A Novel Intelligent Channel Estimation Strategy for the 5G Wireless Communication Systems

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Research Article

Keywords: MIMO-OFDM, Channel Estimation, Channel Parameters, Chimp Optimization, Cat Boost Algorithm

Posted Date: June 14th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1647965/v1

A Novel Intelligent Channel Estimation Strategy for the 5G Wireless Communication Systems

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AbstractNowadays, the Multiple Input Multiple Output (MIMO) Orthogonal Frequency Division Multiplexing (OFDM) is an important method used in wireless communications, especially in 5G cellular communications. As in a wireless network, the input signals pass through a channel, and the input signal undergoes phase shift, attenuation, and interference. So, the password from the user side and the received signals are not the same. Thus, an effective channel estimator is essential to make cellular communication better. Hence, a novel hybrid technique called Chimp-based CatBoost channel estimation (CbCBCE) was proposed. This technique is the combination of the Chimp optimization algorithm and CatBoost algorithm. The channel parameters are estimated and then reduced using the Chimp optimization algorithm. Finally, the proposed model is validated with the case study. Then, the result of the proposed model was estimated, and it was compared with other existing techniques. It is observed that the outcome of the proposed design is more compared with the other conventional methods. The presented model is executed in the MATLAB platform, and it is proved that the proposed model has high throughput, high energy efficiency, less BER, and a high data transfer rate.

Keywords MIMO-OFDM · Channel Estimation · Channel Parameters · Chimp Optimization · Cat Boost Algorithm

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1 Introduction

Wireless communication mediums are very susceptible to multipath channels and have a time-varying character by their very design [1]. This causes unwanted transmission power degradation due to frequency-selective fade and inter-symbol interference that affects the signals traveling through them [2]. Compared to **Orthogonal Frequency-Division Multiplexing (**OFDM) antenna, arrays that divide wide band elevated signals into sub-channels [3]. Moreover, the MIMO antenna systems significantly improve the reliability and diversity characters of the wireless link [4]. Using OFDM-MIMO in a radio receiver can dramatically reduce the impacts of inter-symbol interference and frequency-selective fading to measurable levels [5]. In addition, the MIMO-OFDM systems can deliver high data speeds, short latency times, and less bit-error range while maintaining low power consumption [6]. If the transmitter-receiver connection is fixed, the channel parameters have only a minor impact on the transmission signal [7]. Nevertheless, when there is a change in velocity between the transmitter-receiver, the effects of channel conditions become more evident, necessitating more analysis [8].

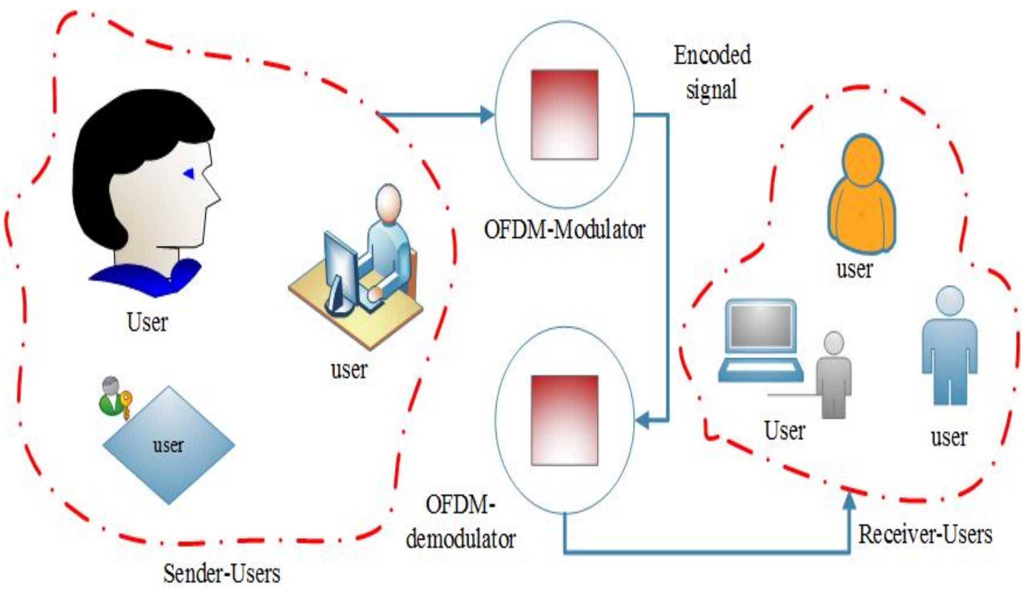

Fig. 1MIMO_OFDM

Compared to the older wired network communication methods, wireless technology has quickly gained popularity [9]. The expansion in mobile phone usage and other personal communication gadgets for data and voice transmission worldwide has added to the strain on the wireless broadband communication infrastructure [10]. These systems have become the subject of more intensive investigation both in academic and industrial sectors as a result of this high bandwidth rate [11], less BER, and low delay [12], which are accomplished by wireless applications for data and voice given the enormous volume of traffic in the wireless communication medium for data communication [13]. Furthermore, the Radio systems [14]are mainly regulated by the characteristics of the wireless medium and the surrounding environment [15]. While the wired channel is usually predictable and static, the wireless channel is unpredictable and high dynamic making [16]. So, analyzing the signal range is more complex [17]. The MIMO OFDM architecture is detailed in fig.1.

Hence estimating the channel to allocate the required resource is more critical to making the most acceptable wireless communication framework. Several channel estimation models, such as sparsity matching [18], linear compression model [19], etc., were implemented in the past, But the relevant, appropriate estimation results are not found. So the present research has aimed to design a novel optimized neural approach to end the channel estimation issues. The presented research concept is controlled as follows: section 2 describes related works, section 3 demonstrates a system model with a problem, section 4 explains the proposed model, section 5 illustrates the result of the presented method, and the research arguments end in a conclusion section 6.

2 Related Work

Few recent associated works have described below

A hybrid compressive sampling and sparsity matching has been implemented by Albataineh et al. [18], for the 5G communication system to achieve channel estimation outcomes. Here, the MIMO systems have spread sparsely based on spatial correlations. This pattern helped gain better channel estimation results by enabling all possible nearest channels for the conned users in the MIMO-OFDM. However, it has consumed more energy.

Ge et al. [19] have described a compression-based linear system for the 5G channel estimation model. The suggested approach generates channel autocorrelation matrices by examining the channel's prior information using compressive-sensing theory and taking advantage of the sparsity block of the massive MIMO medium to minimize the number of autocorrelation matrix occurrences. Then, to further reduce computation cost, it replaces matrix inverse operations with singular-value decomposition.

Poor channel estimation in cellular communication might degrade the channel performance. So, Kansal et al. [20] described a novel discrete wavelet with Fourier expression to estimate the possible channel at a high possible rate. Finally, the designed system has gained a better spectra efficiency score. Also, it has minimized the BER and energy consumption. But it has recorded high computational complexity because of design complexity.

Beam-forming model has been described for the channel estimation and allocation process in the multi-user environment by Chen-Hu et al. [21]. The multi-user environment's conventional channel estimation and resource allocation have taken more time and need high resources to complete the process. So, the present beam-forming method has intended to estimate and allocate the channels for the multi-users in a straightforward way. Finally, the signal noise and complexity score have been measured.

Bai et al. [22] have presented Deep Echo to detect the available receivers before sending the resource sharing process. The key motive of this receiver availability estimation is to mitigate energy consumption and resource wastage. In addition, awareness of the receiver status is more critical for the wireless application. Finally, it has predicted receiver status with a good exactness score. But, it has required more time for the receiver status estimation process.

