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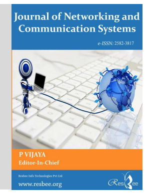

Deep Learning Enhanced Channel Estimation with user Scheduling using Chrono-Fairy Wren Optimization in MIMO-OFDM Networks

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Abstract: Multiple Input Multiple Output-Orthogonal Frequency Division Multiplexing (MIMO-OFDM) is one of the advanced wireless broadband technologies commonly used due to its high spectral efficiency, data transmission rate, and resistance against multipath fading. Effective channel estimation and optimal user scheduling are vital for reliable data transmission and maximizing the quality of service (QoS), spectral efficiency, and throughput. The traditional Deep Learning (DL) methods exploited for channel estimation failed to obtain high throughput or fairness. Hence, the Chronological Fairy Wren Optimization Algorithm with Deep Convolutional Neural Network (ChFWOA+DCNN) is presented for channel estimation and user scheduling in MIMO-OFDM. Here, the input data is encoded using Space-Time Block Coding (STBC) and then modulated employing Quadrature Amplitude Modulation (QAM). Further, Orthogonal Frequency-Division Multiplexing (OFDM) and precoding are applied. After that, user scheduling is performed employing ChFWOA. At the receiver side, channel estimation is done using DCNN, and then the received signal is subjected to OFDM demodulation. Later, QAM demodulation is effected for recovering the original transmitted signals. Finally, the original data is recovered by the STBC decoder. Moreover, the ChFWOA+DCNN attained a maximum throughput of 9.009 Mbps, and minimum Bit Error Rate (BER) and Symbol Error Rate (SER) of 1.54x10-7 and 2.47x10-5.

Keywords: Multiple Input Multiple Output, Channel Estimation, Orthogonal Frequency Division Multiplexing, User Scheduling, Deep Learning.

Nomenclature

Abbreviation	Description
MIMO	Multiple Input Multiple Output
OFDM	Orthogonal Frequency Division Multiplexing
DL	Deep Learning
CSI	Channel State Information
CE	Channel Estimation
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
CFWO	Chrono-Fairy Wren Optimization
SNR	Signal-to-Noise Ratio
BER	Bit Error Rate
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
QoS	Quality of Service

1. Introduction

Wireless communication has been regarded as the most efficient zone of technical development, where quick developments are made to enhance the wireless system's performance. In the past few decades, several generations of mobile wireless technologies have been introduced to permit numerous services, like voice-to-data and multimedia transmission [1]. Furthermore, the data rate and spectrum for 4 G and 5 G wireless standards are in great demand for enabling a variety of applications [2]. In addition to this, more developments with a huge range of applications are aimed to be implemented in future wireless systems. Considering this, the MIMO-OFDM system provides high data transmission rates, higher capacity, and bandwidth, and these systems are also more resistant to multipath effects and noise [1]. MIMO is a system in which several antennas at the receiver and transmitter are employed to exploit many independent channels. Furthermore, OFDM has become more prominent in 4 G and 5 G wireless standards because of its simple implementation, robustness to multipath fading, high spectral efficiency, and throughput [2]. In MIMO-OFDM wireless networks, the most challenging problem is channel estimation [5]. In general, channel estimation is essential in communication networks as it has a direct impact on the quality of the system. Moreover, the channel experiences major temporal fluctuations because of the mobility of the dispersion obstacles, receiver, or transmitter [6]. Besides, the channel state information is utilized by channel estimation for receiving and transmitting the wireless signal. Further, the OFDM system's channel capacity is increased by enhancing the BER performance of the system [7].

DL approaches are driving significant technological advancement in the means, methods, patterns, and concepts of wireless communication networks [14] [15] [16]. Moreover, DL techniques are regarded as a current trend in several wireless communication applications, such as channel estimation, channel decoding, physical security, radio resource allocation, and channel equalization. Among all these applications, channel estimation is considered the most frequently analyzed problem [9]. One of these key aspects is that DL-based approaches are data-driven, which makes them more suitable for handling real-time application challenges. In addition, the DL technique can reduce the computational complexity, which requires many layers of essential operations, like matrix-vector multiplications. Furthermore, the execution of DL approaches is greatly parallelized and created simply by utilizing the low-precision data types [6]. In channel estimation applications, an effective way to evaluate the channels is to exploit a tuned Deep Neural Network (DNN) approach facilitated by a pilot signal. Besides, the DNN approach is employed for performing channel estimation through the use of channel correlation in both frequency and time domains [8]. ReEsNet increases the performance of channel estimation by incorporating residual learning based on the design of the neural network. Nowadays, researchers are also investigating attention-based designs for channel estimation tasks because of the promising performance exhibited by the transformer and attention mechanism in natural language processing [10].

The major intent of this work is to devise a new method termed ChFWOA+DCNN for channel estimation and user scheduling in MIMO-OFDM. Here, the input data to be transmitted is encoded using STBC, and then the encoded data is modulated using QAM, which is later split into multiple sub-carrier frequencies using OFDM. Next, the precoding is applied based on channel conditions, and then the user scheduling is done utilizing ChFWOA, which is engineered by the incorporation of the Chronological concept and Superb-Fairy Wren Optimization Algorithm (SFOA). At the receiver side, channel estimation is done using DCNN, and the received signal is then subjected to OFDM demodulation to combine the signal from multiple subcarriers to a single stream. After this, QAM demodulation is effected for recovering the original transmitted signals. At last, the original data is recovered by the STBC decoder.

