

$$soc_{n,i}^{q,t} = lb_i e + \mu \times (us_i - ls_i) \tag{12}$$

$$e = \left| d.\, y_{goal}(t) - w.\, y_{chp}(t) \right| \tag{13}$$

where, $n$signifies the number, $q$indicates the group, t denotes the time, the random value $\mu \in [0,1]$, $us_i$and ls_irepresents the upper and the lower bound of ith variable, the position vectors of the chimp and goal (prey) is indicated as y_{chp} and y_{goal}.

Step 2: Fitness function

The fitness function is used to attain the objective function. This is applied to optimize χ_{time} and γ_{MC} weight parameters of DCSNN. The fitness function equation is labelled in Eq. (14),

$$\boldsymbol{Fitness\_Function_{OFDM/FQAM}} = \boldsymbol{Optimize(\chi_{time}, \gamma_{MC})} \tag{14}$$

Step 3: Position updation /updating the subcarriers and optimize the parameter χ_{time}

Every coyote's cost function can be defined in the Eq. (15).

$$obj_d^{q,t} = f\left(soc_{d,i}^{q,t}\right) \tag{15}$$

The location of groups is updated randomly and it can be expression as,

$$Q_m = 0.05 \times R_d^2 \times e_n \tag{16}$$

Assume $R_d \leq \sqrt{200}$, $Q_m > 1$ and $e_4 = e_{attacker}, e_{barrier}, e_{chaser}, e_{driver}$ from which $e_{attacker} = |d_n y_{attacker} - m_n y|$ and vice versa.

The alpha coyote is said to be every iteration's best solution and it is obtained by the Eq. (17),

$$\alpha^{q,t} = soc_d^{q,t} forminimumobjective_d^{q,t} \tag{17}$$

Step 4: By using social behaviour, optimize the error parameter γ_{MC}

The obtained new cost can be mathematically formulated in the following Eq. (18) by considering the updating equations is:

$$mobj_d^{q,t} = f\left(msoc_d^{q,t}\right) * y_{chp}(t+1) \tag{18}$$

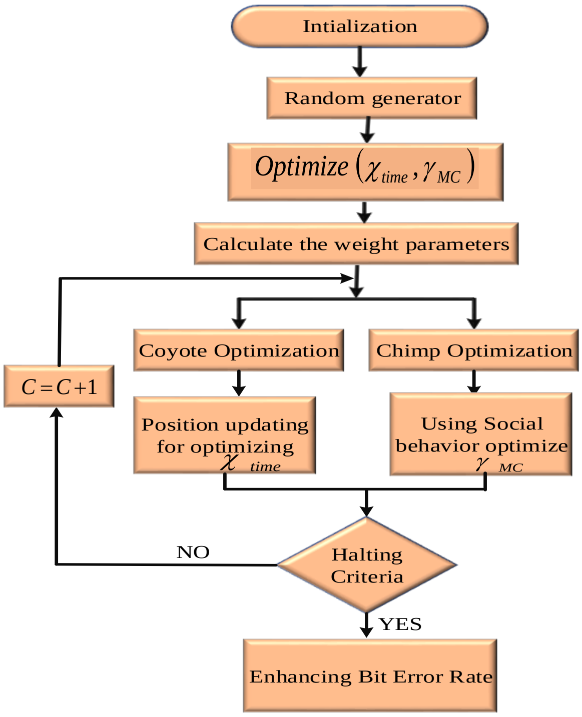


Figure. 3 Flowchart of HCOOA

$$\text{Here, } soc_d^{q,t+1} = \begin{cases} msoc_d^{q,t}, mobj_d^{q,t} & < obj_d^{q,t} \\ soc_d^{q,t} & \end{cases} \tag{19}$$

And

$$y_{chp}(t+1) = \begin{cases} y_{goal} & \eta < 0.5 \\ chatic\_value & \eta > 0.5 \end{cases} \tag{20}$$

The significant feature of this HCCOA is its capability to escape from the local optimum and achieves faster convergence rate and optimize the parameters of DCSNN simultaneously.