- Initially, the MIMO-OFDM channel is created with the required number of nodes, and the high data rate has been fixed.

- Then a novel CbCBCE was designed with the channel estimation parameters.
- Consequently, the data sharing process was started, and the communication parameters were calculated.
- The channel estimation performance has been measured with and without chimp fitness.
- Finally, the robustness score of the designed channel estimation model is validated in terms of throughput, BER, delay, data transfer rate, SNR, and energy consumption.

3 System Model with Problem

Estimation of the channel in the wireless medium is the most required task for uninterrupted communication. Hence, the channel estimation system has been introduced. The track has been estimated based on neural approaches or other statistical models. But in many cases, the appropriate outcome hasn't been obtained because of the node's movable nature. Also, predicting the channel for the multi-user dynamic system is very challenging because of the different communication pathways in the dynamic range. In addition, while allocating the track to the user, the receiver user has disabled, which tends to attain high energy consumption and resource wastage. These issues have attracted researchers to implement an efficient channel estimation scheme for the wireless communication framework.

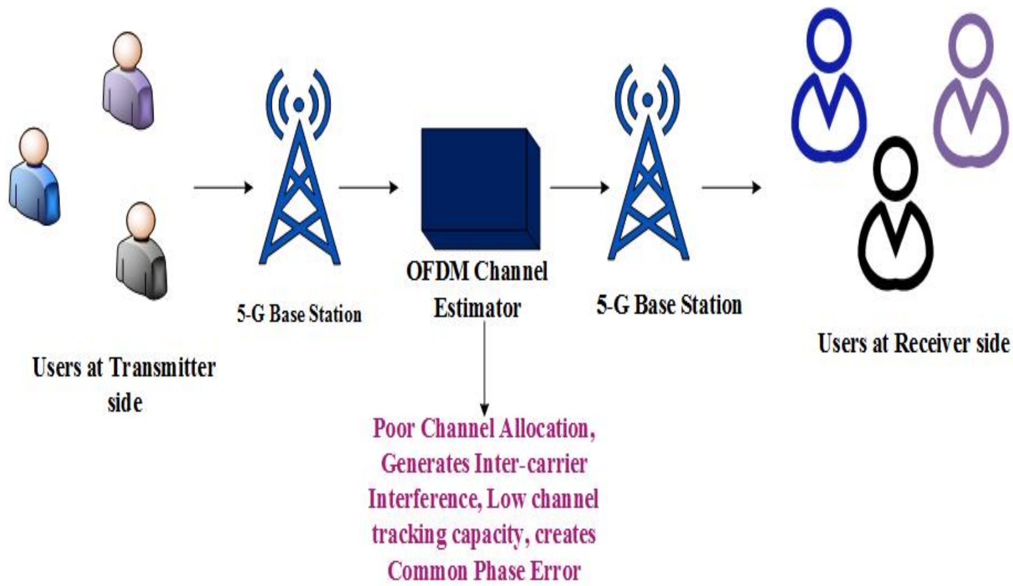

Fig. 2 Problems with the OFDM channel estimation

Hence, an efficient channel estimation system should be implemented for uninterrupted communication. Fig. 2 shows the problems with the OFDM channel estimation. The major problem with OFDM channel estimation is the arrangement of the pilot data, where pilot data refers to the reference signal used by the sender and the receiver. This makes the channel tracking capacity low and makes the design challenge. Also, the OFDM design is susceptible to laser phase noise, which reduces the system's performance as it creates inter-carrier interference and Common Phase Error (CPE).

4 Proposed CbCBCE for Channel Estimation

A novel Chimp-based CatBoost channel estimation (CbCBCE) model has been introduced to enrich the 5G communication system. Here, the proposed channel estimation modules are executed in the MIMO-OFDM channel. Then the outcome of the system is calculated by initiating the data broadcasting process. Finally, the communication metrics have been calculated and compared with an existing model to value the improvement rate in the channel estimation process. The proposed architecture is detailed in fig. 3.

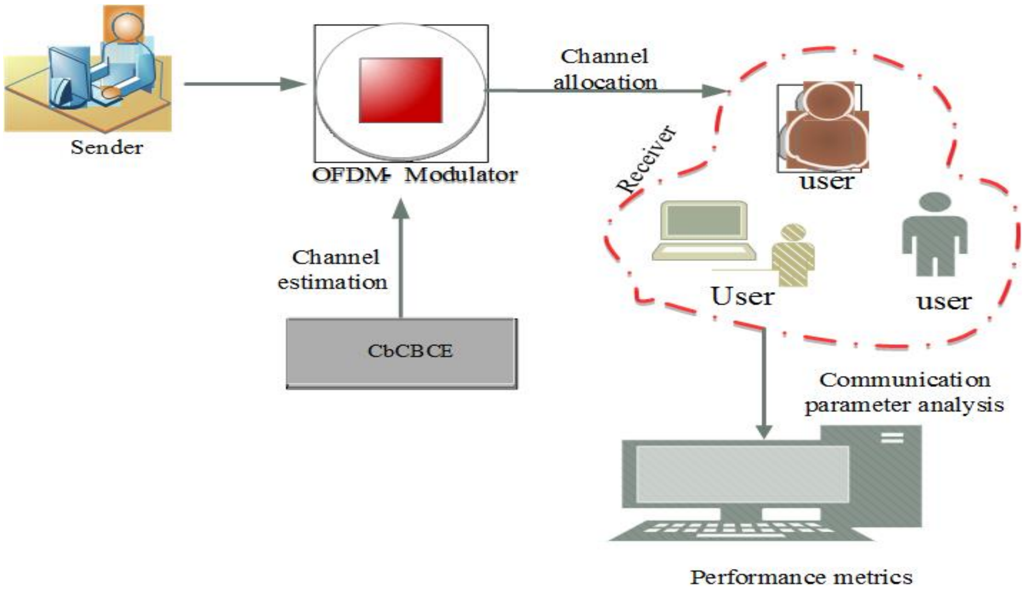

Fig. 3 Proposed CbCBCE architecture

Here, the input signal (from the central station) is transmitted to the OFDM modulator. The proposed technique is executed in an OFDM modulator. The channel and noise parameters are estimated and determined by the OFDM modulator. Then the communication parameters are analyzed, and the performance metrics are calculated.

4.1 Design of CbCBCE

In a cellular communication system, the transmitted signal passes through a medium called channel. When the signal goes through a medium, it gets distorted or attenuated, and also it undergoes phase shift, and some noise will be added. Therefore, the transmitted and received signal will not be exact. To correctly decode the received signals without errors, the noise and distortion provided by the channel must be removed. Initially, the characteristics of the track should be found to remove distortion and noise provided by the channel. The process of finding the parts of the channel is called channel estimation. Hence, channel estimation plays an essential role in uninterrupted communication in a cellular system.

A novel intelligent channel estimation technique was proposed, named the Chimp-based CatBoost Channel Estimation (CbCBCE) algorithm. It is the combination of the Chimp optimization algorithm and the CatBoost algorithm. CatBoost is a gradient boosting technique on decision trees, and also it has categorical features. This algorithm helps in determining the channel matrix from the received signal. The Chimp optimizer optimizes the estimated motion. The different layer of CbCBCE is shown in fig. 4. In addition to this, the proposed model has different phases: node generation, classification phase, training phase, and input and output phase.