The key contribution of this paper is,

- ***Proposed ChFWOA+DCNN for channel estimation and user scheduling in MIMO-OFDM:*** A new technique termed ChFWOA+DCNN is employed for channel estimation and user scheduling in MIMO-OFDM systems. Here, the user is scheduled by utilizing ChFWOA, which is formulated by combining SFOA and the chronological concept. Furthermore, the channel estimation is performed by exploiting the DCNN technique.

The remnant sections are ordered as follows: Section 2 explicates the pros and cons of traditional approaches, Section 3 explains the ChFWOA+DCNN technique, Section 4 elucidates the results of ChFWOA+DCNN, and the conclusion is portrayed in Section 5.

2. Motivation

In MIMO-OFDM, precise channel estimation is vital to realize the full potential of frequency and spatial diversity. At the same time, user scheduling is also regarded as a vital role in optimizing the system performance by choosing a group of users that increases the fairness or throughput. However, several techniques employed for this process are more complex for dense networks, which obtain high error rates with poor performance. Therefore, a new method known as ChFWOA+DCNN is developed for channel estimation and user scheduling. Further, the limitations of prevailing models are given below.

2.1 Literature Review

Data Aided Channel Estimation (DACE) was introduced by Khan, I., *et al.* [1] for channel estimation in MIMO-OFDM. This approach effectively selected the reliable data symbols by lowering the Mean Square Error (MSE). However, this model increased the estimation delay, which made it less appropriate for ultra-low latency applications or fast-fading channels. Chitra, S., *et al.* [2] devised a Pilot-based Carrier Frequency Offset (CFO) to estimate the channel in MIMO-OFDM. This technique provided accurate channel estimation, which enhanced the overall performance with high reliability. However, this method failed to implement channel estimation together with beamforming to improve the coverage. Enhanced Modified-Subspace Pursuit (EM-SP) was presented by Mehrabani, M.R., *et al.* [3] for channel estimation in MIMO-OFDM. This method achieved a satisfactory tradeoff between high complexity and spectral efficiency. Nevertheless, this approach attained high computational complexity, particularly in high-dimensional settings, like high-resolution OFDM or massive MIMO. Silpa, C., *et al.* [4] developed a Hyper Convolutional Neural Network with Tunicate Swarm Optimization and Long Short-Term Memory (Hyper CNN-TSO-LSTM) for channel estimation in MIMO-OFDM. This method used a highly enhanced strategy to maximize the estimation accuracy with a low error rate. Nevertheless, this model failed to improve the capability of interference mitigation for optimizing the overall performance.

2.2 Challenges

The challenges faced by prevailing models for channel estimation and user scheduling are,

- In [1], the DACE technique was effective, accurate, and simple to use. However, the performance of BER was reduced due to the increase in the number of transmit antennas. Further, it was also difficult to select the symbols with an increase in data.
- In [2], the pilot-based CFO provided maximum Carrier-to-interference power ratio (CIR) because of its high estimation accuracy. Nevertheless, this approach failed to utilize DL techniques for attaining high throughput or fairness with a lower error rate.
- In [4], the Hyper CNN-TSO-LSTM method demonstrated a high-performance rate with less BER and more satisfactory results. Still, this approach did not focus on devising a deep channel estimator to obtain higher mobility channels.
- Several existing techniques ensured a high error rate in complex networks as the number of users and antennas increased, which introduced computational delays in channel estimation. However, the small increase in BER also decreased the throughput by affecting the entire service quality.

3. Proposed Chronological Fairy Wren Optimization Algorithm with Deep Convolutional Neural Network for channel estimation and user scheduling in MIMO-OFDM networks

In MIMO-OFDM, the channel estimation with user scheduling is considered a critical challenge. Channel estimation is needed for determining the CSI, while user scheduling ensures effective allocation of resources to users based on their QoS requirements, CSI, and so on. Various DL techniques are exploited for this process, but they have failed to decrease the bit error values to improve the performance. Thus, a new method termed ChFAOA+DCNN is devised for channel estimation and user scheduling in MIMO-OFDM. Here, the input data to be transmitted is encoded using STBC for improving reliability. The encoded data is then modulated utilizing QAM, and later it is split into multiple sub-carrier frequencies using OFDM. Following this, the precoding is applied to optimize the signal transmission based on channel conditions. Next, user scheduling is performed based on priority, throughput, and fairness. Here, the user scheduling is done utilizing ChFWOA, which is engineered by the incorporation of the Chronological concept and SFOA [12]. At the receiver side, channel estimation is done using DCNN [13] to determining the wireless channel's effects. The received signal is then subjected to OFDM demodulation to combine the signal from multiple subcarriers to a single stream, and following this, QAM demodulation is effected for recovering the original transmitted signals. Lastly, the original data is recovered by the STBC decoder. Fig. 1 shows the general outline of ChFWOA+DCNN for user scheduling and channel estimation in MIMO-OFDM.