Step 5: Termination

The weight parameters $\chi_{time}$and $\gamma_{MC}$of DCSNN is optimized with the help of HCCOA. Fig. 3 illustrates the flow chart of hybrid optimization algorithm.

4. Results and discussion

The DeepMIMO dataset is used to gather the data for training and testing in the proposed model. This research has been proposed to determine and compare the introduced channel estimation system with other models such as, LS, MMSE, Linear MMSE (LMMSE), CNN, FDNN, LS-Cubic Spline Interpolation (LS-CSI), LS-Bayesian Interpolation (LS-BI), DNN, DL-MIMO-OFDM etc. Evaluate the proposed method based on BER, MSE, NMSE, ISI and ICI. By varying the SNR of the system regarding number of transmitter and receiver antennas. The introduced method is run on the NS3 tool successfully.

4.1 Performance analysis

In this section, the considered metrics for the analysis of proposed system with implemented methods are mathematically given as below:

4.1.1. BER

It is one of the essential data channel performance parameters. BER is the proportion of number of bits in error to the entire amount of transmitted bits.

$$B_{ER} = \frac{NB(E)}{TN(T_B)} \tag{21}$$

4.1.2. MSE

The signal-to-signal error is defined by the MSE parameter. It can be mathematically written in the Eq. (22),

$$M_{SE} = \frac{1}{rs}\sum_{m=0}^{r-1}\sum_{n=0}^{s-1}\left[G_Q(m,n) - G_q'(m,n)\right]^2 \tag{22}$$

where the channel input is denoted as r, the channel output is represented as s, the initial value of input signal is given as G_q' and the term G_Q indicates the terminal value of the signal.

4.1.3. Normalized MSE

The NMSE is an assessment index of denoising property in the proposed method. It can be formulated in the Eq. (23),

$$N_{MSE} = \frac{1}{M}\sum_{j=1}^{M}\frac{\|P-P^e\|_L^2}{\|P\|_L^2} \tag{23}$$

where M be the total number of signals and P denotes the matrix of CE.

Fig. 4 shows the NMSE and BER analysis of proposed DCSNN-HCCO for 16 FQAM with some of the previous approaches such as LS-CSI, Ls-BI approach and DNN. Here, the high-order digital modulation approaches will minimize the CE's performance. But the NN based CE technique will provide excellent results by gathering data via MIMO-f-OFDM channels and utilizing offline training model. If the value of SNR is too maximum, then the NMSE and BER values of the models becomes decreasing. The achieved NMSE and BER value of proposed DCSNN-HCCO at 25 dB is 0.02 and 0.02 respectively [21].

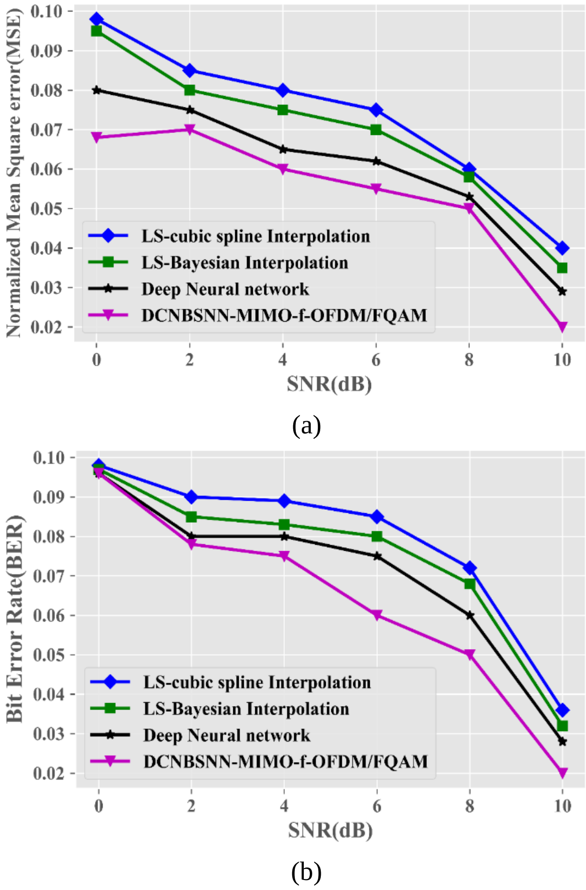
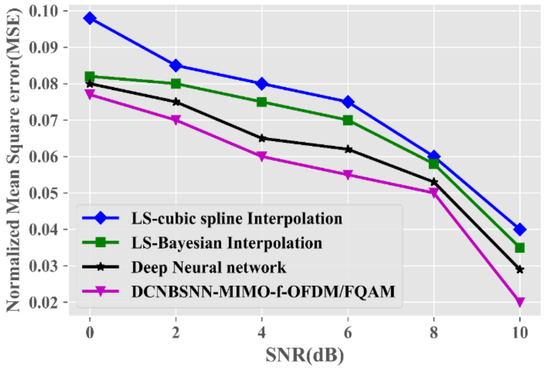


