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RESEARCH ARTICLE

Hybrid AE and Bi-LSTM-Aided Sparse Multipath Channel Estimation in OFDM Systems

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ABSTRACT OFDM is a powerful modulation technique that efficiently transmits high-speed digital data over frequency-selective fading channels. It divides the signal into multiple subcarriers, each experiencing flat fading, and compensates for independent noise using a simple one-tap equalizer. In wireless systems, coherent detection is often employed, and accurate channel knowledge is crucial for optimizing performance. Traditional channel estimation methods, such as Least-Squares (LS), utilize randomly spaced pilot patterns, which can compromise spectral efficiency. Significant losses in BER and MSE affect many such existing methods in detrimental manner. To counter such failure, this paper proposes a new hybrid deep learning-aided sparse multipath channel estimation approach for OFDM communication systems. Additionally, a hybrid deep learning HA-Bi-LSTM model is developed by combining Bidirectional Long Short-Term Memory (Bi-LSTM) and Auto-Encoder (AE) to enhance data communication performance. Further, an efficient Grasshopper Electric Fish Optimization Algorithm (G-EFOA) is developed to optimize the parameters of AE and Bi-LSTM, resulting in superior solutions. AE handles feature extraction, while Bi-LSTM performs estimation. The proposed model aims to minimize BER and MSE values. Results show about an average 77 % improvement in BER across varied modulation schemes, along with a significant drop in MSE values by 84 %. Also, a sizable drop-in simulation time proves the contribution of the algorithm. Finally, the proposed model's effectiveness is demonstrated through performance evaluations.

INDEX TERMS Auto-encoder, sparse multipath channel estimation, bidirectional long short-term memory, orthogonal frequency division multiplexing, grasshopper electric fish optimization algorithm.

I. INTRODUCTION

A. IMPORTANCE OF THE WORK

For reducing the Inter Symbol Interference (ISI), the OFDM scheme has been utilized for decades. Many subchannels are classified and transferred in a parallel manner across the bandwidth of OFDM signals. To decrease the delay, narrow subchannels have been selected. Eventually, the effects of co-channel interference are reduced by integrating the OFDM with antenna diversity and Turbo Coding [1]. Information or input data to such a system can be in the form of text data, images, and audio. To share these data, classification of wireless channel is essential [2]. It has the potential to attain a high bit rate value at reasonable low lost computational loads [3]. Hence, it has been utilized in mobile acoustic communication, in which the channel has exhibited long multipath delays that help to neglect the requirement for the time-domain equalizers [4]. This system can separate the frequency selection channels into several series of frequency-flat subcarriers along with scalar gains [5]. The number of multipath components (MPC) is essentially less than the amount of channel tap in the subcarriers or frequency-time domain. Then, the wireless channel technique also does not typically assume the sparsity complex Gaussian distribution in every channel sample [6].

For identifying the OFDM signals, there is a requirement to use channel coefficients on the frequency domain [7]. Moreover, the channel has been typically evaluated on the impulse response domain, in which some of the delay domains are described [8]. The sparse channel evaluation for the acoustic

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OFDM systems has been reviewed in recent times [9]. These techniques have reflected that the physical path delays might have a continuum of values. Moreover, the enhancement in the working performance of the channel evaluation has resulted from utilizing the finer dictionaries that come at maximized computational complexity [10]. Subsequently, the importance of this work lies in finding optimal channel estimation scheme for a sparse multipath channel. To tackle these issues, path-based channel techniques are used to exploit the channel estimations, in which the channel has been parameterized through several distinct paths and has been characterized through delay and complex amplitude [11].

B. MOTIVATION

As mentioned in subsection I-A, the data transmission by reducing ISI is made possible by the OFDM systems. Moreover, it has less complexity and provides effective communication. The dispersive wireless channel has received a lot of interest in recent days owing to its time variant and frequency selective nature [12]. Modulation in OFDMA might be differential or coherent. If a greater number of receiving and transmitting antennas is employed, then to perform diversity combining and coherent detection by the OFDM receiver, the CSI is needed. By transferring data symbols with pilots, the CSI is effectively determined. For wireless transmission, channel estimation with the pilot's assistance is essential. This is because of the inherent improvement in data transmission at high bit rates as promised for 5^{th} generation mobile services. The ubiquitous demand for High-Definition (HD) videos can essentially get disturbed due to lack of proper understanding of channel assessment [13]. Even after all the remedial strategies, ISI will still exist on a minimal scale. This is apparently due to the channels expanding the symbol periods when the data is transferred at high bit rates among mobile radio channels [14]. Accordingly, many such strategies exist, of which the non-zero channel taps follow the Gaussian distribution through Center Limit Theorem (CLT) [15] is one. A few massive MIMO frequency-flat channel techniques have described sparsity concerning its angles of arrival and departure [16]. More likely, the sparse identification techniques, including the coverage as well as the resolution in delay, have given enhanced arbitrarily with low complexity with the Path Identification (PI) techniques [17]. The PI algorithm is intended on the evaluation of complex as well as delay amplitudes of the channel paths. Moreover, multi-channel pre-processing is done on higher rate underwater acoustic (UWA) communication signals that have acquired the computationally expensive receiver algorithms, as well as maximized the count of receiving elements that have essential for increasing the receiver complexity. In this research work, the developed HA-Bi-LSTM model can provide better channel estimation pertaining to OFDM based transmission. Moreover, the developed model tends to minimize BER and MSE rate significantly, which assists in enhancing communication performance. Owing to these, a novel G-EFOA algorithm is introduced for tuning the optimal parameters for boosting the system performance. These tuning parameters help to enhance the feature propagation of the model. The result analysis also validated to provide the effective outcomes of the designed method.

C. LITERATURE SURVEY

1) RELATED WORKS

Junejo et al. [18] have recommended the Inter-block-interference (IBI) free region, which has been used to evaluate the accurate UWA Channel Impulse Response (CIR) and mitigate its interference. In the case of the underwater Time division synchronization OFDM (TDS-OFDM) technique on the real sparse time differing multipath channel, the orthogonal matching pursuit-based sparse channel evaluation technique has been suggested. Moreover, the Doppler shift of the UWA channel has been compensated and evaluated through a Pseudo-random noise (PN) sequence in the time domain. The working ability of this recommended model has been demonstrated and estimated by utilizing the Monte Carlo iterations. In the end, the simulation analysis has also shown the superiority of the recommended model and attained high spectral and energy efficiency.

Gómez-Cuba and Goldsmith [19] have analysed the effect of non-Gaussian MPC amplitude distribution over the working performance of the CS for an OFDM technique. The total number of dominant MPCs, in the CS algorithm, has been required to accurately evaluate the depiction of the channel, which was characterized. Further, this number has been related to the channel of the Compressibility Index (CI), which is based on the MPC amplitude distribution. The connectivity among MPC amplitude distribution fourth moment and the MSE in the CS algorithm has been revealed, which has shown the fourth moments amplitude gain. Thus, the simulation analysis has shown that the recommended technique has acquired low computational cost, as well as the analytical outcomes were estimated.

Tadayon and Stojanovic [20] have addressed the issues of coherent identification of acoustic OFDM signals, which utilized the sparse channel evaluation technique depending on n the physical model of multipath propagations. In the initial stage, the channel evaluation has been accomplished by element-by-elements. This has been carried out by employing the individual element by the PI algorithm. Hence, the correlation among the elements has been exploited. This technique was utilized to minimize the signal processing complexity without influencing the working ability. The algorithm has learned the spatial coherence patterns over the carriers, which effectively have broadband beam forming. Thus, this recommended technique has demonstrated the minimized complexity pre-combination scheme.