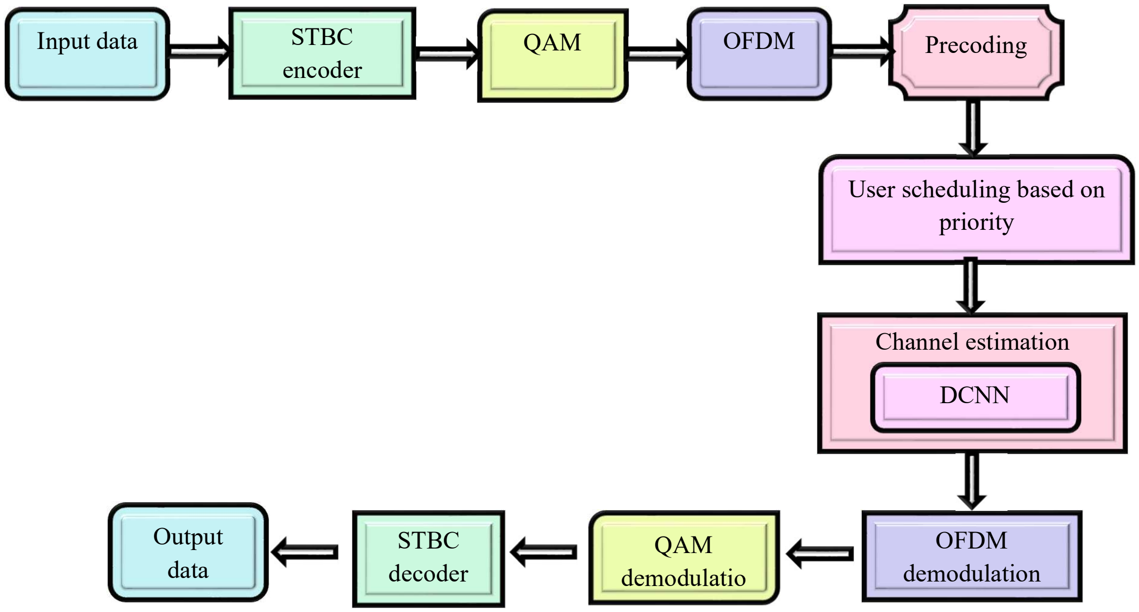


Fig. 1. *A general outline of ChFWOA+DCNN for channel estimation in MIMO-OFDM*

3.1 Transmitter Model

The transmitter model is employed for describing how a communication system sends and processes the information from the source to the receiver. The user's data is taken as input and passed to the STBC encoder, which produces multiple copies of the same data. After this, the user data is subjected to QAM, and the resultant is mapped to various subcarrier frequencies using OFDM. Next, the precoding is added to every frame, and after this, the user scheduling is carried out based on fairness, throughput, and priority.

3.2 User Scheduling

The purpose of user scheduling is to identify which users have to be served at the specified time and on which time-frequency resources to enhance the entire system's performance. Here, user scheduling is performed for allocating resources to the users and is done by employing the ChFWOA approach. Moreover, the ChFWOA model is formulated by the integration of the Chronological concept and SFOA [12]. Furthermore, the fitness, solution encoding, and description of ChFWOA are given beneath.

3.2.1 Solution Encoding

Solution encoding is used to represent the scheduling decisions in a structured format, which is processed by the optimization techniques. This process plays a crucial role in optimization-based scheduling, especially in MIMO-OFDM, where several users share spatial resources, frequency, and time. Here, the solution with maximum fitness is searched, which corresponds to the best scheduling decision. The Solution encoding of ChFWOA is specified in Fig. 2.

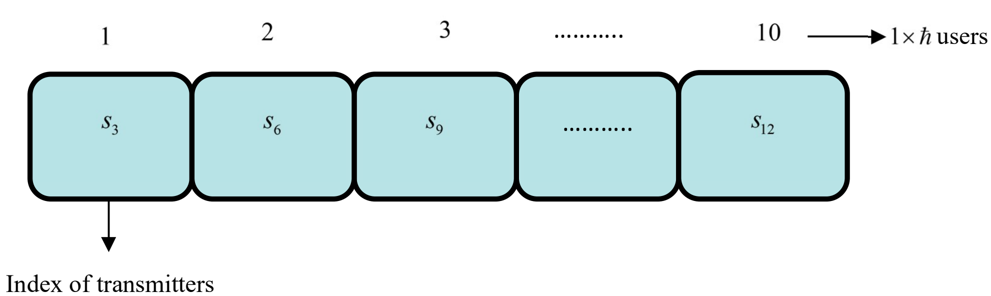


Fig. 2. *Solution encoding of ChFWOA*

3.2.2 Fitness Function

The fitness function is employed for evaluating the candidate solution's quality in an optimization problem. Here, the fitness value is used for analyzing how optimal a scheduling solution is, and optimization intends to determine the solution that maximizes the fitness. Furthermore, the fitness function is framed based on priority, throughput, and fairness constraints. Besides, the expression of the fitness function is formulated as,

$$Fitness_{(\max)} = \frac{1}{3}\left[R_1 + R_2 + R_3\right] \tag{1}$$

Here, R_1 designates the priority, R_2 implies the throughput, and R_3 represents the fairness constraint.

a) Priority: The priority [11] is employed for determining the order in which the user waits for admission, and it is designated by the equation below.

$$R_1 = \frac{1}{E_w}\sum_{\sigma=1}^{E_w}\left(\frac{\beta - U_\sigma}{\beta}\right) \tag{2}$$

wherein, the number of users admitted to the antenna is designated as E_w, the overall number of users waiting for admission is specified as β, and the assignment number of the σ^{th} user is indicated as U_σ.