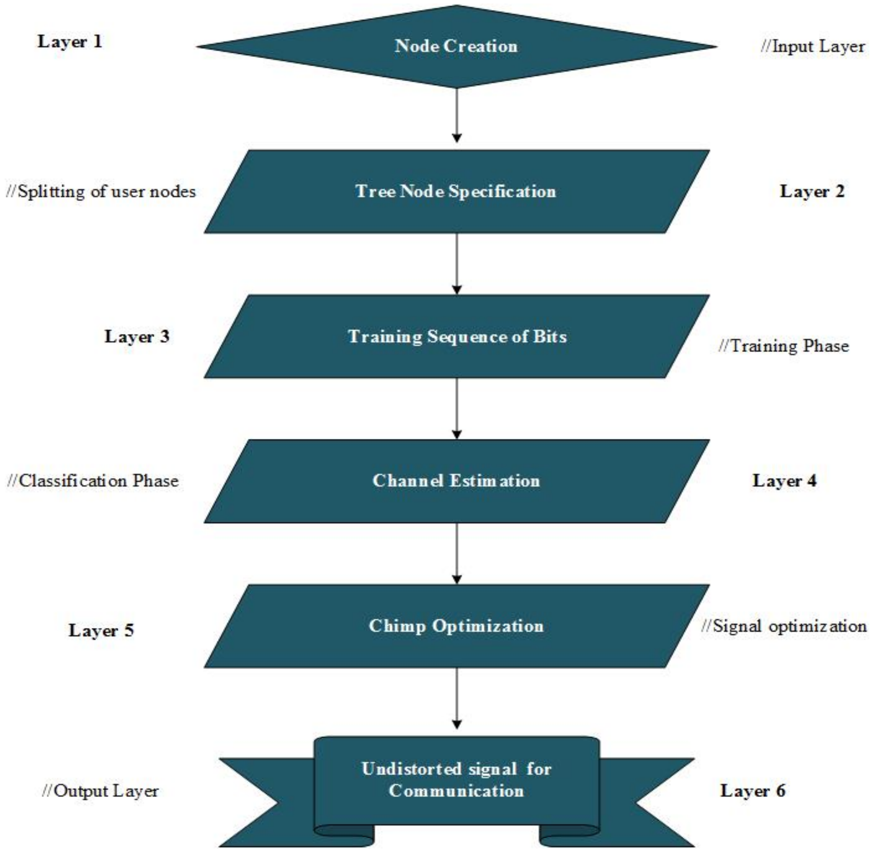

Fig. 4 Layers of CbCBCE

4.1.1 Tree Node Specification

Generally, in the channel estimation process, to determine the characteristics of the channel, a correlative mathematical model will be set up which relates the transmitted and received signal through a channel matrix. In CbCBCE, a known signal (reference signal) is generated. This is called node generation. Here, the transmitted reference signal $x(t)$ is considered as node. The transmitted reference signal $x(t)$ features will be split in the form of a balanced tree; this is called tree node specification.

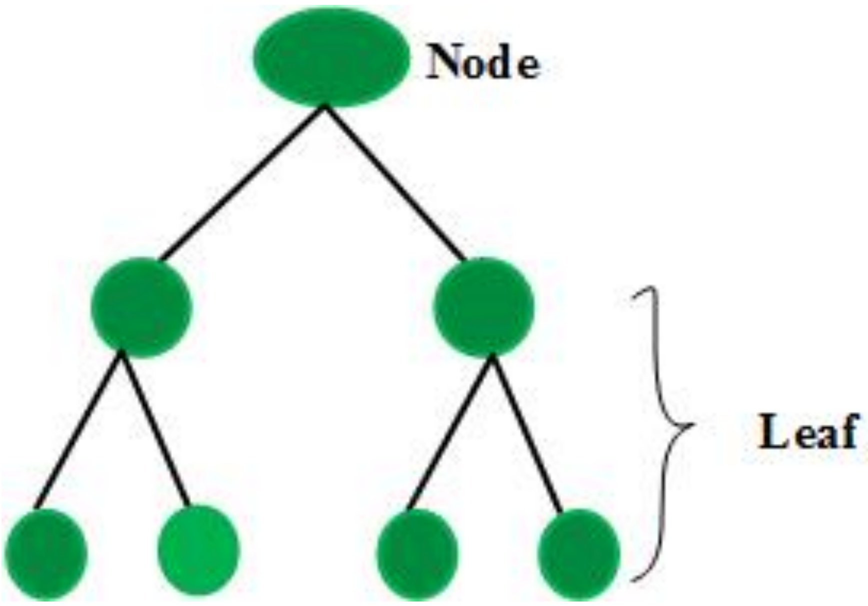

Fig. 5 Structure of Tree Node Specification

The splitting of features of the transmitted signal continues till it reaches its threshold. The splitting stops after reaching the threshold value and the output is the sum of the leaf responses.

4.1.2 Estimation of Channel Coefficient

Generally, in order to determine the channel coefficient, the transmitted reference signal and received reference signal are considered as $x(t)$ and $y(t)$. The received reference signal is given by Eqn. (1),

$$y(t) = [h(t) \times x(t)] + n(t) \tag{1}$$

Where, $h(t)$ is the channel coefficient and $n(t)$ denotes the noise added in the transmitted signal. In CbCBCE, the estimation of channel coefficient is expressed in Eqn. (2),

$$\sum_{i=1}^{m-1} h_i(t) = \frac{y(t) - \sum_{i=1}^{m-1} n_i(t)}{\sum_{i=1}^{m-1} x_i(t)} \tag{2}$$

4.1.3 Estimation of Noise Parameters

With this channel coefficient, the noise parameters can be determined by using Eqn. (3),

$$\sum_{i=1}^{m-1} n_i(t) = \frac{\left[\sum_{i=1}^{m-1} h_i(t) \times \sum_{i=1}^{m-1} x_i(t)\right]}{y(t)} \tag{3}$$

The transmitted reference signal and the received reference signal values are already known. The channel coefficient can be calculated in accordance with the equation (4). By knowing all these values, the noise parameter can be calculated.

4.1.4 Chimp Optimization

The chimp Optimization algorithm is based on the hunting behavior of chimpanzees. This optimization is mainly used to reduce the transmitted signal's estimated channel parameters and noise parameters to make the received signal distortion less or error-free. The output of this algorithm provides an undistorted indication (same as the transmitted signal) to the user at the receiver end. Here the estimated channel parameters are tracked and removed from the input signal. The tracing equation to remove the channel and noise parameter can be expressed as in Eqn. (4),

$$T_{n,c} = \left| v.\, S_{n,c}(t) - r.C(t) \right| \tag{4}$$

Where, *v, r* indicates the vectors, $S_{n,c}(t)$ indicates the vector of position of channel and noise parameter, *t* refers to the number of iteration.

The mathematical equations for channel estimation are modeled in the pseudo-code format shown in algorithm 1.Also, the program code and the flowchart for this algorithm were developed and executed. Fig. 6 shows the flowchart of the CbCBCE algorithm.