Nandi et al. [21] have recommended a new channel evaluation technique that depends on the machine learning model. The inter-symbol interference (ISI) on the MIMO-OFDM system has introduced errors in the decision devices on the receiver. The major intention of this technique was to restrict the collision of ISI on the receiving and transmitting filter, which has been designed to deliver digital data with a low error rate. Here, the Elman-RNN (E-RNN) has been applied to evaluate the channel in the MIMO-OFDM regarding the scalability as well as reliability. Therefore, the recommended technique has achieved enhanced MSE performance by utilizing the E-RNN.

Li et al. [22] have recommended the channel estimator depended on the Denoising Auto Encoder-Deep Neural Network (DAE-DNN) technique. This suggested technique is depended on the data-driven deep learning model. In the initial stage, the DAE-aided pre-processed signals were utilized to learn the damaged data and recover the complete signals along with the occurrence of noise. Further, these transmitted data have been processed through DAE were utilized. Here, the DNN was utilized for training in the offline process. In the end, the evaluated CSI has been given through the recommended DNN model and has demonstrated that the recommended technique has enhanced the OFDM as well as outperformed better.

Jeya and Amutha [23] have recommended the Optimized Semi-Blind Sparse (OSBS) algorithm for MIMO-OFDM. In the initial phase, the QPSK modulation has been designed for modulating the input signals. Moreover, the Pulse Shaping Algorithm (PSA) has been utilized for tuning the ISI. In the case of symbol mapping, the Inverse Fast Fourier Transforms (IFFT) has been considered at every transmitter. At next stage, it transmitted the symbol via a multipath channel through transmitter antennas. Finally, the Channel Capacity (CC) has been determined as the gauge. The investigational results were better than the suggested model.

Ji et al. [6] have recommended the Off-Grid Sparsity Adaptive Matching Pursuit (OSAMP) depends on compressive sensing technique along with the low computational complexity. In this technique, angle-delay information and path gains have been accurately evaluated, which were further utilized for uplink channel reconstruction. The Angle-Decay reciprocity among the downlink and uplink has been exploited as well as the downlink channel evaluation was accomplished along with the aid of uplink multipath extraction. The downlink pilots were utilized to minimize the downlink training process. Therefore, the empirical outcomes have proved the system efficiency of the recommended technique.

Jia et al. [24] have recommended sparse Bayesian learning (SBL) to carry out the channel evaluation. The designed technique has been utilized to minimize the use of pilots and to enhance the transmission efficiency as well as the Multi-Blocks Sparse Bayesian learning (MBSBL) channel evaluation algorithm has also been recommended. Then, the fractional Fourier transform technique was implemented to decrease the impact of the Doppler frequency shift, which further has enhanced the output as well as the estimation performance. The sea trial data, as well as the simulations, have shown that the recommended algorithm has outperformed better.

Seyman et al. [25] have developed the Adaptive Neuro-Fuzzy Inference System (ANFIS) for channel estimation with the help of OFDM. Hence, the recommended approach was used to compare with the MSE, MMSE, Least Square (LS), and BER to show the effective performance. The simulation result of the designed ANFIS model has achieved superior performance compared to the other-state-of-art approaches. Nie [37] have designed a deterministic pilot pattern placement optimization scheme. The designed method has been combined with a Quantum Genetic Algorithm (QGA) for enhancing channel estimation performance. Here, the problem of local optima and the complex optimization were solved by the QGA algorithm. The result analysis has revealed that the designed method has achieved superior performance. Necmi et al. [31] have developed a Firefly Algorithm (FA) to optimize the pilot position to enhance the OFDM-Interleave Division Multiple Access (OFDM-IDMA) systems. Hence, the designed method was utilized to avoid errors in MSE. Fateme et al. [32] have designed a new learning automata method that was utilized for effective channel estimation. Moreover, the computational complexity has attained low in the developed method. Consequently, the MSE and BER error was reduced to improve the system's robustness. Şakir et al. [33] have implemented a Grey Wolf Optimizer (GWO) algorithm for optimizing the pilot tones in the OFDM-IDMA. Here, the objective function of the Gershgorin disc theorem was generated. The validation of the designed method has attained better performance in terms of low complexity.

Vijayakumar et al. [34] have developed an enhanced DNN method for effective communication between the channels. Hence, the parameters were optimized with the help of the Adaptive Foraging Speed-based Krill Herd Algorithm (AFS-KHA). The simulation outcome of the developed method has attained superior performance regarding MSE and BER. Ganesh and Jayakumari [35] has introduced the Genetic Algorithm (GA)-based channel estimation for identifying the efficient channel matrix. Hence, the designed method has achieved better performance other than the MMSE, DFT, and LS approaches. Muhammed et al. [36] have designed a MLP-based deep learning strategy with the help of the Levenberg–Marquardt algorithm for effective channel estimation. Nie [37] have investigated a pilot location optimization based on minimum Mutual Coherence (MC). Hence, the location of the OFDM pilot platform was updated by Q-bit. Şakir et al. [38] has implemented the Harmony Search (HS) algorithm to optimize the pattern of the pilot in the OFDM-IDMA system. Based on the Gershgorin disc theorem, the fitness function of the HS algorithm was evaluated. Vidhya and Kumar [39] have introduced the hybrid PSO and GA algorithm for channel estimation. Additionally, the hybrid model was used to fine-tune the parameters to

TABLE 1. Advantages and limitations in state of the art channel estimation techniques.

Author [citation]	Techniques	Advantages	Limitations
(Junejo et al. 2018)	TDS-OFDM	• This technique is used to attain energy efficiency and higher spectra. • It has also achieved a higher significant performance to enhance the model.	• Due to the delay over multipath channels, the model's performance is affected.
(Gómez-Cuba and Goldsmith 2020)	MPC	• This technique has the potential to lower the Compressibility Index of the channel. • It is also used to analyze the impact of the amplitude distribution.	• The single antenna system technique is needed to be explored in the future.
(Tadayon and Stojanovic 2019)	OFDM)	• This technique plays an important role in paramount significance for practical implementation. • It has also attained a higher bit rate value when assimilated over other models.	• This method has faced an issue while identifying the propagation path.
(Nandi et al. 2022)	E-RNN	• This technique has higher scalability as well as reliability. • It reduces the bit error rate to enhance the performance of the model.	• It requires much computational cost.
(Li et al. 2022)	DAE-DNN	• This method has the capacity to learn the damaged data as well as recover it. • It has demonstrated the performance estimation significantly.	• But it is robustness over impulsive noise.
(Jeya and Amutha, 2019)	OSBS	• This method is used to modulate the input signal as well as its cost function is decreased.	• It acquires a smaller number of receivers and transmitters that are not detailed in this study.
(Ji et al. 2021)	OSAMP	• The computer analysis of this technique has reduced the complexity and wider transmission bandwidth.	• The delay and the angle information are restricted.
(Jia et al. 2022)	SBL	• This technique has been utilized to minimize the use of pilots. • It has also been used to improve transmission efficiency.	• But this technique has attained high computational cost.

show better efficiency of the designed method. Vidhya and Kumar [40] have developed an improved PSO algorithm for effective channel selection. The designed method has been performed to minimize computational complexity. Muhammet et al. [41] have designed a Differential Evolution (DE) algorithm for tuning the pilot tones in the MIMO-OFDM communication system.

Vidhya and Kumar [42] have designed a cuckoo search algorithm for optimizing the MIMO-OFDM channel. Consequently, the values of mutation and crossover of all the iterations were evaluated in the LS and MMSE methods. Muhammet et al. [43] have designed an Artificial Bee Colony (ABC) algorithm to tune the pilot in the communication system. Thus, the analysis of the designed model has attained enhanced performance compared to the other existing approaches.