b) Throughput: The maximum throughput [11] represents the total amount of throughput of all available users at each time instance of scheduling, and it is modeled as,

$$R_2 = \sum_{\sigma=1}^{\beta} L_\sigma \tag{3}$$

Here, the throughput of the σ^{th} individual user is exemplified as L_σ. Here, the maximal throughput improves the system capacity and the user's order, which guarantees that the user rate is chosen as the finest solution.

c) Fairness constraint: Fairness is a crucial parameter that ensures that the user who experiences poor channel conditions gets fair service, while those with better conditions are served better. Further, the fairness constraint is expressed by,

$$R_3 = \sum_{\sigma=1}^{\beta}\log_2\left(\overline{L_\sigma}\right) \tag{4}$$

3.2.3 Proposed Chronological Fairy Wren Optimization Algorithm

ChFWOA, which is engineered by the amalgamation of the Chronological concept and SFOA [12], guides the optimization process, and it helps the algorithm converge more quickly to near-optimal or optimal scheduling solutions. SFOA [12] is regarded as a meta-heuristic optimization approach formulated based on swarm intelligence. This technique is developed for high-dimensionality feature selection classification, engineering design, and numerical optimization, and it draws inspiration from the superb fairy wren's behaviors. Moreover, the strategies of birds to evade predators, the birds' behavior to feed the young ones, and the birth of young birds in superb fairy-wren colonies are incorporated by this algorithm. In addition, the Chronological concept is exploited to improve the workflow, and it is utilized to maximize the analytical capabilities. This approach handles complex multi-user environments and is used to obtain high throughput. Henceforth, the combination of SFOA and the Chronological concept is used to attain better user scheduling. Moreover, the mathematical process of ChFWOA is given below.

(i) Initialization: The member of ChFWOA is regarded as a candidate solution to the issue, and it is mathematically exhibited using the vectors. Here, every vector's element is associated with a decision variable, while all the ChFWOA members produce the entire model as expressed in Equation (5). Moreover, the initialization is performed as designated in Expression (6).

$$T = \begin{bmatrix} T_1 \\ \vdots \\ T_\alpha \\ \vdots \\ T_h \end{bmatrix}_{h\times u} = \begin{bmatrix} Q_{1,1} & \cdots & Q_{1,V} & \cdots & Q_{1,u} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ Q_{\alpha,1} & \cdots & Q_{\alpha,V} & \cdots & Q_{\alpha,u} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ Q_{h,1} & \cdots & Q_{h,V} & \cdots & Q_{h,u} \end{bmatrix}_{h\times u} \tag{5}$$

$$T = (W - A)\times rand(0,1) + A \tag{6}$$

wherein, the number of global members is represented as h, the upper bound of V^{th} variable is typified as W, the α^{th} candidate solution is denoted as T_α, the problem dimension in the search space is stipulated as $Q_{\alpha,V}$, the global matrix is implied as T, the lower bound of V^{th} variable is characterized as A, and a random number among $(0,1)$ is embodied as F.

(ii) Fitness function: The expression of the fitness function is represented in Equation (1). Here, the solution with the maximum fitness value is considered the finest solution.

(iii) Young bird's growth phase: In this phase, the population member's location is modified based on dynamic simulations, which requires more experience for the growth of young birds. Since the population involves a huge number of young birds, which is unfavorable to population survival, the members' location in the problem-solving space is imitated via position updates and continuous learning during the rapid growth of young birds. Furthermore, every member's location is determined for obtaining optimal fitness, and it is modeled as,

$$Tnew_{\alpha,r} = T^{B}_{\alpha,r} + \left[A + (W - A) \times rand\right], \; F > 0.5 \tag{7}$$

Here, α^{th} the location of the superb fairy-wren in r^{th} dimensionality after B iteration is exemplified as $T_{\alpha,r}$, a random number among $(0,1)$ is indicated as $rand$ the location after population renewal is symbolized as $Tnew_{\alpha,r}$.

(iv) Breeding and feeding stage: The superb fairy-wren's teaching mechanism during its breeding and feeding process is simulated for updating the population member's location. Moreover, the wren enters the breeding phase when there is a low-risk threshold, and thus it utilizes unique paternity testing during egg incubation to avoid attack by other species. Here, the danger threshold γ is computed as,

$$\gamma = F_1 * 20 + F_2 * 20 \tag{8}$$

Here, random numbers with a normal distribution are epitomized as F_1 and F_2.

Several birds incubate eggs throughout the year to realize identification because of the cooperative breeding behavior. During this cycle μ, the birds take turns teaching and feeding, even though it is not motionless; thus, the local search is increased. Further, a factor J is considered that increases with the decrease in the teaching cycle, which expands every member's activity range. Moreover, the change in location of every member is computed using the following expression,

$$Tnew_{\alpha,r} = T_{\varpi} + \left(T_l T^{B}_{\alpha,r}\right) \times J, \; F < 0.5 \text{ and } \gamma < 20 \tag{9}$$

$$T_{\varpi} = T_l \times \xi \tag{10}$$

where a constant with a value of 0.8 is indicated as ξ the present optimum location is designated as T_l.

$$J = \sin\left[(W - A) \times 2 + (W - A) \times H\right] \tag{11}$$

$$H = \left[\frac{\lambda}{\max \lambda}\right] \times 2 \tag{12}$$

Here, a maximum number of evaluations is typified as $\max \lambda$, and the present number of evaluations is symbolized as λ.