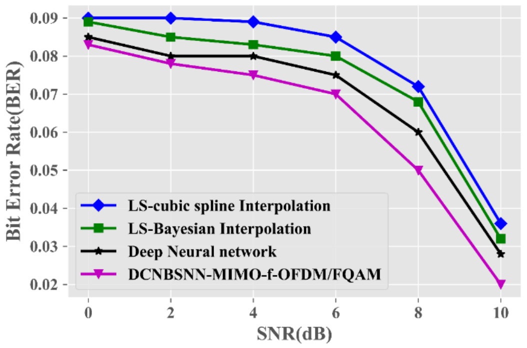
Figure. 4 NMSE and BER performance analysis for 16 FQAM [21]: (a) NMSE for 16 FQAM, and (b) BER for 16 FQAM

NMSE and BER performance comparison for 32 FQAM is provided in the Fig. 5. The experimental outcome denotes the existing estimator BER gain is high with the varying SNR values. But the proposed method BER value is significantly less with the increasing SNR values. The obtained NMSE and BER of proposed DCSNN-HCCO at 10 dB is 0.06 and 0.75 correspondingly. It clearly proves that the proposed DCSNN-HCCO method can have the ability to eliminate the noise from outside [21].

Fig. 6 demonstrate the NMSE and BER comparison of implemented approaches and proposed technique by speed in a 4×4system. The below graphical representation is drawn if the speed is 50Km/h. The gained performance of all methods decreases with increasing SNR. The introduced MIMO-f-OFDM/FQAM requires minimum computational time while reducing BER and CE error performance. Due to this factor, the obtained NMSE and BER value of the introduced DCSNN-HCCO method at 10 dB SNR is 0.073 and 0.073 respectively,

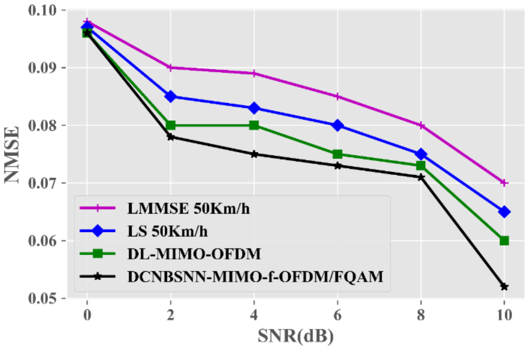


(a)

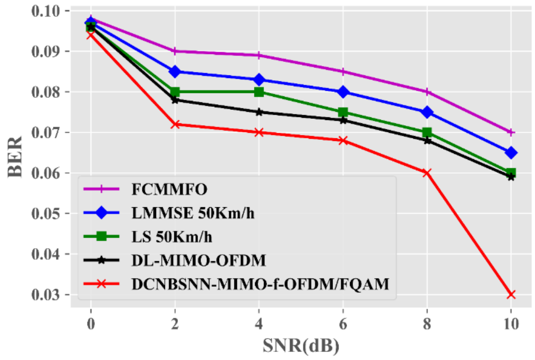


(b)