2) PROBLEM SPECIFICATIONS

OFDM is defined as the prominently utilized technique to attain a higher rate of data on wireless communications for pre-processing the single subcarrier modulation technique on the multipath fading channels and frequency selective. channels. Various channel estimation technique on the OFDM technique has been overview in Table 1. The TDS-OFDM [17] technique is used to attain energy efficiency and higher spectral. It has also achieved a higher significant performance to enhance the model. Due to the delay over multipath channels, the model's performance is affected. MPC [19] technique has the potential to lower the Compressibility Index of the channel. It is also used to analyse the impact of the amplitude distribution. The single antenna system technique needs to be explored in the future. The MIMO-OFDM [20] technique plays an important role in paramount significance for practical implementation. It has also attained a higher bit rate value when assimilated over other models. This method has faced an issue while identifying the propagation path. E-RNN [21] technique has higher scalability and reliability. The bit error rate is minimized to enhance the performance of the model. Here, the technique requires much computational cost. DAE-DNN [22] method can learn the damaged data and recover it. It has demonstrated the performance estimation significantly. But it is robustness over impulsive noise. OSBS [23] method modulates the input signal, and its cost function is decreased. It acquires a smaller number of receivers and transmitters that are not detailed in this study. OSAMP [27], the computer analysis of this technique has reduced the complexity along with wider transmission bandwidth. The delay and the angle information are restricted. SBL [24] technique has been utilized to minimize the use of pilots. It has also been used to improve transmission efficiency. But this technique has achieved high computational cost.

3) CONTRIBUTIONS OF THE DEVELOPED MODEL

The major attributions of the recommended channel estimation processes in the OFDM systems are given below.

- To develop multipath channel estimation scheme by implementing an improved optimization algorithm called G-EFOA. This is further aided by deep learning techniques like HA-Bi-LSTM in order to attain the demodulated noise free data signals the real time extension of this proposal can be further extended for military based applications.
- Subsequently, a hybrid algorithm termed HA-Bi-LSTM has been implemented through AE and Bi-LSTM. In order to reduce computational complexity, tuning of parameters are crucial. This is achieved by using G-EFOA amalgamated with AE and Bi-LSTM. Moreover, the issues of overfitting are resolved using the developed model.
- To implement the G-EFOA, the advantages of EFO and GOA algorithms are cascaded for improving the performance of the recommended technique. It further optimizes the parameters in the HA-Bi-LSTM. Here, the developed G-EFOA algorithms help to propagate the system performance.
- To validate the performance of the channel estimation technique by examining the MSE and BER measures when assimilating over other models.

The fore-coming sections of the designed model are depicted as follows. The sparse multipath channel estimation model by deep learning strategy has been detailed in Part II. The description of the channel estimation model in the OFDM system and other techniques are explained in Part III. Hybrid deep learning techniques for sparse multipath channel estimation model in OFDM system using meta-heuristic algorithm are given in Part IV. The outcomes of the suggested sparse multipath channel estimation model are given in Part V. The recommended sparse multipath channel estimation model is concluded in Part VI.

II. SPARSE MULTIPATH CHANNEL ESTIMATION MODEL USING AN ADVANCED DEEP LEARNING MODEL

A. PROPOSED SPARSE CHANNEL ESTIMATION MODEL

In the channel estimation of the OFDM system, it has been performed among the correlation between the channel frequency responses at various frequencies and times. The estimators in the channel have been described by using the time-domain filtering and the frequency on the OFDM systems. Further, the channel estimators have been implemented by utilizing the SVD technique. But this technique does not regard any assumptions on the channel techniques, which arises estimation issues. In wireless communications technique, the radio channel has been described through utilizing multipath propagations. On processing huge cells on the large base station antenna platform, multipath sharing is developed for utilizing various dominant specular paths. Moreover, high-speed data transmission was performed through wireless communications, which leads to the sparse multipath fading channel. The sparsity in the multipath channel has been determined as the ratio of time interval on the OFDM techniques, which is spanned through multipath to the amount of multipath. Even more, the parametric channel technique is utilized for designing the correlation matrix for the channel, in which the working channel of the estimator is improved. But, it has minimized the dimensionality in the subspace of the specific correlated matrix. Further, the technique has been integrated into the digital video broadcast techniques well as the Global System for Mobile Communications (GSM) to enhance the channel equalizer as well as for improving the performance of the estimator. Moreover, the multipath time delays on mobile communication [46] (Madhavi et al. 2021) techniques are very slow. Hence, the sparse multipath channel estimation in OFDM Systems is developed.

The sparse multipath estimation of the channel has been designed to attain decreased computational complexity as well as to achieve demodulated signals without the effect of noisy signals. In this channel estimation technique, the hybrid deep learning algorithm, HA-Bi-LSTM, is attained through AEand Bi-LSTM and utilized to increase the data communication performance. Further, the parameters in the AEand Bi-LSTM have been tuned by utilizing the newly designed optimization algorithm known as G-EFOA, which involves the GOA and EFO algorithms. This hybrid architectural model has demodulated the retrieved data from the channel estimation along with BER and MSE. Hence, the investigational setup has given the outcomes as the coefficient of the estimated channel is more effective over other conventional techniques in terms of various performance metrics.

B. AUTO-ENCODER-BASED FEATURE EXTRACTION

The AE [52] is defined in other words that it tries to learn the approximation to the detection function. The major intention of the AE is to minimize the dimensionality function that depicts the data as a non-linear representation. The original input jv that belongs to the ch dimensionality space as well as the new depiction vj that belongs to the hc dimensionality space, the AE is defined as the tricky and special three-layered neural networks, and the output is set as $sa_{X,Y}(T) = (T_1, T_2, \cdots, T_{bn})^W$ that has been equal to the input $jv = (T_1, T_2, \cdots, T_{bn})^W$, the reconstruction error is termed as S. It is defined as the unsupervised learning algorithms and utilizing the back propagation algorithm to be useful for training.

$$sa_{X,Y}(T) = xz(zx(T)) \in T \tag{1}$$

$$S(X, T, vj) = \frac{1}{2}\left\|sa_{X,Y}(T) - vj\right\|^2 \tag{2}$$

The AE is considered as the essential way to transform depictions. On tackling the number of hidden layer nodes ch, which is higher than the number of original input nodes hc as well as adding the sparsity constraints, thus the outcomes are like that of sparse coding. On reducing the number of hidden layer nodes ch, which is lesser than the original input nodes hc,

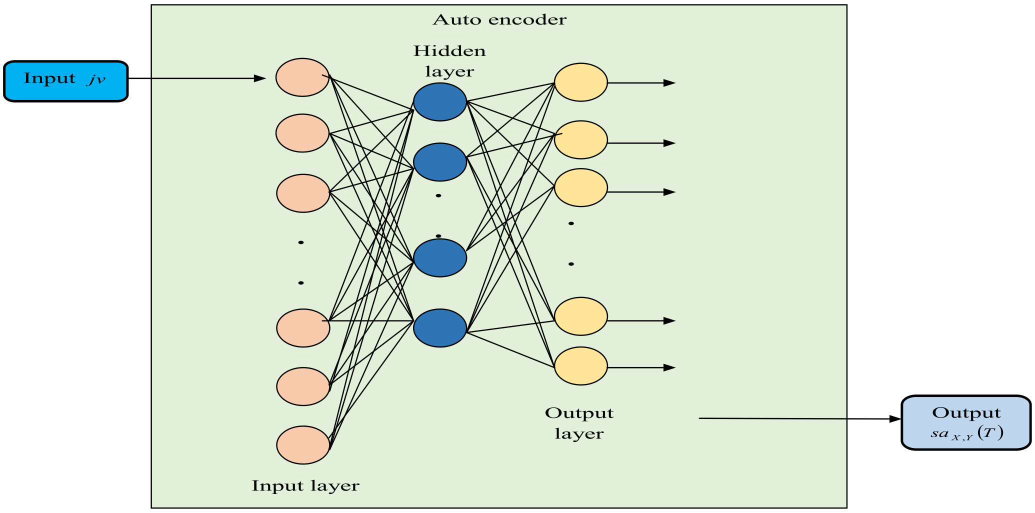

FIGURE 1. AE-based feature extraction for channel estimation model.

it provides the compressed representation of the input that attains the effective dimensionality decreased effects, and the diagrammatic representation of AE-based feature extraction to estimate the channel is depicted in Fig. 1.