(v) Avoiding natural enemies' stage: In this phase, the population member's location is modified based on the superb fairy-wren's defense mechanism against the attack of the predator. When the predator spots the superb fairy-wren, it escapes rapidly with a slight location change. Moreover, the other members hover to avoid, which results in a large location change. Further, the two expressive forces improve the search range and the local search capability. Here, the modes of motion are represented by,

$$T_{\alpha}(B+1) = T_l + T_{\alpha}(B) \times Y \times S, \; F < 0.5 \text{ and } \gamma > 20 \tag{13}$$

Here, the Levy flight random step size is signified as Y the adaptive flight balance factor is specified as S, which is written as,

$$S = 0.2 \times \sin\left[\frac{\pi}{2} - g\right] \tag{14}$$

$$g = \frac{\pi}{2} \times \frac{\lambda}{\max \lambda} \tag{15}$$

wherein, the call frequency value is represented as g. In addition to this, SFOA [12] is incorporated with a Chronological concept for attaining better solutions by maximizing the convergence toward optimum results. From the Chronological concept,

$$T_{\alpha}(B+1) = \frac{T_{\alpha}(B+1) + T_{\alpha}(B+1)}{2} \tag{16}$$

Moreover, at iteration B, Equation (13) becomes,

$$T_{\alpha}(B) = T_l + T_{\alpha}(B-1) \times Y \times S \tag{17}$$

By substituting Equation (17) in (13), we get

$$T_{\alpha}(B+1) = T_l + \left[T_l + T_{\alpha}(B-1) \times Y \times S\right] \times Y \times S \tag{18}$$

$$T_{\alpha}(B+1) = T_l + T_l \times Y \times S + T_{\alpha}(B-1) \times Y^2 \times S^2 \tag{19}$$

$$T_{\alpha}(B+1) = T_l\left[1 + Y \times S\right] + T_{\alpha}(B-1) \times Y^2 \times S^2 \tag{20}$$

By substituting Equations (20) and (13) in Equation (16), we get

$$T_\alpha(B+1) = \frac{\left[T_l + T_\alpha(B) \times Y \times S\right] + \left[T_l(1 + Y \times S) + T_\alpha(B-1) \times Y^2 \times S^2\right]}{2} \tag{21}$$

The updated expression of the ChFWOA technique is represented by the equation below.

$$T_\alpha(B+1) = \frac{1}{2}\left[T_l(2 + Y \times S) + T_\alpha(B) \times Y \times S + T_\alpha(B-1) \times Y^2 \times S^2\right] \tag{22}$$

(vi) Re-evaluation: Once the Superb Fairy-wren's position is updated, the fitness is estimated, and the solution with the maximum value is regarded as the finest solution.
(vii) Termination: The aforementioned procedures are performed repeatedly until the maximum number of iterations is accomplished.

3.3 Receiver Side

In MIMO-OFDM, the receiver side is responsible for processing the transmitted signals that are received over several antennas and across multiple subcarriers. In addition to this, the detailed explanation of on the receiver side is explicated as follows.

3.3.1 Received Signal

The received signal is a superposition of several spatially transmitted signals, as the signals are transmitted over various subcarriers, which are affected by noise, wireless channels, and so on. Furthermore, the received signal can be recovered by effective channel estimation.

3.3.2 Channel Estimation

Channel estimation is considered a vital process in MIMO-OFDM networks, which allows the receiver to know how the transmitted signals are affected by the wireless channel. Moreover, precise channel estimation permits the receiver to handle channel impairments, like delays and throughput, which are vital for decoding, demodulation, and so on. Here, the channel is estimated by employing DCNN [13] by taking the received signal M as an input.

a) Architecture of DCNN

DCNN [13] is a DL architecture, and it is more efficient in detecting the temporal or spatial patterns in the network. In channel estimation, this approach is tuned for learning the mapping of the received signals to a channel matrix. The local patterns are captured effectively via several Convolutional (Conv) layers. Moreover, the estimation error can also be lessened as the network is tuned on the labeled data, considering the known channel matrix. The DCNN model includes multiple layers, namely fully connected, pooling, batch normalization, non-linearity, and a Conv layer. Besides, the description of these layers is elucidated below.
(i) Conv layer: This layer is exploited for mining the significant features from the received signal. The initial Conv layer is used for mining the low-level features, whereas the other Conv layers are utilized for extracting the complex features. Here, the Conv layer is computed by,

$$\hat{N}_t = \sum_k N_k \otimes \eta_{k,t} + \rho_t \tag{23}$$

Here, the Conv kernel is specified as $\eta_{k,t}$, the bias is implied as ρ_t, the t^{th} output feature map is indicated as $\hat{N}_t$, the 2-D convolution operation is exemplified as $\otimes$, and the k^{th} input feature map is epitomized as N_k.
(ii) Non-linearity layer: This layer is utilized for enhancing the CNN's fitting capability, and it is attained by exploiting many activation functions, including Rectified Linear Unit (ReLU), Sigmoid, Leaky ReLU, and so on. Here, the ReLU is employed mostly as it is simple and easy to use, which is also expressed as,

$$\mathrm{Re}LU(M) = \begin{cases} M, & if\ M > 0 \\ 0, & otherwise \end{cases} \tag{24}$$

(iii) Batch normalization: To attain the finest optimum outcomes, this layer is employed after every Conv layer. The batch normalization is also used for speeding up the convergence and tuning the data.
(iv) Pooling layer: The downsampling manner is adopted by the pooling layer for compressing the signal by reducing the parameters. This layer makes the network computationally effective, more robust, and helps to avoid overfitting problems.
(v) Full connected layer: It is regarded as the final layer, and it is used for flattening the preceding layer's output. The output attained in the DCNN model is signified as Z, which is the estimated channel. Fig. 3 displays the DCNN structure.