Algorithm 1 CbCBCE

start

{

MIMO-OFDM channel *// design of OFDM communication channel*

$\text{int } N_t, = 1,2,3,4,5,6.......n$

//initializing the number of users

Node Generation()

{

$Input \quad signal = x_i(t)$

// Generating the transmitted reference signal as node

$x_i(t) = x_1(t) + x_2(t) + ... + x_{m-1}(t)$

// Splitting the node (transmitted reference signal) into leaf

}

Estimation of channel coefficient()

{

$$\sum_{i=1}^{m-1} h_i(t) = \frac{y(t)}{\sum_{i=1}^{m-1} x_i(t)}$$

// Assume the noise parameters as zero

}

Estimation of noise ()

{

$$n(t) = \frac{y(t)}{[h(t) \times x(t)]}$$

// Noise parameters are estimated with the known values of channel coefficient, transmitted and received reference signals

}

Optimization()

{

$T_{n,c} = \left| S_{n,c}(t) - C(t) \right|$

//Signal optimization (reducing the channel coefficient and noise parameters)

}

}

end

Once the channel coefficient and the noise parameters are estimated in a communication system, the signal is sent to the chimp optimizer. The chimp optimizer traces and reduces the channel and noise parameters and provides a less distorted signal as output. Therefore, the optimizer provides the motion, which makes the communication uninterrupted.

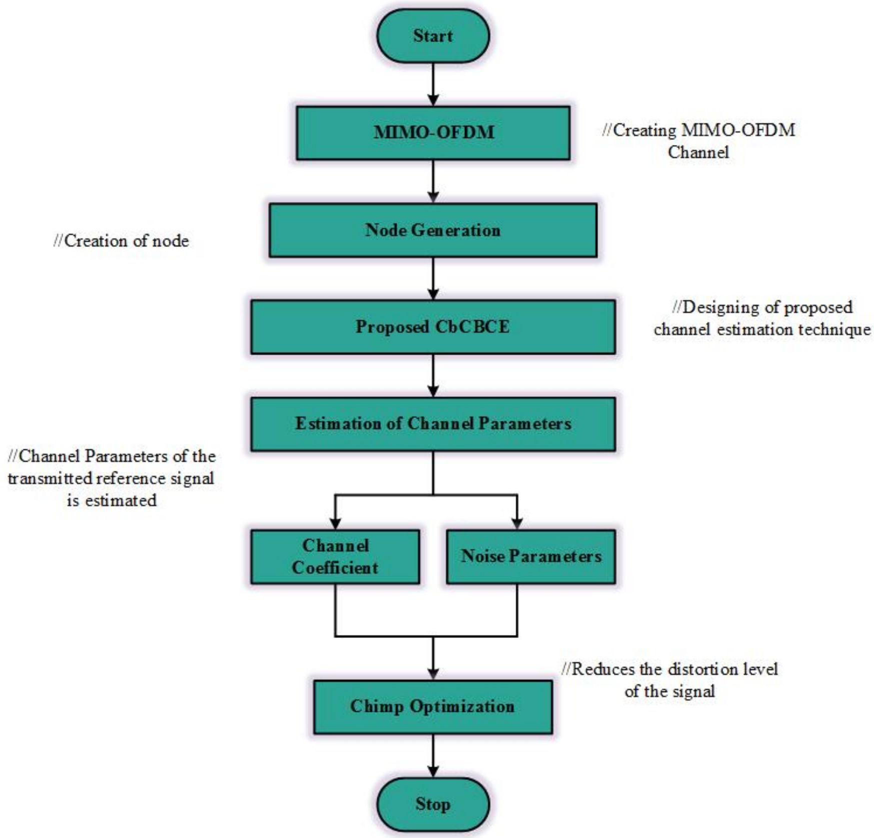

Fig. 6 Flowchart of CbCBCE

5 Result and Discussion

The proposed model has been designed in a MATLAB environment and running on the Windows 10 platform. Initially, the MIMO-OFDM channel was created with n number of nodes. Consequently, novel CbCBCE procedures are executed in the MIMO-OFDM medium. Then the outcome of the system is calculated by initiating the data broadcasting process. Finally, the communication metrics of the presented model were calculated and compared with the other methods.

5.1 Case Study

In this case study, the transmitted reference signal is considered the input signal to estimate the channel and noise parameters. The channel parameters can be easily calculated as the shared known signal parameters. When the known signal is transmitted through a medium (channel), the signal usually undergoes a phase shift and gets attenuated. Also, some noise parameters will get added to the signal. Therefore, the received signal on the receiver side will not be the same as we send on the transmitter side. The channel parameters and the noise must be reduced from the signal to make communication uninterrupted. To make the transmitted signal distortion less, the channel parameters (the characteristics of the channel) must be estimated. Hence, a novel intelligent channel estimation technique was proposed. In this proposed method, the input signal is considered as $x_i(t)$, which is considered as the node. Then, the input signal gets split into leaf nodes in the form of a balanced tree structure. In this process, the channel coefficient $h_i(t)$ and the noise parameters $n_i(t)$ are estimated from the transmitted signal. By then, using the chimp optimization algorithm, the estimated channel parameters are reduced from the signal. Hence, the received signal at the receiver side will be distortionless and noiseless. Fig. 7 displays the execution of CbCBCE.

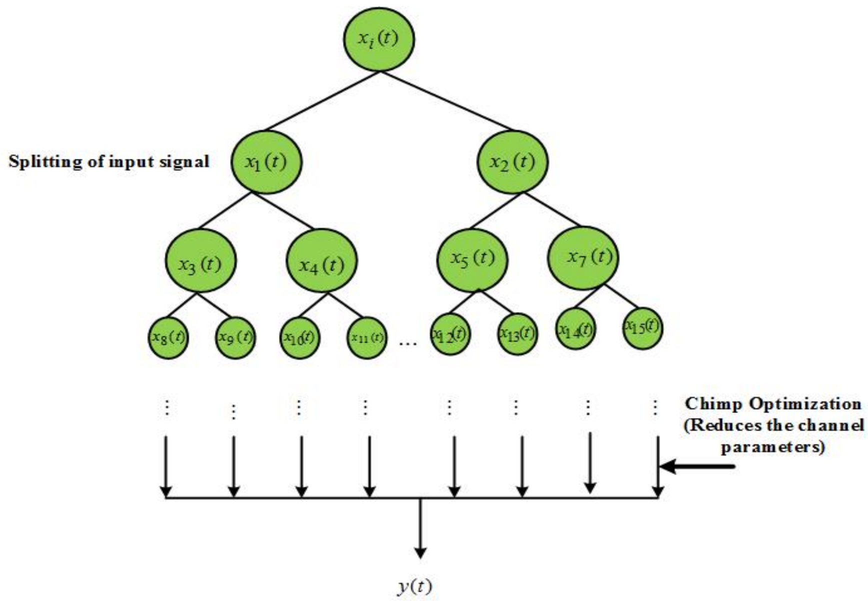

Fig. 7 Execution of CbCBCE

In case of numerical example, if the input signal $x_i(t)$ is taken as 16. When it is transmitted in a channel, the channel parameters $h_i(t)$ and $n_i(t)$ will get added to the input signal that causes distortion in cellular communication. By using CbCBCE technique, the input signal is splitted into leaf nodes in the form of a balanced tree as $x_i(t) = x_1(t) + x_2(t) + \ldots.. + x_{m-1}(t)$.The splitting of input signal is shown in fig. 8.