C. BI-LSTM-BASED CHANNEL ESTIMATION

The Bi-LSTM [53] depended on a deep learning technique that has been designed to estimate the channel on various multipaths. This technique has played a significant role in which every component in the input signal combines the relevant details from both the present and past. In this case, it generates various more adequate outputs. The simplest linear deep learning technique $fd(si, vx) = \sum_{bc=1}^{hd} si_{bc} vx_{bc}$, where the input is termed as hd, as well as the terms, $vx, fd(.)$ denotes the weights and output of the given network accordingly. The Bi-LSTM technique contains two LSTM layers on side-to-side arrangements. One of the layers in the LSTM has been trained along with the input sequence on the forward orientation. The input sequence has been given in the reserve order for training another LSTM layer on the backward orientations. These input sequences have both the imaginary as well as the real parts for simulated training data.

The LSTM network has been considered to rectify the gradient problem in the RNNs regarding long sequence data. The LSTM has included four gates, which are given in Eq. (3), (4), (5) and (6).

$$rv_{mn} = \phi\left(R_{rv}da_{mn} + V_{rv}gd_{mn-1} + ha_{rv}\right) \tag{3}$$

$$vr_{mn} = \tanh\left(R_{vr}da_{mn} + V_{vr}gd_{mn-1} + ha_{vr}\right) \tag{4}$$

$$ti_{mn} = \nu\left(R_{ti}da_{mn} + V_{ti}gd_{mn-1} + ha_{ti}\right) \tag{5}$$

$$ho_{mn} = \nu\left(R_{ho}da_{mn} + V_{ho}gd_{mn-1} + ha_{ho}\right) \tag{6}$$

Here, the weight matrices are denoted as $R_{vr}, R_{rv}, R_{ti}, R_{ho}$ on the input state da_{mn}. Also, the weight metrics from the previous short term gd_{mn-1} is given as $V_{vr}, V_{rv}, V_{ti}, V_{ho}$. Here, the variables $ha_{vr}, ha_{rv}, ha_{ti}, ha_{ho}$ are indicated as bias. The current long-term state in the network cd_{mn} is derived as in Eq. (7)

$$cd_{mn} = rv_{mn} \otimes cd_{mn-1} + ti_{mn} \otimes vr_{mn} \tag{7}$$

Finally, the output f_{mn} is derived as in Eq. (8)

$$yf_{mn} = gd_{mn} = ho_{mn} \otimes \tanh\left(cd_{mn}\right) \tag{8}$$

The variable cd_{mn-1} is expressed as a previous long-term state. In the end, the diagrammatic representation of Bi-LSTM-based feature extraction for estimating the channel is given in Fig. 2.

III. SPARSE MULTIPATH CHANNEL ESTIMATION MODEL IN OFDM SYSTEM: GENERAL DESCRIPTION AND OTHER TECHNIQUES

A. CHANNEL ESTIMATION MODEL

The CSI has been regarded as a significant model of the OFDM receiver for managing coherent detection. The CSI has been sorted by including the addition of the data symbols along with the pilot symbols to be useful in the OFDM transmission. The pilots have been utilized in the wireless channels as it has worked on various time intervals. Different channel estimation methods have been used that are performed without channel estimation, which affects the working ability of the coherent systems. In the conventional detection based on the coherent model, the receiver processing has realized on relevant CSI. Various modulation techniques have been affected regarding the fast-fading channels, where the Channel Impulse Response (CIR) varies in terms of duration in the symbols. Then, the existing modulation method regards the channel to be stable at the time of two OFDM symbols, but it does not valid on some of the fast-fading channels. On considering OFDM, the subcarriers in the orthogonal

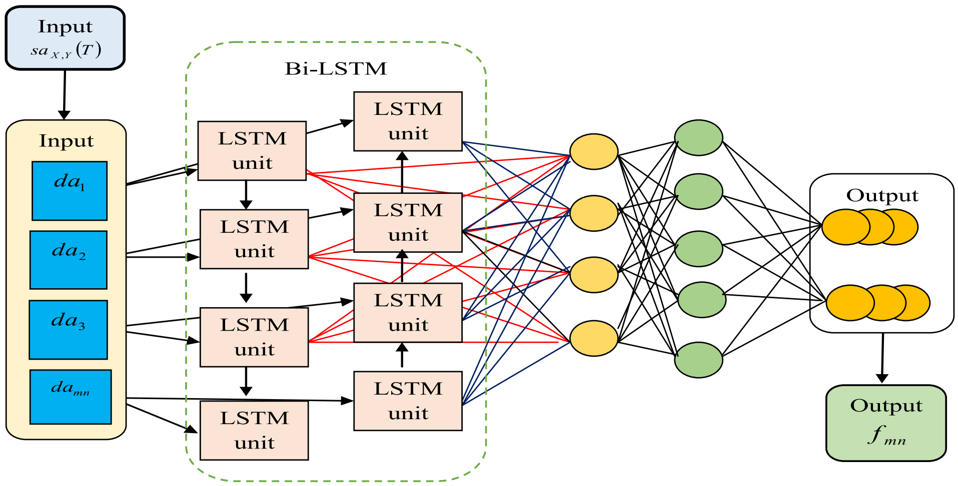

FIGURE 2. Bi-LSTM model for channel estimation.

property have been neglected, which resulted in Inter Carrier Interference (ICI), which may further lead to increased BER values without acquiring the ICI. The Minimum Mean Square Error (MMSE) is the interference between the subcarrier's frequency response as well as the interference between the subcarriers in every OFDM to process the fast-fading channels. Hence, the channel estimation while considering the fast-fading channel is more complex when assimilating the channel estimation of slow-fading channels, in which the receivers acquire channel estimation overall OFDM symbol.

The wireless communication based on channel estimation has been described as the undefined theory in the case of the receiver as well as the pilot symbol depended on modulation techniques is applied for channel estimation that describes the pilot signals that are transmitted the data in a timely manner. In particular, the estimation of the channel performance has been analysed based on the count of pilot symbols, power as well as location, which are embedded in the OFDM blocks. These have been estimated mathematically through the fading multipath channel with the higher Doppler frequency as well as the multipath delay spread.

To regain the CSI, the space between the pilot symbol on the time domain and the frequency can fulfil the Two-Dimensional (2Di) sampling theorem, which is equated in Eq. (9)

$$y_z DT_{time} \leq \frac{1}{2} \tag{9}$$

$$\sigma_{MAX} \Delta GT_{rf} \leq 1 \tag{10}$$

Here, the subcarrier spacing is indicated as ΔG, the OFDM block duration is termed as DT, the number of samples among symbol of pilot based on the frequency and time domain is depicted as T_{rf} and T_{time} accordingly. Here, the pilot symbols count has been similar to that of the delay propagation in the frequency domain. On the other hand, when regarded as the time domain, the symbols in the pilot count are the same as that of the normalized Doppler frequency $y_z D$. In the pilot symbols, the 2-Di alignment is highly complicated regarding 2-Di channel estimation in its practical applications. Hence, the OFDM channel estimations are progressed only through one Dimension (1-Di).

Regarding the slow-fading estimated channels, the channels have been simplified in the OFDM symbol blocks. These channels have regarded the symbols in the pilot, which have been integrated into the subcarriers to manage the estimation in the channel at a particular period. The included pilot symbol has been indicated as training symbols followed through a batch of OFDM symbols. Nevertheless, the channel-aided training symbol of CSI is estimated based on their respective training symbols. Depending on these details, CSI and its regarding data symbols have been analysed as well as further improved by using directed decision-based channel estimations.