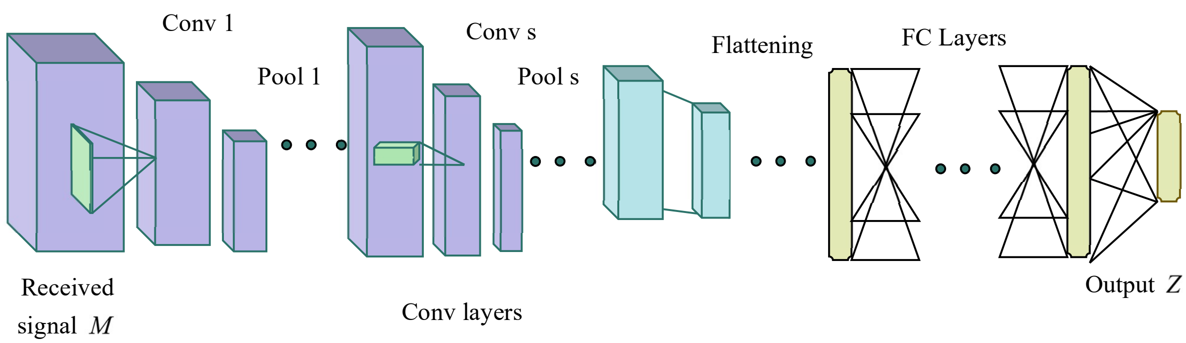


Fig. 3. *DCNN architecture*

3.3.3 OFDM Demodulator

In modern wireless communication systems, an OFDM demodulator is a key component that is responsible for recovering the original transmitted data from the received signal. This process is performed by reversing the modulation steps that are applied at the transmitter for converting the time-domain received signal into frequency-domain symbols per subcarrier.

3.3.4 QAM Demodulator

The QAM demodulator is utilized in digital communication networks for recovering the data from a signal that is modulated using QAM. Here, the QAM signal is received by this demodulator, and then the original digital data is mined by evaluating the phase and amplitude of the carrier.

3.3.5 STBC Decoder

The transmitted data from a space-time encoded signal is recovered by the STBC decoder by exploiting the temporal and spatial diversity that is presented by transmitting the data across various antennas and time slots, which improves reliability.

4. Results and Discussion

The experimental outcomes of ChFWOA+DCNN employed for channel estimation with user scheduling are correlated with numerous prevailing techniques regarding Rician and Rayleigh channels, as exemplified in this section.

4.1 Experimental Setup

The implementation of the ChFWOA+DCNN technique for channel estimation with user scheduling is done in a Python tool with a simulation network.

4.2 Evaluation Metrics

The performance metrics, including SER, throughput, and BER exploited for examining the efficiency of the ChFWOA+DCNN model. Furthermore, the explanation of the above-mentioned metrics is given below.
a) BER: In digital communication systems, the BER is a major performance metric that is used for measuring the rate at which errors occur in the transmitted data.
b) SER: This metric is employed for measuring the rate at which the symbols are received incorrectly. Moreover, it is the same as the BER metric, but it differs in measuring the errors at the symbol level instead of the bit level.
c) Throughput: Throughput refers to the rate at which the data is effectively processed or transmitted over a network in a specified period.

4.3 Comparative Methods

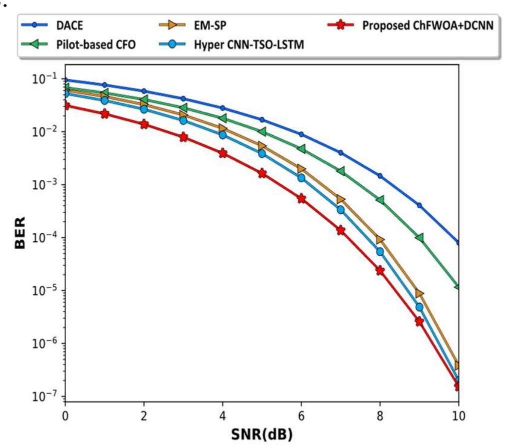
Several traditional approaches, including DACE [1], Pilot-based CFO [2], EM-SP [3], and Hyper CNN-TSO-LSTM [4], are contrasted with the newly formulated ChFWOA+DCNN technique for estimating the effectiveness during channel estimation with user scheduling.

4.4 Comparative Analysis

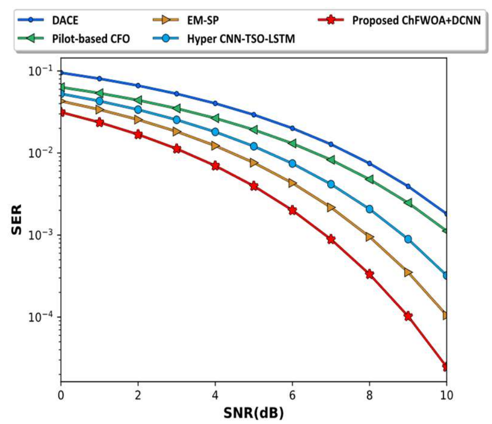
The newly presented ChFWOA+DCNN model used for channel estimation with user scheduling is correlated with existing models based on two channels, like Rayleigh and Rician. Furthermore, the investigation of ChFWOA+DCNN concerning various measures, namely BER, throughout, and SER, is demonstrated here.