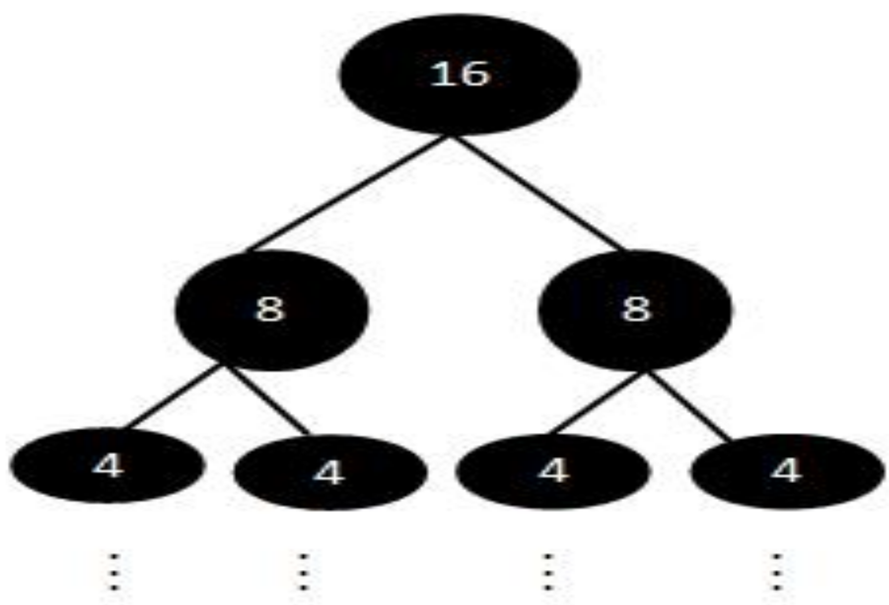

Fig. 8 Splitting of the input signal

The splitted input signal will have channel coefficient and noise parameters. Initially, the channel coefficient was calculated by considering the channel has no noise ($n_i(t)$ =0). Let us consider 22 as the numerical value of output signal ($y(t)$= 22). Then, according to the formula of channel coefficient, $h_i(t)$ can be determined. Substituting these values in Eqn. (2), Eqn. (5) was obtained.

$$\sum_{i=1}^{m-1} h_i(t) = \frac{22-0}{16} = 1.375 \tag{5}$$

Similarly, input and output signal values noise parameters can be calculated after knowing the channel coefficient.

5.2 Performance Analysis

The proposed model is implemented in the MATLAB platform, and the efficiency of the proposed model has been measured in terms of throughput, BER, Delay, data transfer rate, SNR, and energy consumption.

5.2.1 Throughput

Throughput refers to the successful quantity of signal/ data transmitted or received over the communication channel. Generally, throughput is expressed as Kbps, Mbps, or Gbps. The throughput can be calculated using Eqn. (6),

$$Throughput = \frac{Data\ \ Received}{Time\ taken\ \ in\ receiving\ the\ quantity\ of\ data} \tag{6}$$

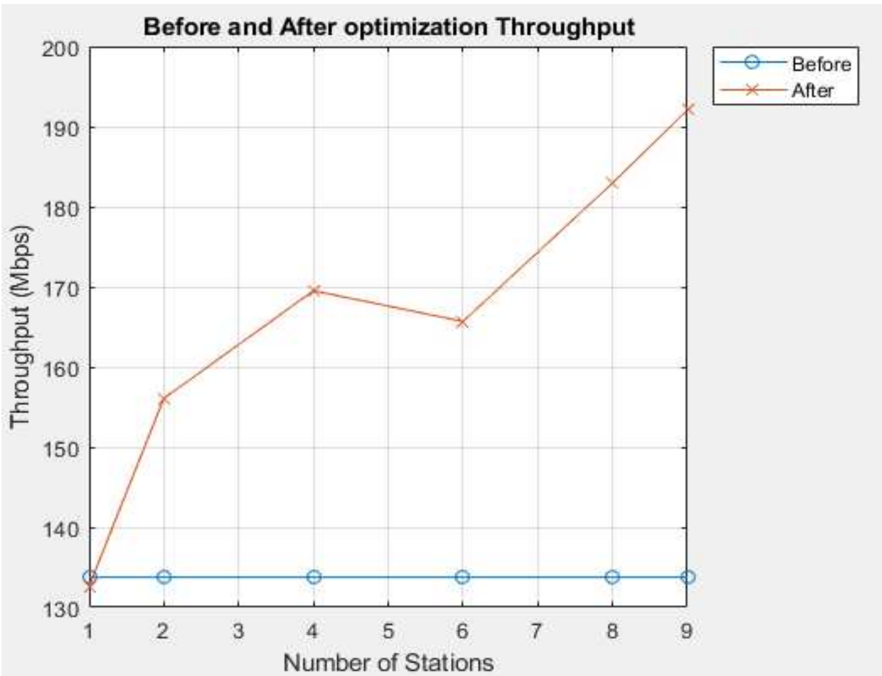

Fig. 9 Before and After Optimization Throughput

The throughput was calculated in the communication channel before and after the optimization process. Fig. 9 displays the system's throughput before and after the optimization process. From the figure, it is clear that the throughput of the communication system is more after optimization. Before optimization, the throughput is 134 Mbps from 1to 9 stations. But, after the optimization process for 1 station, the throughput value is 134 bps. For two stations, the throughput is 156 Mbps; for 3stations, the throughput is 163 Mbps; and for four stations throughput is 170 Mbps. After reaching 170 Mbps, the throughput value decreases slightly for four and five stations. After that, the throughput increases again, and for seven stations, the throughput is 175 Mbps; for eight stations, the throughput is 183 Mbps. From this analysis, it is clear that the throughput increases if the number of stations increases after the optimization process.

5.2.2 Bit Error Rate (BER)

Generally, bit error rate (BER) refers to the number of bit errors per unit time. BER is determined as the ratio of bit errors to the total number of transmitted bits in cellular communication. It is expressed as shown in Eqn. (7),

$$BER = \frac{N_{be}}{N} \tag{7}$$

Where, N_{be}refers to the number of bit errors and N denotes the total number of transmitted bits.

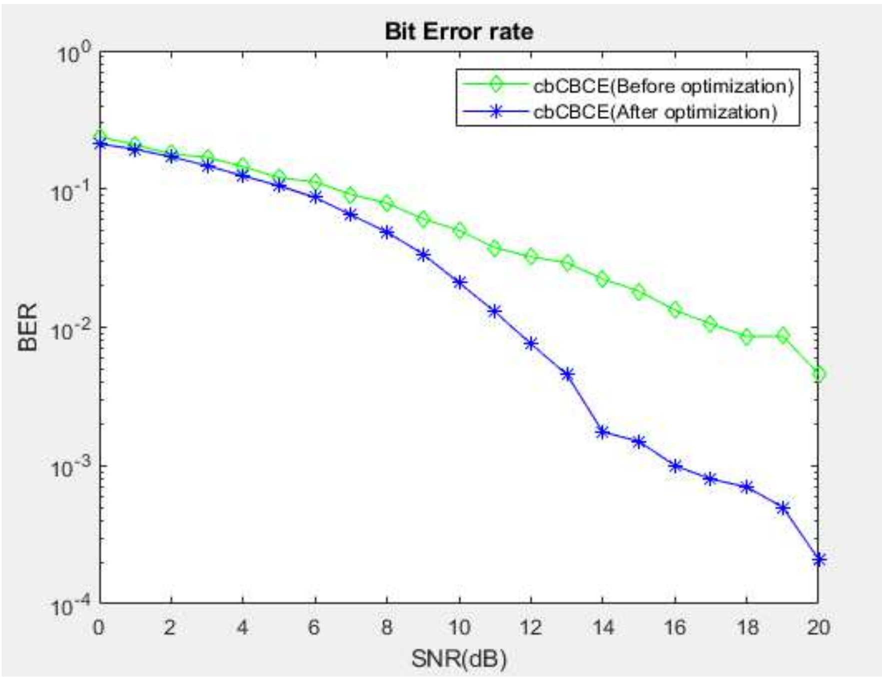

Fig. 10 Bit Error Rate (BER) before and after optimization

The bit error rate (BER) is determined under the signal-to-noise ratio (SNR). Generally, if SNR increases, the bit error rate decreases. Fig 10 displays the bit error rate before and after the optimization process. It is denoted that the BER is high SNR is zero. From the figure, it is clear that if SNR increases, the value of BER starts decreasing. Initially, for low SNR values, the bit error rate is more. Therefore, the system must maintain a high SNR value to reduce BER.BER is calculated under the SNR. If SNR is low, the BER is high. It is clear from the figure that the Bit Error Rate decreases if SNR increases. After optimization, the bit error rate range is 0.0002. It is low when compared to BER before optimization.