IV. HYBRID DEEP LEARNING FOR SPARSE MULTIPATH CHANNEL ESTIMATION MODEL IN OFDM SYSTEM USING A NEW META-HEURISTIC ALGORITHM

A. PROPOSED G-EFOA

The recommended channel estimation technique in OFDM has been designed by using the new meta-heuristic optimization algorithm named as G-EFOA, which includes the GOA [54] and EFO [55] algorithms. The GOA algorithm has the strongest ability in the exploration of search space. It is also easy to implement and consumes limited time for execution. But it faces the issues of premature convergence and its property. On the other hand, the EFO algorithm has outperformed well in the overall optimization as well as provides better results. But it still faces problems in real-world designing and unconstrained clustering. To overcome the issues in the existing technique, the newly recommended G-EFOA has been developed. In the newly recommended G-EFOA model, the position is updated, and it is given in Eq. (11).

$$A(m+1) = \frac{mean\left\{\left(A_a^e\right)_{GOA}, (A_{xk})_{EFO}\right\} + std\left\{\left(A_a^e\right)_{GOA}, (A_{xk})_{EFO}\right\}}{2} \tag{11}$$

Here, the term A is given as position, n is the maximum iteration, the position in the GOA algorithm is termed as $\left(A_a^e\right)_{GOA}$, and the position in the EFO algorithm is termed $(A_{xk})_{EFO}$.

In The GOA algorithm has been regarded as the recent swarm intelligence algorithm, which has been inspired by the swarming as well as the foraging behaviour of the grasshopper. It has been successfully employed to resolve the issues of various optimizations on various domains. The grasshoppers are considered as dangerous pesticides which highly damage agricultural production. Their life cycle has included two steps, namely, the nymph as well as adulthood, that constitutes the diversification and intensification stages of the GOA. The mathematical depiction of the GOA's swarming mannerism is given in Eq. (12)

$$A_a = B_a + C_a + D_a \tag{12}$$

Here, the term D_a depicts the wind advection, A_a represents the a^{th} grasshopper's location, the gravity force on the a^{th} grasshopper is termed as C_a; the social interaction among the grasshoppers is given as B_a. To produce the random behaviour of the grasshoppers, Eq. (13) has been used.

$$A_a = b_1 B_a + b_2 C_a + b_3 D_a \tag{13}$$

Here, the random numbers among the interval [0, 1] have been depicted as b_1, b_2, b_3. Then, the term B_a is defined as social interaction, and it is expressed in Eq. (14).

$$B_a = \sum_{\substack{c=1 \\ c\neq 1}}^{Z} d\,(e_{ac})\hat{e}_{ac} \tag{14}$$

Here, the term $\hat{e}_{ac} = \frac{A_c - A_a}{e_{ac}}$, which is described as the unit vector among a^{th} to the c^{th} grasshopper, a number of grasshoppers are termed as Z the Euclidean distance among a^{th} to the c^{th} grasshopper is given as $e_{ac} = |A_c - A_a|$ as well as the social forces d are equated as in Eq. (15).

$$d\,(b) = g \exp^{\frac{-b}{f}} - \exp^{-b} \tag{15}$$

Here, the attraction length scale, as well as the attraction intensity, has been indicated as f and g.

Then, the term C_a is defined as in Eq. (16).

$$C_a = -h\hat{i}_h \tag{16}$$

Here, the term $\hat{i}_h$ is defined as the unit vector towards the centre of the earth and the variable h indicated as the gravitational constant.

Then, the term D_a is defined as the wind advection, and it is expressed as in Eq. (17).

$$D_a = j\hat{i}_k \tag{17}$$

Here, the unit vector in the wind direction is depicted as $\hat{i}_k$, and the term j indicates the drift constant.

The attained equation for replacing the terms B, C, D is given in Eq. (18).

$$A_a = \sum_{\substack{c=1 \\ c\neq 1}}^{Z} d\,(|A_c - A_a|)\,\frac{A_c - A_a}{e_{ac}} - h\hat{i}_h + j\hat{i}_k \tag{18}$$

But then Eq. (18) is not utilized to resolve the optimization issues as well as the swarm technique has not converged to a target position. Hence, the improved version of the above equation is indicated in Eq. (19)

$$A_a^e = l\left(\sum_{\substack{c=1 \\ c\neq 1}}^{Z} l\,\frac{U_e - L_e}{2}\,d\left(\left|A_c^e - A_a^e\right|\right)\frac{A_c - A_a}{e_{ac}}\right) + \hat{E}_e \tag{19}$$

Here, the term $\hat{E}_e$ is given as the best solution in the e^{th} dimensions, the upper as well as the lower bounds are termed as U_e and L_e accordingly. The terms l_1 and l_2 regarded as single parameters, which has been indicated in Eq. (20).

$$l = l_{mx} - m\frac{l_{mx} - l_{mn}}{m_{mx}} \tag{20}$$

Here, the term m is described as the current iteration, and the minimum and maximum iteration of l are indicated as l_{mn} and l_{mx}. Here, the variable m_{mx} is represented by the maximum number of iterations.

In EFO algorithm, it is a nature-inspired algorithm that is developed through communication mannerism as well as the electric fish's prey location.

1) POPULATION INITIALIZATION

In this initial phase F, the population of the fish has been randomly propagated by the search space on, considering the boundaries of the space.

$$n_{op} = n_{\min p} + \xi\left(n_{\max p} - n_{\min p}\right) \tag{21}$$

Here, the terms $n_{\max p}$ and $n_{\min p}$ are regarded as the upper and lower boundaries in the dimension p where $p \in 1, 2, \cdots, q$ accordingly. The location of the o^{th} individual in the population of size on considering the q-dimensional search space is termed as $|F| = (1, 2, \cdots, |F|)$. The random value attained through uniform distribution is given as $\xi \in [0, 1]$. The individual population around the search space by using the active or passive electro-location ability after the initial stage. The frequency of the EO algorithm plays an essential role to balance the exploitation as well as the exploration, and it is utilized to attain the performance of the individual depending on the active or passive electro-location. In these EFO algorithms, the active electro-location has been applied in the case of higher frequency. On the other hand, passive electro-location has been applied in the case of other frequencies. The frequency values among the individual population range between the minimum values $r_{\min}$ to the maximum value $r_{\max}$. Hence, the frequency range of the fish at the time s is defined as the closeness to the food sources, where the individual frequency r_o^s has been equated by using Eq. (22) through the fitness values.

$$r_o^s = r_{\min} + \left(\frac{ft_{wrst}^s - ft_o^s}{ft_{wrst}^s - ft_{bst}^s}\right)(r_{\max} - r_{\min}) \tag{22}$$

Here, the fitness value of the o^{th} individual at iteration s is termed as ft_o^s. The best as well as the worst fitness values attained through individual at iteration s is depicted as ft_{bst}^s, ft_{wrst}^s accordingly. The values for $r_{\min}, r_{\max}$ has the value 0 and 1.

The individual population is based on the weight of the previous individual amplitude. The value of the amplitude in the o^{th} individual H_o has been expressed using Eq. (23).

$$H_o^s = \omega H_o^{s-1} + (1-\omega)\, r_o^s \tag{23}$$

Here, the initial amplitude value of the o^{th} individual has its own initial frequency value of r_o, ω is termed as constant, which defines the magnitudes of the previous amplitude values.

2) PASSIVE ELECTRO-LOCATION

The passive electro-location can be required in the exploration or global searching mechanisms in the EFO algorithm. The individual in the passive phase, which has chosen other individuals in the active phase that shares its electrical signal based on the probability as well as changes their positions.