Figure. 5 NMSE and BER performance analysis for 32 FQAM [21]: (a) NMSE for 32 FQAM and (b) BER for 32 FQAM



(a)



(b)

Figure. 6 NMSE and BER analysis by 50 Km/h speed [22]: (a) NMSE and (b) BER

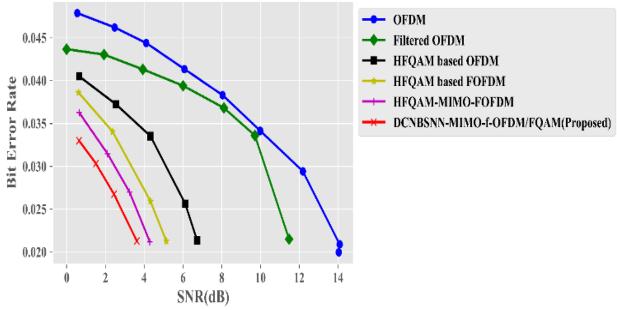


Figure. 7 BER analysis [23]

which is very much less than the compared approaches such as, LMMSE, LS and DL-MIMO-OFDM [22].

Fig. 7 demonstrates the comparison of proposed work with existing modulation methods. The introduced algorithm delivers the low BER if compared to the other implemented approaches. Because, the proposed f-OFDM produces a large data rate along with an extended symbol duration by integrating minimum data rates. The graphical represented clearly provides the accomplished BER value at 14 dB SNR is 0.030 which is also far better than other modulation techniques [23].

Fig. 8 (a) and (b) illustrates the MSE of various channel estimations approaches. As the SNR increases, all the channel estimation approaches MSE value becomes gradually declining. In both cases, LMSSE yield the worst MSE and BER performance, it causes due to not considering the statistical channel information into concentration while carryout the channel estimation. The proposed model achieves better MSE and BER values because it provides high robustness in denoising compared to the previous estimation models. The obtained MSE and BER values of introduced method is 0.030 and 0.020 respectively [20].

Fig. 9 shows the effectiveness of the deep learning approaches. The performance of the existing and proposed estimator remains unchanged with varying SNR value. Because, the introduced DL system maximizes the magnitude of the pilot symbols which helps to meet less MSE performance. The achieved MSE value of introduced work is very less i.e. 0.017, 0.15 and 0.010 for ¼ pilot, 1/8 pilot and 1/16 pilot respectively. Therefore, conclude that the proposed estimator is more robust to various pilot densities [20].

Fig. 10 shows the performance comparison of Inter Symbol Interference (ISI), Inter Channel Interference (ICI) and BER [24]. The proposed f-OFDM produces excellent network system by eliminating ISI through transmitting various low-

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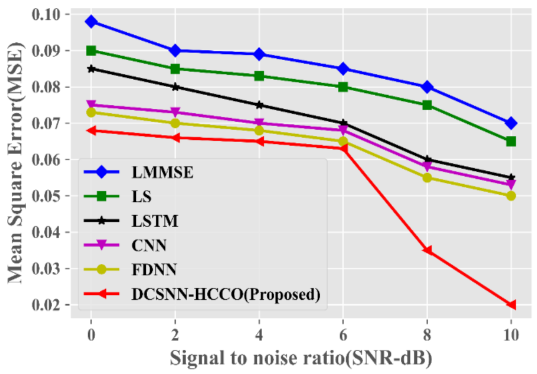
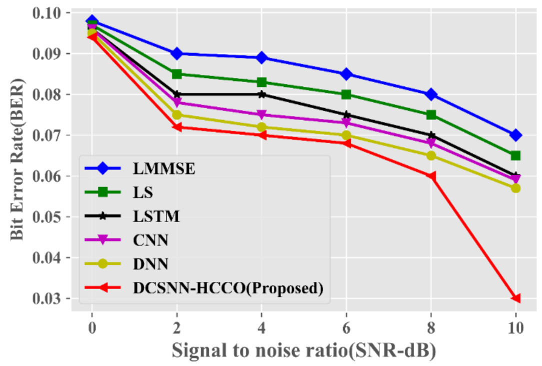