5.2.3 *Communication Delay*

Delay in communication is defined as the time taken to transmit a signal on a communication channel. This is mainly caused by the data rate of the communication link. Generally, delay in communication is of three different types: transmission delay, propagation delay, and queuing delay.

- Transmission Delay: Transmission delay is defined as the time taken to put data packets into the transmission link. The transmission delay of the channel can be expressed in Eqn. (8),

$$Transmission\,delay = \frac{L}{S} \tag{8}$$

Where, *L* refers to the length of the data and *S* denotes the size of the data packet.

- Propagation Delay: Propagation delay refers to the channel length ratio to the propagation speed of the signal over the channel. It is expressed in Eqn. (9),

$$\Pr opagation\ delay = \frac{L_c}{S_c} \tag{9}$$

Where, L_c refers to the channel length and S_c refers to the propagation speed of the signal.

- Queuing Delay: Queuing delay is when the signal/ data stand in a queue to transmit over a medium (channel). Queuing delay in cellular communication can be expressed in Eqn. (10),

$$Queuing\ delay = \frac{1}{(N_p - v)} \tag{10}$$

Where, N_p refers to the number of signals/data transmitted and v denotes the average rate at which the signal arrive.

These delays are reduced or low in proposed technique when compared with the other existing techniques.

5.2.4 *Data Transfer Rate*

Data transfer rate is the quantity of data/ signal transmitted over a communication system at a particular period.

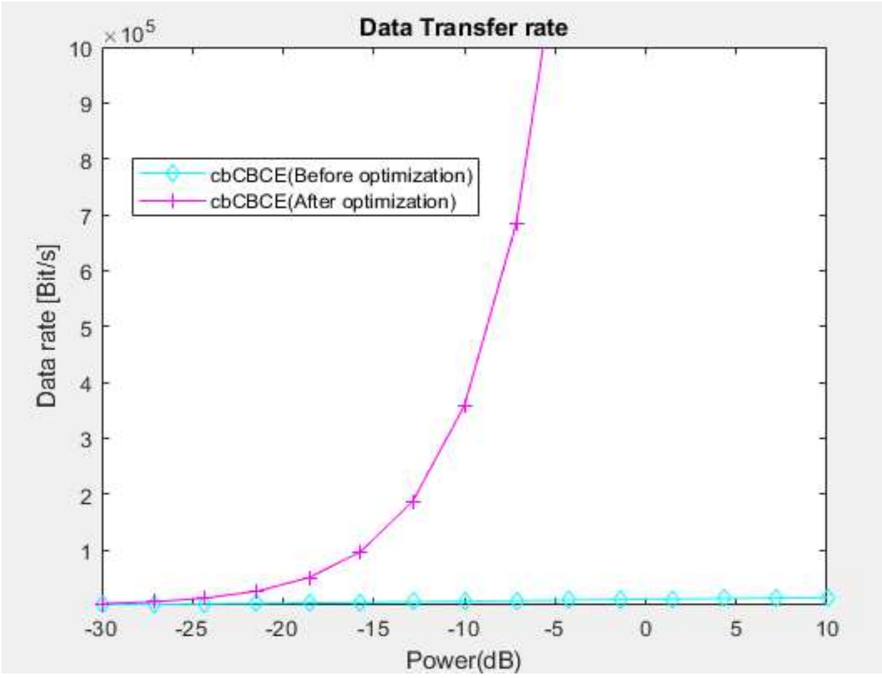

Fig. 11 Data Rate before and after optimization

In other words, the data transfer rate is defined as the speed at which the data is transmitted over a network. It is expressed in Eqn. (11),

$$Data\ transfer\ rate = \frac{A_d}{T_t} \tag{11}$$

Where, A_d refers to the amount of data transmitted and T_t denotes the transmission time.

The data rate in the 5G cellular communication system is calculated at high bandwidth. Fig 11 displays the data rate before and after optimization. The data rate is calculated following the bandwidth and the transmit power. Before the optimization process, the transmission rate improved at high bandwidth if the transmit power rose. But, after reaching the threshold value, the system's data rate decreases. After optimization, the data rates increase if the transmit power increases. The data rate is calculated at high bandwidth. It is clear from the figure that the data rate does not fall even after reaching the threshold value. The data rate keeps increasing if the transmit power increases.

5.2.5 Signal to Noise Ratio (SNR)

SNR refers to the ratio of the signal's power to the power of noise. Generally, the SNR is expressed in dB. When SNR is high, the signal power is more than the noise. On the other hand, if SNR is low, the signal power is low compared with the noise power. Hence, for a better communication system, the SNR must be high. SNR can be calculated using Eqn. (12),

$$SNR = \frac{P_s}{P_N} \tag{12}$$

Where, P_s denotes the signal power and P_N refers to the noise strength. In proposed technique SNR is high compared with other existing techniques.

5.2.6 Energy Efficiency

Energy efficiency refers to the quantity of data received on the receiver side to the energy spent by the communication system to transmit these data. It can be expressed in Eqn. (13),

$$Energy\ Efficiency = \frac{A_{dr}}{E_t} \tag{13}$$

Where, E_t refers to the total energy spent by the communication channel and A_{dr} indicates the total amount of data received at the receiver end.

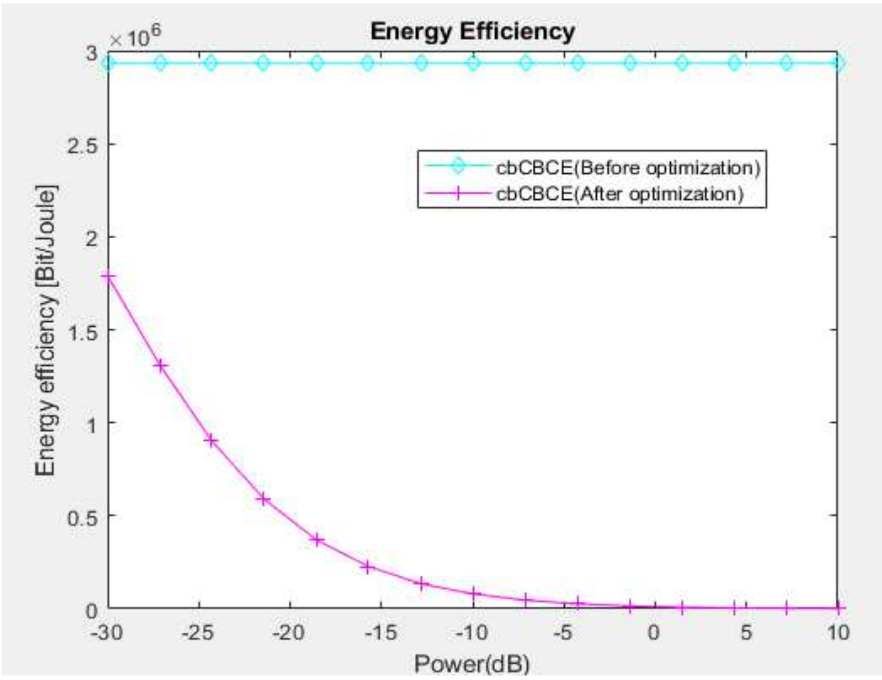

Fig. 12 Energy efficiency before and after optimization

The bandwidth and the transmit power calculate the system's energy efficiency. Usually, for a 5G cellular system, the energy efficiency is estimated at high bandwidth, and the energy efficiency must be more. Fig. 12 displays the energy efficiency before and after optimization. Before optimization, it is observed that for more transmit power is more the energy efficiency increases. But, after reaching the threshold value, the energy efficiency decreases suddenly and becomes low. From fig. 12, it is clear that if the transmit power increases, the energy efficiency increases. The energy efficiency is evaluated at high bandwidth. After optimization, the energy efficiency is more when compared with before optimization. After reaching the threshold value, the energy efficiency does not decrease.