In the active mode, the probability of the $u \in K_J$ individuals, this is perceived through $w \in K_t$ individuals in the passive mode, which is expressed in Eq. (24).

$$t_u = \frac{J_u / v_{wu}}{\sum_{k \in K_J} J_k / v_{wk}} \tag{24}$$

It is significant that the probabilistic neighbour's selection has forced the passive mode individuals to perform the explorations phase before the exploitation phase. The dominant factor of the amplitude that causes the local search as well as the selection of the best individuals.

On utilizing various strategies like roulette wheel selection has been applied, on depending on Eq. (24), the individual U has chosen through K_J as well as reference position A_a^e has been described as in Eq. (25). The new position is then produced by using Eq. (26).

$$A_a^e = \frac{\sum_{u=1}^{U} J_u A_a^e}{\sum_{u=1}^{U} J_u} \tag{25}$$

$$A_a^{new} = A_{wk} + \zeta\left(A_a^e - a_{wk}\right) \tag{26}$$

The higher frequency can perform passive electro-location. In that case, the individuals have lost the position details completely that does not accept owing to the region that it is located. With the aim of overcoming these challenges, the EFO Equation regards to describe the modified parameters. The probability for such an individual to modify its whole trait is essential decreases the acceptance condition that is depicted in Eq. (27).

$$A_a^{cnd} = \begin{cases} A_a^{new} & rnd_k(0,1) > r_w \\ A_a^{new} & else \end{cases} \tag{27}$$

Here, the random number produced through uniform distribution is termed as $rnd_k(0,1)$.

In the end, the passive electro-location has been modified one of the parameters in the w^{th} individual is utilized by using Eq. (28) to enhance the probability of the trait has been changed.

$$A_a^{cnd} = A_{min\,k} + \zeta\left(A_{max\,k} - A_{min\,k}\right) rnd(0,1) \leq rnd(0,1) \tag{28}$$

Here, the random number produced through uniform distribution is termed as $rnd(0,1)$. When the k^{th} parameter values in the w^{th} individual, which the boundaries of the search space, it is then relocated to the boundary of the space it exceeds.

$$A_a^{cnd} \begin{cases} A_{\min k} & A_a^{cnd} < A_{\min k} \\ A_a^{cnd} & A_{\max k} > A_a^{cnd} > A_{\min k} \\ A_{\max k} & A_a^{cnd} > A_{\max k} \end{cases} \tag{29}$$

Finally, the overall process in the algorithms gets over, and the pseudo-code for the recommended model is given in Algorithm1.

Algorithm 1 Developed G-EFOA

```
Initiate population
Adjust random parameters l_mx, l_mn, m_mx
While m < m_mx
    For m = 1toZ
        Update the position using GOA in Eq. (19)
        Update the position using EFO in Eq. (24)
        Determine the mean among GOA and EFO
        Determine the standard among GOA and EFO
        Update the solution by position A (m + 1)
        using Eq. (11)
        End for
End while
End
Return the best solution
```

Finally, the flowchart for the recommended G-EFOA model for the channel estimation technique in OFDM is given in Fig. 3.

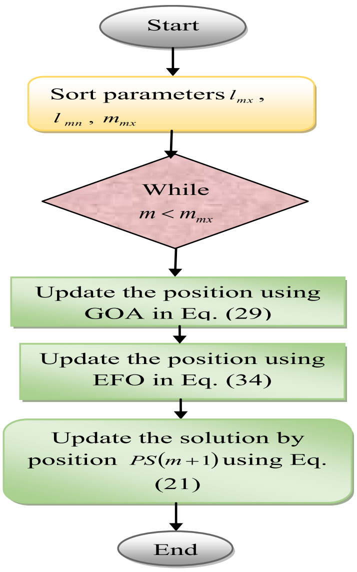

FIGURE 3. The flowchart for the recommended G-EFOA model for channel estimation technique in OFDM.

B. HYBRID AE AND BI-LSTM: HA-BI-LSTM

In the recommended sparse multipath-based channel estimation model, the newly developed hybrid model is given as HA-Bi-LSTM, which includes the AE and Bi-LSTM models. In the AE model, this technique faces some restrictions on performing the process, such as not having enough datasets. In the case of Bi-LSTM, it performs better only on the small data that degrades the performance. To solve the drawbacks in the existing model, the HA-Bi-LSTM model has been developed. In addition to that, the recommended G-EFOA in the AE and Bi-LSTM models and, thus, the objective function of the developed channel estimation method is detailed in Eq. (30).

$$OBJF = \underset{\{HN_{bi-l}, EP_{ae}, EP_{bi-l}\}}{\arg\min} \; BER + MSE \tag{30}$$

Here, the term EP_{bi-l} is defined as the epoch in Bi-LSTM among the range [50-100], EP_{ae} is described as the epoch in AE among the range [50-100] as well as the term among the range HN_{bi-l} is the hidden neurons in the Bi-LSTM among the range [5-255], which are all optimized by using the G-EFOA algorithm. The MSE is given as "the average squared difference between the predicted and the actual output", which is derived in Eq. (31).

$$MSE = \frac{1}{JA} \sum_{gv=1}^{J} \sum_{bx1}^{A} \left[gc^{gv}(bx) - \hat{g}c^{gv}(bx) \right]^2 \tag{31}$$

Here, the actual and predicted results are depicted $gc^{gv}(bx)$ and $\hat{g}c^{gv}(bx)$ accordingly.

Then, the BER is given as "the number of received bits of a data stream over a communication channel that has been altered due to noise, interference, distortion or bit synchronization errors" that has been derived in Eq. (32).

$$BER = \frac{1}{2}\left(1 - \frac{\sqrt{SNR}}{\sqrt{(2+SNR)}}\right) \tag{32}$$

SNR given as "the ratio between the desired information or the power of a signal and the (33).

$$snr = 10 \log \frac{pp_{si}}{pp_{ni}} \tag{33}$$

Here, the actual signal noise is termed as pp_{si}, and the demodulated signal noise is indicated as pp_{ni}. The hybrid HA-Bi-LSTM mode for the sparse multipath channel estimation is given in Fig. 4.

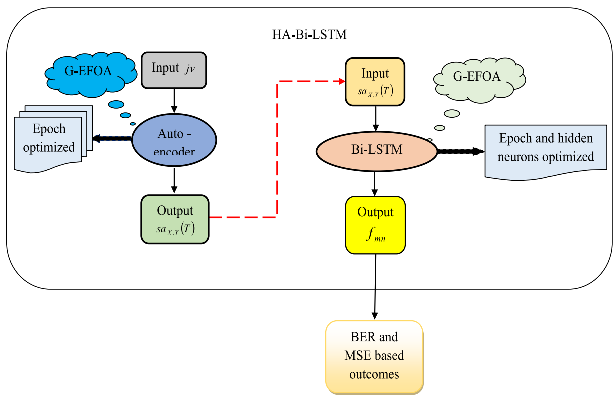

FIGURE 4. The hybrid HA-Bi-LSTM mode for the sparse multipath channel estimation.

V. RESULT AND DISCUSSIION

A. SIMULATION SETTINGS

The designed channel estimation on the sparse multipath model has been developed in MATLAB 2020a, and the simulated analysis was performed. Here, the performance of the designed method has been compared over the conventional models regarding Symbol Error Rate (SER), MSE, etc. The algorithms and classifiers used were Grey Wolf Optimizer (GWO) [51], Krill Herd Algorithm (KHA) [56], Deep Neural Networks (DNN) [57], and Long Short-Term Memory (LSTM) [26]. The simulation parameter of the developed channel estimation channel is given in Table 2.