4.4.1 Rayleigh Channel

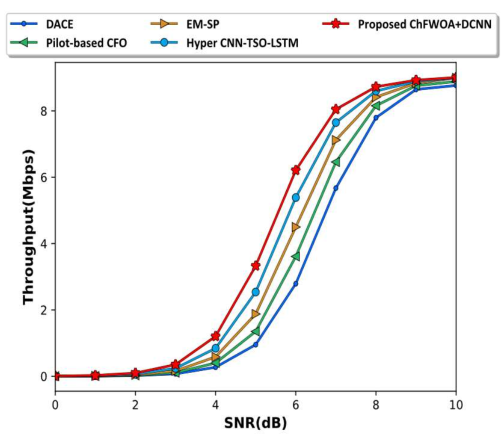
Fig. 4 displays the valuation of ChFWOA+DCNN concerning the Rayleigh channel, concerning several measures. In Fig. 4(a), the BER-based examination of ChFWOA+DCNN is illustrated. For Signal-to-Noise Ratio (SNR) 10 dB, the BER calculated by ChFWOA+DCNN is 1.54×10^{-7}, while the other traditional methods, like DACE, Pilot-based CFO, EM-SP, and Hyper CNN-TSO-LSTM, measured the BER of 8.00×10^{-5}, 1.16×10^{-5}, 3.83×10^{-7}, and 2.00×10^{-7}. The examination of ChFWOA+DCNN regarding SER is specified in Fig. 4(b). When assuming SNR 9 dB, the SER recorded by DACE, Pilot-based CFO, EM-SP, Hyper CNN-TSO-LSTM, and ChFWOA+DCNN is 0.039, 0.0025, 0.0004, and 0.0001. Fig. 4(c) represents the plot drawn between throughput and SNR. Here, the throughput calculated by prevailing methods, namely DACE, Pilot-based CFO, EM-SP, and Hyper CNN-TSO-LSTM for SNR 8 dB is 7.795 Mbps, 8.155 Mbps, 8.415 Mbps, and 8.599 Mbps, while the ChFWOA+DCNN technique figures a throughput of 8.728 Mbps.



(a)



(b)



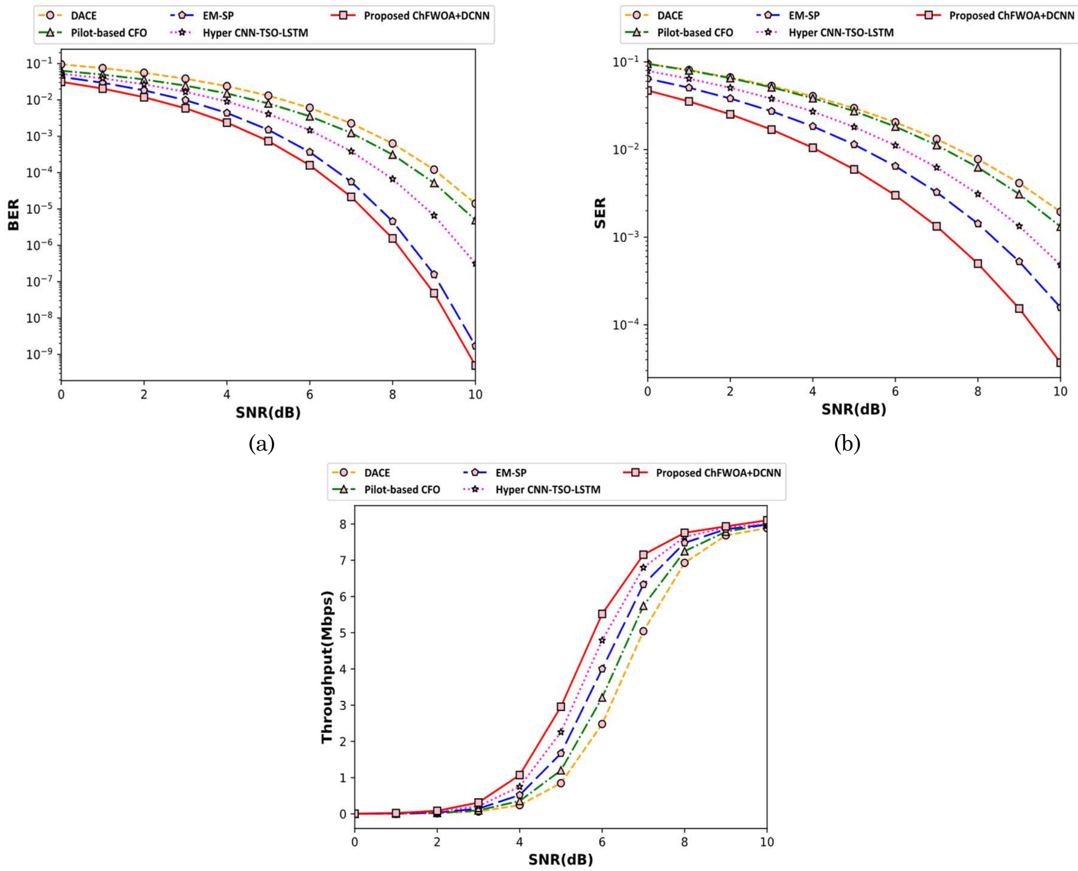
(c)