5.3 Comparative Analysis

To estimate the proposed method's best outcome, the proposed model's parameters are compared with some recent techniques associated with this work. The recent techniques used for comparison are Bilinear Channel Estimation based on Convex Optimization (BECbCO) [23],Channel Estimation based on Optimized Semi Blind Sparse channel (CEbOSBS) [24], Precoding Method based on Phase Rotated- SVD (PMbPR-SVD) [25], Channel estimation based on tensor-based algebraic (CEbTbA) [26],IRS twin Structure for channel estimation (IRStS) [27], Deep Learning based Channel Estimation (DLbCE) [28],Channel Estimation based on Beam Space (CEbBS) [29] and Chimp based CatBoost Channel Estimation(CbCBCE(B.O)). These techniques validated that the proposed design has low NMSE and BER.

5.3.1 Normalized Mean Square Error (NMSE)

Normalized Mean Square Error (NMSE) refers to the mean square error (MSE) normalized by the strength of a signal. NMSE can be expressed in Eqn. (14) and Eqn. (15). Where x and y input and output signals.

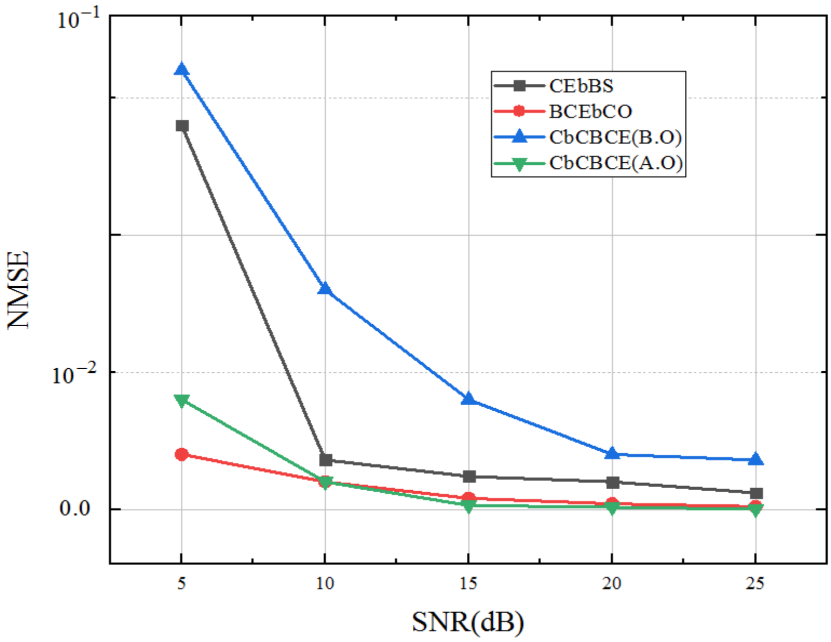

Fig. 13 Comparison of NMSE of proposed (CbCBCE) design with othermethods

$$NMSE = \frac{MSE(x,y)}{MSE(x,0)} \tag{14}$$

$$NMSE = \frac{E\{\|x-y\|_2^2\}}{E\{\|x\|_2^2\}} \tag{15}$$

Fig. 13 displays the comparison of NMSE of proposed design with other methods. From the figure, it is observed that on increasing SNR value the NMSE decreases. The NMSE of the proposed model is compared with other techniques such as CEbBS, BCCEbCO and CbCBCE.

The NMSE of the proposed model is 8.0036×10^{-6} which is small compared to other techniques. The NMSE of the existing techniques are 0.003, 0.009 and 5.0×10^{-4}.

5.3.2 *Bit Error Rate (BER)*

Generally, bit error rate (BER) refers to the number of bit errors per unit time. BER is determined as the ratio of bit errors to the total number of transmitted bits in cellular communication. It is expressed as shown in Eqn. (16),

$$BER = \frac{N_{be}}{N} \tag{16}$$

Where, N_{be} refers to the number of bit errors and *N* denotes the total number of transmitted bits.

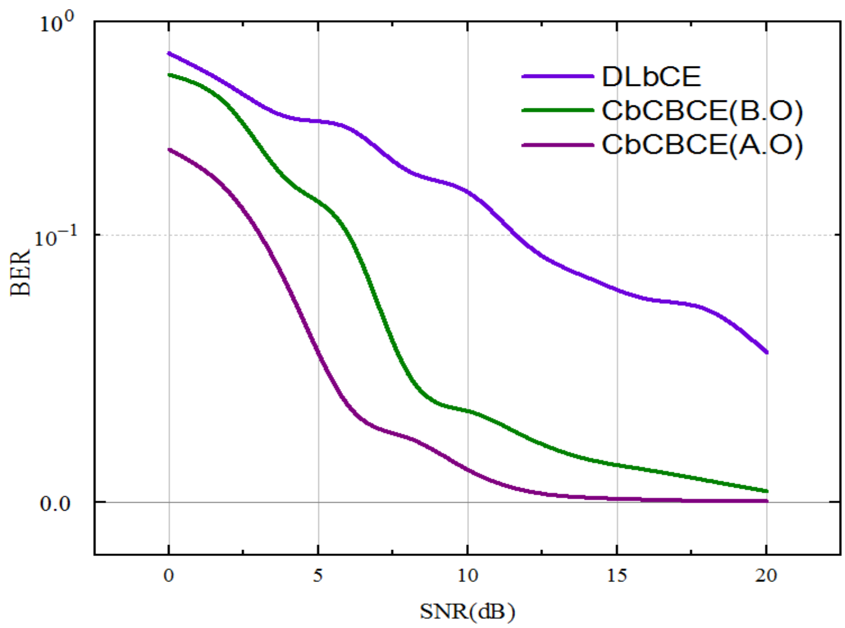

Fig. 14 Comparison of BER of proposed with DLbCE, CbCBCE (B.O)

Fig. 14 displays the comparison of BER of proposed with DLbCE and CbCBCE (B.O). The Bit error rate (BER) of the proposed model is compared with the other techniques such as DLbCE and CbCBCE (B.O). It is observed that the BER of proposed design is 5×10^{-4} which is smaller than other techniques. Generally, the BER decreases if the SNR increases. The BER in CbCBCE (B.O) and DLbCE decreases on increase of SNR. But, its BER is high when compared with the proposed model. The BER of CbCBCE (B.O) and DLbCE are 0.1 and 0.14 respectively.

5.3.3 *Channel Capacity*

The channel capacity of the communication system is defined as the maximal rate at which the data can n.