B. EVALUATION OF VARIOUS ALGORITHMS CONCERNING BER AND MSE

In the recommended channel estimation technique, the evaluation has been carried out based on the SNR variable, which is given in Fig 5 and Fig 6 regarding BER and MSE. The values of BER in the recommended G-EFOA-HA-Bi-LSTM channel estimation model have shown an enhanced working performance, which gives high-quality data without the impact of noise. Hence, it has been proven that the evaluation over BER and MSE of the recommended G-EFOA-HA-Bi-LSTM model is higher when assimilated over other models.

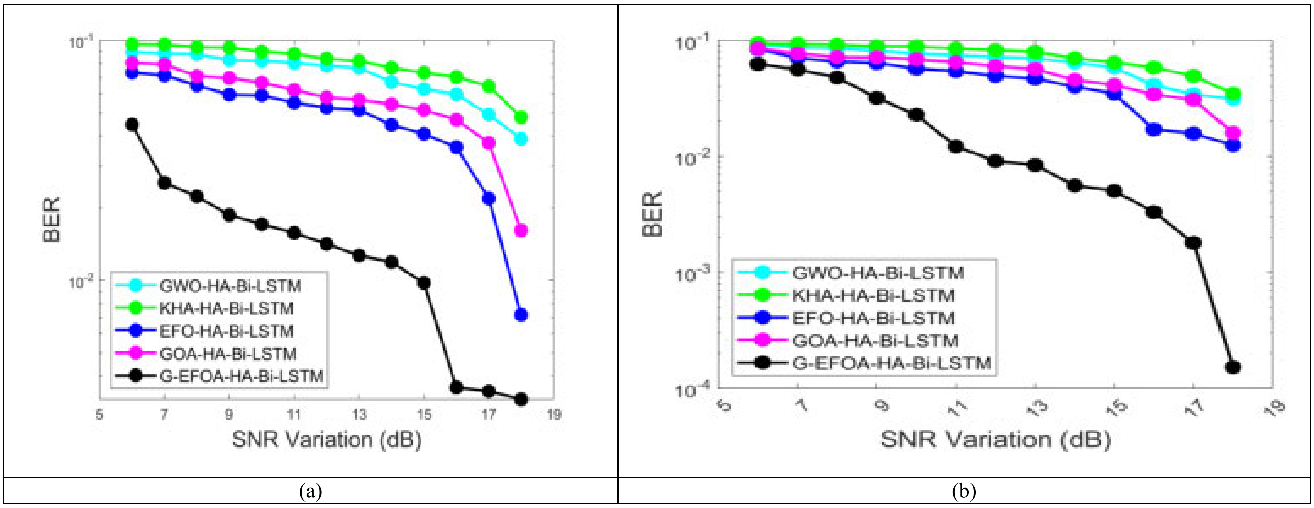

FIGURE 5. Analysis of BER on the recommended channel estimation model with a set of algorithms in terms of "(a) 16-QAM and (b) QPSK modulation."

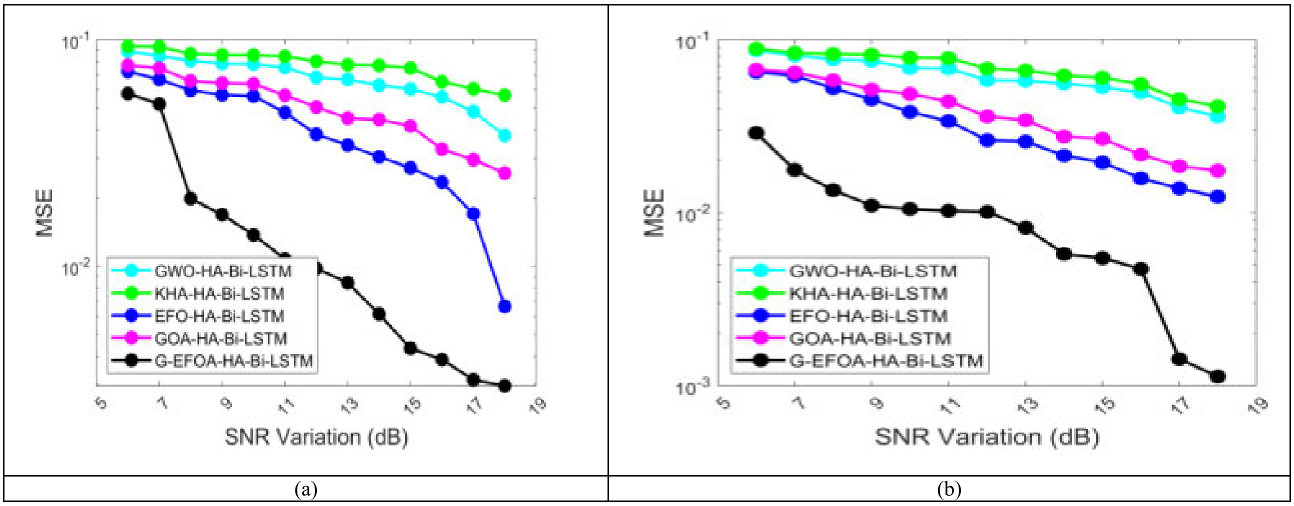

FIGURE 6. Analysis of MSE on the recommended channel estimation model with a set of algorithms in terms of "(a) 16-QAM and (b) QPSK modulation."

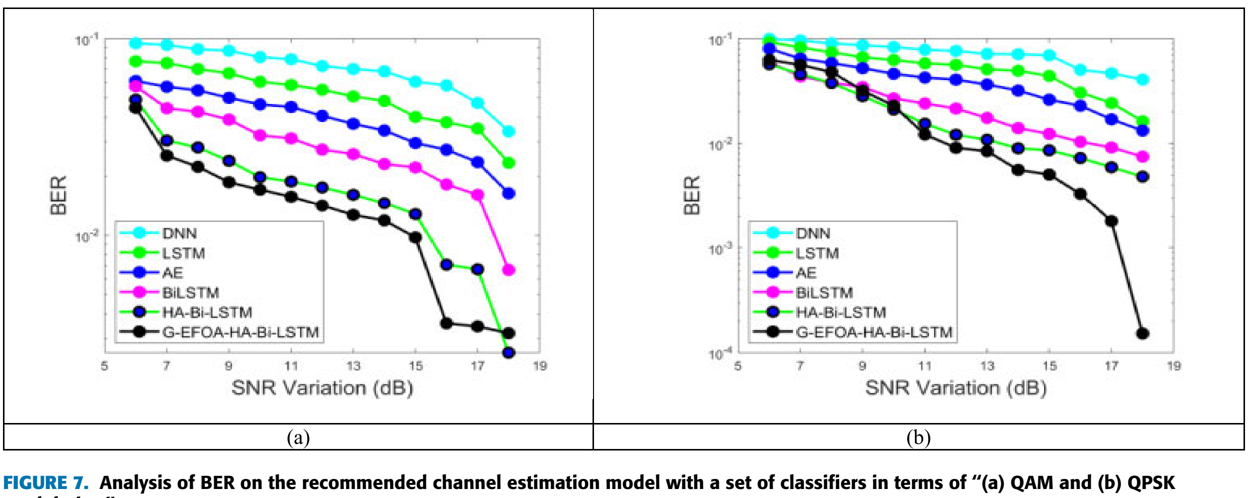

FIGURE 7. Analysis of BER on the recommended channel estimation model with a set of classifiers in terms of "(a) QAM and (b) QPSK modulation."