(a)



(b)

Figure. 8 Analysis of proposed work with Doppler effect as 36 Hz [20]: (a) MSE and (b) BER

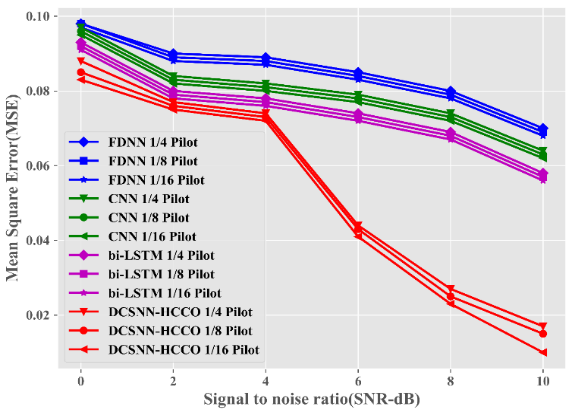


Figure. 9 Comparison of MSE value with different pilot densities [20]

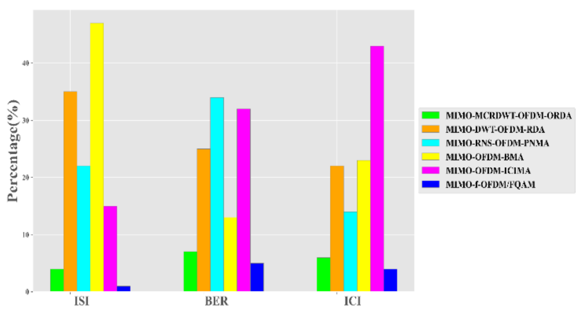


Figure. 10 Comparison of ISI, BER and ICI performance [24]

speed transmissions and maximizing the throughput of network. The proposed system acquires excellent result in the channel estimation system. The obtained ISI values of existing and proposed method are 4, 35, 22, 47, 15 and 1 accordingly, which is minimum. The gained BER and ICI performance of proposed system is 5 and 4, it is also less when compared with the other methods as well. Finally, the introduced method achieves much better performance than other implemented MIMO-OFDM.

5. Conclusion

The introduced DCSNN-HCCOA performs better channel estimation than the other existing estimators based on BER performance in MIMO/f-OFDM/FQAM. The BER get minimized, while the number of subcarriers increases. Including optimization technique in DCSNN will enhances the BER performance. The time and computational complexity of the proposed approach is depending on the count of antennas in the MIMO model. The introduced method is very easy to implement and less complicated. When compared to the other implemented CE systems, this proposed DCSNN-HCCOA achieves maximum efficiency. The achieved performance measure value of NMSE is 0.02, BER is 0.02, ISI is 1% and ICI is 4%.

Notations:

Notation	Description
M_t	Transmit antennas
M_r	Receive antennas
$\boldsymbol{x}_{i,p}$	Received sequence
$z(m)$	Resultant signal
$h(m)$	Modulated signal
$f_i^*(-m)$	Filter
$\tilde{\boldsymbol{x}}_{j,p}, \tilde{\boldsymbol{s}}_{j,p}$	f-OFDM output
$D_{i,j,p}$	Matrix of channel frequency response
$\boldsymbol{D} \in C^{M_t \times M_r \times L \times M}$	CSI data
$a_{i,p}$	Offset
$*$	Convolution function
q'	Padding
MC'	Membrane time constant
Φ	Transformation function
χ_{time}	Time domain
$\gamma_{MC'}$	Membrane constant
$\widehat{\boldsymbol{D}} = [\widehat{D}_1, \cdots, \widehat{D}_L]$	DCSNN
$\alpha^{q,t}$	Best solution
y_{chp}, y_{goal}	Position vectors

Conflicts of interest

The authors declare no conflict of interest.

Author contribution

The paper conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing – original draft preparation, writing – review and editing, visualization, have been done by 1st author. The supervision and project administration have been done by 2nd author.

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