7)

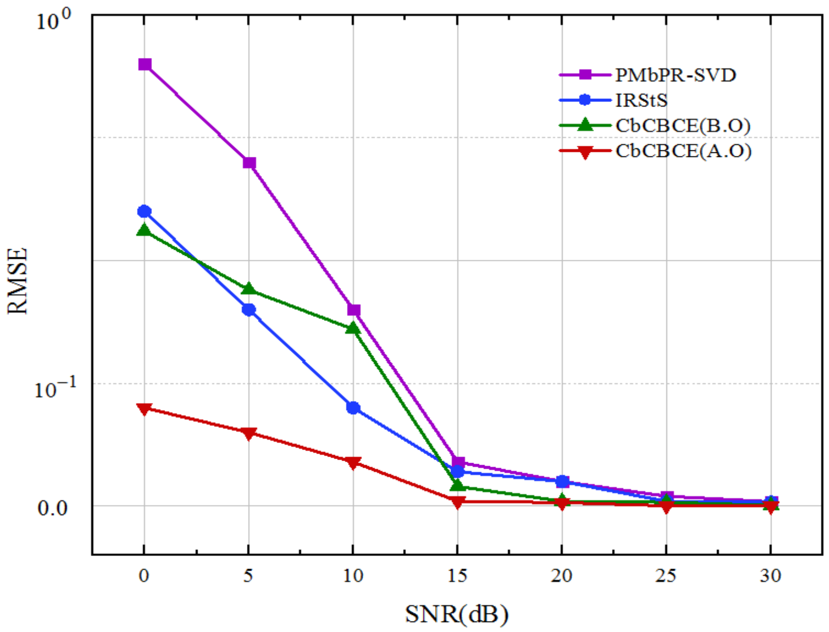

Fig. 16 Comparison of RMSE of proposed with other techniques

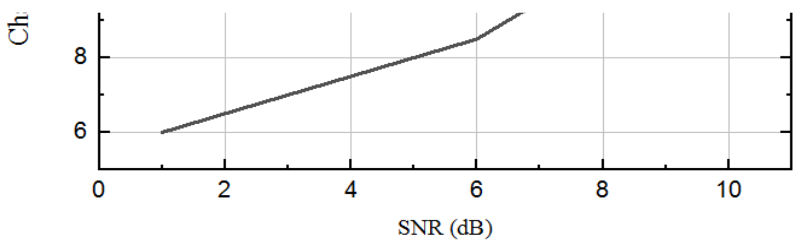

Fig. 15 Comparison of channel capacity of proposed model with other techniques

Generally, the channel capacity increases when the noise signal is high. A comparison of the channel capacity of the proposed model with other techniques is illustrated in fig 15. It is observed that the channel efficiency increases if SNR increases. The power of the executed model is compared with some other techniques such as CEbOSBS, CEbTbA, and CbCBCE (B.O). The capacity of the presented model is more when compared with other conventional methods. When SNR is equal to 10dB, the channel capacity of CEbOSBS and CEbTbAare 12 bits/sec, 9.79 bits/sec, and 12.2 bits/sec, respectively, while the proposed model has a high channel capacity of 18 bits/sec.

5.3.4 Root Mean Square Error (RMSE)

Root Mean Square Error refers to the standard deviation of the residuals (prediction error). It is the traditional way to calculate error in the model in the residual quantitative input.

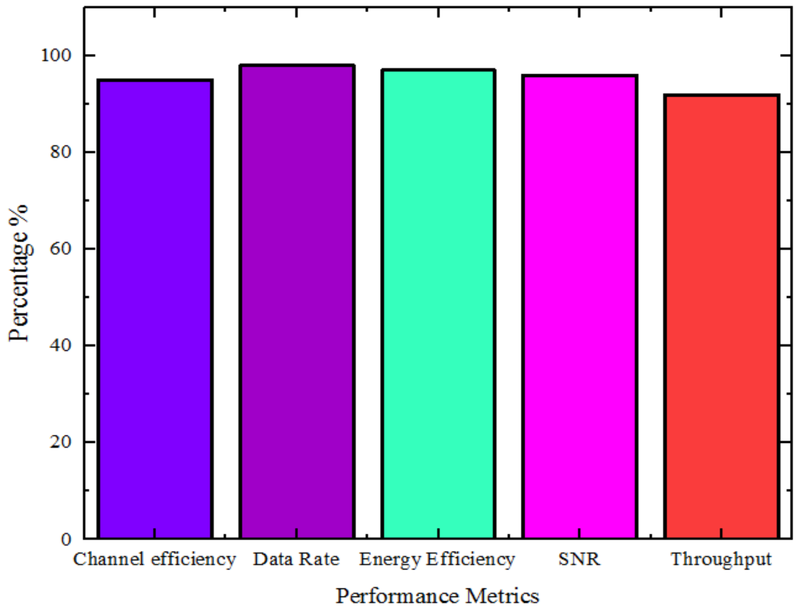

Fig. 17 Overall chart for performance metrics

be

expressed in Eqn. (18),

$$RMSE = \sqrt{\sum_{i=1}^{a} \frac{\hat{x}_i - x_i}{a}} \tag{18}$$

Where, number of observations are denoted by a, $\hat{x}_i$ and x_i indicates the predicted and observed values respectively.

A comparison of RMSE proposed with other techniques is displayed in fig 16. Generally, if the signal-to-noise ratio increases, the RMSE decreases. Here, on increasing the SNR value, the RMSE decreases. From fig 16, it is clear that the RMSE of the presented design is significantly less than the other existing techniques. It is observed that the RMSE of the executed model is 1.25x10e-6 which is low when compared with the different techniques, namely, PMbPR-SVD, IRStS, and CbCBCE (B.O). The RMSE of the other techniques is 0.009, 0.008, and0.0016, respectively.

5.4 Discussion

The main objective of the presented model is to determine and reduce the channel parameters for uninterrupted communication. Here, the channel parameters are estimated using the CatBoost algorithm, and then the estimated parameters are reduced by the chimp optimization process.

The performance analysis and comparative analysis prove that the proposed model attained high throughput of 192 Mbps, low BER of the range below 0.0002, high data rate of $1.8 \times 10^{7}\, Kbit/s$, and high energy efficiency of $3 \times 10^{6}\, Kbit/Joule$. The overall chart for performance metrics of the implemented model is displayed in the fig 17. For all performance metrics, the executed technique achieved high performance percentage. Finally the outcome of the presented design is compared with other conventional techniques and the executed model attained high performance than other techniques.

6 Conclusion

Channel estimation plays a significant role in wireless communication systems, especially in 5G communication. Hence, for uninterrupted communication, channel characteristics must be analyzed. Therefore, an efficient channel estimation technique is essential for continuous communication. The proposed CbCBCE technique identifies and reduces the channel parameters and makes the transmission uninterrupted in this presented work. Finally, the outcome of the suggested process is compared with the other methods. It is observed that the proposed model attained maximum throughput of 192 Mbps which is 60% more than compared before optimization. Also, it reduces the bit error rate (BER) to 0.0002 dB, which is 0.2 % less than other existing techniques. Thus, the executed model estimates the channel parameters and makes the signal less distorted for uninterrupted communication.

Acknowledgement

None

Compliance with Ethical Standards

1. Disclosure of Potential Conflict of Interest:

The authors declare that they have no potential conflict of interest.

2. Statement of Human and Animal Rights.

   i. Ethical Approval

   All applicable institutional and/or national guidelines for the care and use of animals were followed.

   ii. Informed Consent

   For this type of study formal consent is not required.

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