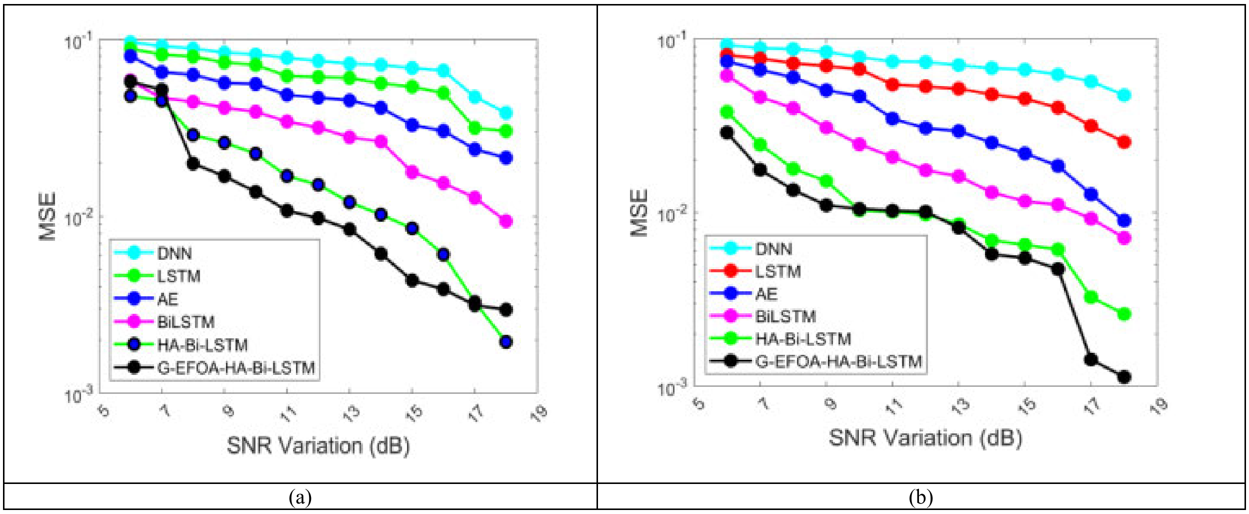

FIGURE 8. Analysis of MSE on the recommended channel estimation model with a set of classifiers in terms of "(a) QAM and (b) QPSK modulation."

TABLE 2. Simulation parameter of the developed channel estimation model.

Description	Values
OFDM parameters	
Number of subcarriers	128
OFDM sample time	1e-7
OFDM symbol time (not considering guard interval)	ofdm. N*ofdm. T
Number of transmit antennas	2
Length of the guard interval	16
Number of blocks in each channel realization	1
Modulation order	4
OFDM symbol time (considering guard interval)	(ofdm.N+ofdm.GI) *ofdm. T
Number of received antennas	3
Channel parameters	
Number of channel taps	3
Channel SNR for sweep	5:2:30
Delay spread profile	(0:1/ (chan. Nt):1)*0
Doppler in Hz	.1
Number of columns in the dictionary	128
Channel SNR	15
Loop parameters	
Number of iterations	1e2
length of inner loop	length (chan. snrdBV)

C. EVALUATION OF VARIOUS CLASSIFIERS IN TERMS OF BER AND MSE

The working performance of the recommended channel estimation technique based on the G-EFOA-HA-Bi-LSTM has been evaluated concerning BER and MSE, which is represented in Fig 7 and Fig 8 accordingly on assimilating over various algorithms. The value of BER in the recommended G-EFOA-HA-Bi-LSTM model has shown as decreased value at all the SNR variables and similarly for the MSE values that show a sliding deviation. Therefore, the offered method has shown high efficacy without the impact of noise.

TABLE 3. Overall analysis of the recommended channel estimation model for algorithm and classifiers.

Time (sec)		
Algorithms	16QAM	QPSK
GWO (Ghalambaz et al. 2021)	0.83237	0.84304
KHA (Kowalski and Łukasik, 2015)	0.8325	0.84308
EFO (Abedinpourshotorban et al. 2016)	0.83233	0.84292
GOA (Arora and Anand 2018)	0.82249	0.82244
G-EFOA-HA-Bi-LSTM	0.81505	0.83256
Methods	16QAM	QPSK
DNN (Sze et al. 2017)	0.85197	0.85651
LSTM (Hochreiter and Schmidhuber 1997)	0.84748	0.85501
AE (Wang et al. 2016)	0.84205	0.85205
Bi-LSTM (Ratnam and Rao, 2021)	0.8426	0.85356
HA-Bi-LSTM (Wang et al. 2016) (Ratnam and Rao, 2021)	0.8326	0.84299
G-EFOA-HA-Bi-LSTM	0.81505	0.83256

D. OVERALL EVALUATION OF TIME COMPLEXITY

The overall performance evaluation on time complexity has been carried out in the recommended G-EFOA-HA-Bi-LSTM model based on QAM16 and QPSK, which is tabulated in Table 3. The value of QAM16 in terms of an algorithm for the recommended G-EFOA-HA-Bi-LSTM model has decreased when assimilated over other existing algorithms. Similarly, the value of QAM16 in terms of classifiers has also shown lesser value when compared to other models. Hence, it has shown better outperformance of the channel estimation model.

E. COMPUTATIONAL COMPLEXITY OF THE DEVELOPED METHOD

The computational complexity of the recommended channel estimation model is shown in Table 4. Here, the term Max_{iter} is defined as a maximum number of iterations. The variable N_{pop} denotes the number of populations, and the term $Chlen$ represents the chromosome length.

TABLE 4. The computational complexity of the developed channel estimation model.

Method	Computational complexity
Proposed (G-EFOA-HA-Bi-LSTM)	$O[Max_{iter} * (N_{pop} + N_{pop} * Chlen)]$

TABLE 5. Comparative analysis of recent existing algorithms.

Algorithms	16QAM	QPSK
OMP (Siyuan et al. 2022)	0.84213	0.86978
BP (Yaohui et al. 2021)	0.83965	0.85965
G-EFOA-HA-Bi-LSTM	0.81505	0.83256

F. COMPARATIVE ANALYSIS OF RECENT EXISTING ALGORITHMS

The comparative analysis of the developed channel estimation model with the recent existing algorithms is depicted in Table 5.

The developed hybridized HA-Bi-LSTM model is validated with BER and MSE analysis. Here, the lower BER shows better performance for effective transmission through the wireless channels. This significant improvement in BER performance is attributed due to the hybrid nature of the proposed optimization algorithm. The addition of G-EFOA on top of HA-Bi-LSTM algorithm shows a significant drop in BER as compared to the state-of-the-art algorithms. Thus, making HA-Bi-LSTM as the second-best performing algorithm. Even the MSE analysis shows G-EFOA-HA-Bi-LSTM model provides best performance in comparison to the other existing techniques using lower time complexity. Further, the diverse classifiers were validated using the QAM and QPSK modulation. Results confirm an enhanced performance both both QAM and QPSK modulations as well.

VI. CONCLUSION

Recently, the OFDM has become mostly applicable in mobile communications where, the high-rate data stream has been spitted into lower streams which are effectively transmitted to several sub-carriers. Here, the OFDM can transmit high speed signals which are concurrently to the computed orthogonal carrier frequencies. Often, some of the techniques do not provide accurate outcomes for providing higher BER and MSE error values. This paper has implemented the sparse multipath-based channel estimation model. In this model, the hybrid deep learning algorithm known as HA-Bi-LSTM has included AE and Bi-LSTM techniques to further enhance the data communication performance through an improved channel estimation model. Then, the parameters in the AE and Bi-LSTM were optimized by using the newly developed G-EFOA algorithm, which included EFO and GOA algorithms. The major intention of this channel estimation model was to attain the minimum computational complexity to enhance the performance of the G-EFOA-based channel estimation model. The simulation results have shown that values of SNR and time have been decreased for the suggested G-EFOA-HA-Bi-LSTM technique over other models. Finally, the simulation results were more effective than other models regarding BER and MSE. In future work, more positive and negative measures like accuracy, precision, FPR, and FNR will be evaluated using enhanced deep learning models. Moreover, the developed model will be applicable for the real time application scenarios for achieving better performance.

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