Fig. 4. *Examination of ChFWOA+DCNN regarding Rayleigh channel (a) BER, (b) SER, and (c) Throughput*

4.4.2 Rician Channel

The valuation of ChFWOA+DCNN concerning the Rician channel, concerning several measures, is shown in Fig. 5. Fig. 5(a) represents the plot drawn between BER and SNR. Here, the BER calculated by prevailing methods, namely DACE, Pilot-based CFO, EM-SP, and Hyper CNN-TSO-LSTM for SNR 8 dB is 1.40×10^{-5}, 4.95×10^{-6}, 1.71×10^{-9}, and 3.15×10^{-7}, while the ChFWOA+DCNN technique figured the BER of 4.93×10^{-10}. The examination of ChFWOA+DCNN regarding SER is specified in Fig. 5(b). When assuming SNR 9 dB, the SER recorded by DACE, Pilot-based CFO, EM-SP, Hyper CNN-TSO-LSTM, and ChFWOA+DCNN are 0.0041, 0.0031, 0.00053, 0.0014, and 0.00015. In Fig. 5(c), the throughput-based examination of ChFWOA+DCNN is illustrated. For SNR 10 dB, the throughput attained by

ChFWOA+DCNN is 8.102 Mbps, while the other traditional methods, like DACE, Pilot-based CFO, EM-SP, and Hyper CNN-TSO-LSTM, measured the throughput of 7.887 Mbps, 7.988 Mbps, 7.987 Mbps, and 8.009 Mbps.



(a) (b)

(c)

Fig. 5. *Examination of ChFWOA+DCNN regarding Rician channel (a) BER, (b) SER, and (c) Throughput*

4.5 Comparative Discussion

The comparative discussion of ChFWOA+DCNN with other prevailing approaches based on Rayleigh and Rician channels is signified in Table 1. Considering the Rayleigh channel, the ChFWOA+DCNN technique calculated a maximum throughput of 9.009 Mbps, and minimum BER and SER of $1.54\text{x}10^{-7}$ and $2.47\text{x}10^{-5}$. Furthermore, the BER value recorded by conventional models, including DACE, Pilot-based CFO, EM-SP, and Hyper CNN-TSO-LSTM, is $8.00\text{x}10^{-5}$, $1.16\text{x}10^{-5}$, $3.83\text{x}10^{-7}$, and $2.00\text{x}10^{-7}$, and these existing methods quantified a SER of 0.00181, 0.00112, 0.00011, and 0.000322. In addition, the throughput measured by DACE is 8.768 Mbps, Pilot-based CFO is 8.888 Mbps, EM-SP is 8.999 Mbps, and Hyper CNN-TSO-LSTM is 8.998 Mbps. It can be observed that the newly devised ChFWOA+DCNN attained superior outcomes than other traditional models. Here, the ChFWOA, which is formulated by integrating the Chronological concept and SFOA, converged faster with high scalability and handled dynamic user environments with high throughput. Furthermore, the DCNN estimated the channel more accurately, which leads to better symbol demodulation, directly lessening the amount of bit-level error.

Table 1. *Comparative discussion of ChFWOA+DCNN for channel estimation with user scheduling*

Metrics	DACE	Pilot-based CFO	EM-SP	Hyper CNN-TSO-LSTM	Proposed ChFWOA+ DCNN
Rayleigh channel					
BER	$8.00\text{x}10^{-5}$	$1.16\text{x}10^{-5}$	$3.83\text{x}10^{-7}$	$2.00\text{x}10^{-7}$	$\mathbf{1.54x10^{-7}}$
SER	0.00181	0.00112	0.00011	0.000322	$\mathbf{2.47x10^{-5}}$
Throughput (Mbps)	8.768	8.888	8.999	8.998	**9.009**
Rician channel					
BER	$8.00\text{x}10^{-5}$	$1.16\text{x}10^{-5}$	$3.83\text{x}10^{-7}$	$2.00\text{x}10^{-7}$	$1.54\text{x}10^{-7}$
SER	0.00195	0.00132	0.00016	0.000483	$3.70\text{x}10^{-5}$
Throughput (Mbps)	7.887	7.988	7.987	8.0089	8.1025

5. Conclusion

In modern wireless communication, user scheduling and channel estimation are considered vital to maximize the system performance. However, conventional DL approaches failed to consider the trade-off between the SER and BER. Henceforth, the ChFWOA+DCNN is presented for channel estimation and user scheduling in MIMO-OFDM networks. Here, the input data is encoded using STBC, and then it is modulated employing QAM. Next, it is split into multiple sub-carrier frequencies using OFDM. After that, the precoding is applied to optimize the signal transmission based on the channel conditions. After that, the user scheduling is performed employing ChFWOA, which is engineered by the incorporation of the Chronological concept and SFOA. At the receiver side, the channel is estimated using DCNN, and then the received signal is subjected to OFDM demodulation. Later, QAM demodulation is effected for recovering the original transmitted signals. Finally, the original data is recovered by the STBC decoder. Moreover, the ChFWOA+DCNN attained a maximum throughput of 9.009 Mbps, and minimum BER and SER of $1.54x10^{-7}$ and $2.47x10^{-5}$. Future works aim to develop end-to-end trainable approaches for optimizing both user scheduling and channel estimation as unified frameworks.

Compliance With Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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