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A Hybrid Intelligence-based Deep Learning Model with Reptile Search Algorithm for Effective Channel Estimation in massive MIMO Communication Systems

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Abstract

Channel estimation poses critical challenges in millimeter-wave (mmWave) massive Multiple Input, Multiple Output (MIMO) communication models, particularly when dealing with a substantial number of antennas. Deep learning techniques have shown remarkable advancements in improving channel estimation accuracy and minimizing computational difficulty in 5G as well as the future generation of communications. The main intention of the suggested method is to use an optimal hybrid deep learning strategy to create a better channel estimation model. The proposed method, referred to as optimized D-LSTM, combines the power of a deep neural network (DNN) and long short-term memory (LSTM), and the optimization process involves the integration of the Reptile Search Algorithm (RSA) to enhance the performance of deep learning model. The suggested hybrid deep learning method considers the correlation between the measurement matrix and the signal vectors that were received as input to predict the amplitude of the beam space channel. The newly proposed estimation model demonstrates remarkable superiority over traditional models in both Normalized Mean-Squared Error (NMSE) reduction and enhanced spectral efficiency. The spectral efficiency of the designed RSA-D-LSTM is 68.62%, 62.26%, 30.3%, and 19.77% higher than DOA, DHOA, HHO, and RSA. Therefore, the suggested system provides better channel estimation to improve its efficiency.

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1. Introduction

Massive MIMO, which stands for Multiple-Input Multiple-Output with a massive array of antennas, is a highly promising technique aimed at significantly enhancing data rates and ensuring exceptional communication reliability for upcoming wireless systems. This technology utilizes more antennas at the base station (BS) to serve multiple users at once, enabling efficient transmission and reception of data in parallel. Because mmWave massive MIMO can give gigabit-per-second data speeds, it has been chosen as the 5th generation's subsequent approach [1]. For mmWave MIMO, the quantity of Radio Frequency (RF) chain is often much less than that of the antennas for minimal power consumption and cost when combined with the electromagnetic lens-based beam space MIMO phase or shifter network assisted hybrid pro-coding [2]. Compared to general cellular models, the wireless situations in automotive networks are far more complicated, and bigger conditions are generated on traditional speed channel evaluation techniques [3]. For the mmWave massive MIMO system, many unique channel estimation algorithms based on deep learning approaches are now proposed [4]. It is proposed to create a "Convolutional Neural Network (CNN)" is effectively suitable and quick than the current channel evaluator while maintaining the ability to return the MSE [5]. For channels with significant noise, the convolutional blind denoising network channel evaluator model is suggested because of its strong robustness and utility [6]. However, these deep learning-assisted channel assessors directly apply the end-to-end system and require more data collection [7]. However, the performance of the LS algorithm suffers significantly when applied to deep zero-fading channels. However, the technique known as the minimal mean square error, or MMSE, performs better than LS. The MMSE algorithm is not practicable for use in the majority of real-world applications due to its noise variance and channel statistics as prior information.

Apart from conventional algorithms like LS and MMSE algorithms, recent research has shown a growing emphasis on employing deep learning-based techniques for channel estimation. Deep learning models' ability to reproduce complex statistical characteristics of actual wireless communication systems [8]-[10]. However, the system's performance might suffer if there is a discrepancy between the training and application situations. To enhance the effectiveness of deep learning-based channel estimation, the integration of metaheuristic optimization algorithms has been implemented. These algorithms, with their straightforward structure and lack of requirement for continuous derivability, have become widely used for tackling difficult optimization problems in both natural and technical disciplines [11]-[13]. Over the past few years, ssubstantial advancements placed in metaheuristic algorithms. These improvements encompass a better balance between exploitation and exploration, the self-adaptation of hyperparameters, the evolution of population structures, and the theoretical analysis of search dynamics [14]. Abualigah presented a novel swarm-based technique called the Reptile Search technique (RSA). It is influenced by the crocodiles' social interactions, hunting techniques, and encircling mechanisms [15]. RSA has recently demonstrated outstanding functionality in tackling complex optimization problems across various engineering fields. The LS approach is very straightforward algorithm for channel estimation. However, its performance is inadequate in highly dynamic environments. The most efficient algorithm, often used as a benchmark for channel estimation, is the MMSE approach. Several modified MMSE algorithms recommended lowering the complexity of computing with same performance. Deep learning-based equalization and channel estimation have been prominent and well-researched topics in the literature in recent times. The Reptile Search algorithm offers numerous advantages that establish it as a viable and efficient optimizer for wireless communications. The Reptile algorithm is known for its simplicity and low computational overhead compared to some other complex optimization algorithms. This characteristic makes it attractive for resource-constrained wireless devices, which are common in practical communication systems.

- **Contributions**

There are several advantages to using the Reptile Search algorithm for channel estimate. First of all, it functions well even without previous knowledge about channel statistics, in contrast to the MMSE method. More deployment options are available for RSA-based channel estimation, which is another advantage over deep learning-based techniques that depend on a training process.
The main objectives of our suggested model are summed up as follows:
•To enhance the efficiency of mmWave communication systems in terms of spectral efficiency and NMSE.
•To achieve the highest possible channel estimation performance in mmWave MIMO communication by deploying a refined D-LSTM framework in conjunction with the RSA.
•To calculate the efficiency of our proposed method, we will assess its performance using commonly recognized performance metrics. Concurrently, we will compare these outcomes with those generated by well-established algorithms to provide a comprehensive evaluation.
The following is the structure of the next parts of the paper: In Section 2, a concise overview of channel estimation is presented, including its historical context and traditional techniques applied to pilot-based channel estimation. Section 3 presents the system model and the novel channel estimation methodology, which depend on the utilization of the Reptile Search algorithm. The outcomes of simulations and corresponding discussions are outlined in Section 4. Ultimately, Section 5 provides the concluson for the paper.

2. Background of Deep learning-based channel estimation

In 2019, Ma et al. [16] introduced a pioneering channel estimation strategy, incorporating Deep Learning Compressed Sensing principles to enhance mmWave channel modeling. The method's offline-trained neural network, receptive to correlations between measurement matrices and received signals, exhibited remarkable performance gains over traditional approaches in terms of spectral efficiency and NMSE. In 2020, researchers Yi and Zou introduced an innovative channel estimation technique termed the "Noise Elimination-aided Discrete Fourier Transform (DFT)" channel estimation method for mmWave vehicular transmissions, as documented in their work [17]. This method utilizes the iterative cancellation approach to comprehensively assess various influencing factors, subsequently applying a predetermined threshold to gauge estimation accuracy. In this procedure, both energy allocation and channel path estimation were carried out. Subsequently, the channel matrix was reconstructed using the evaluated parameters. The findings of their research revealed that the proposed approach exhibited superior performance when contrasted with existing systems. These results indicate that their approach has made substantial advancements over traditional models in terms of accuracy and reliability for channel estimation in the context of mmWave vehicular transmissions. In 2021, Manasa et al. [18] estimated MIMO channel coefficients at a transmitter. This method referred to as the Swarm Intelligence-based Deep Ensemble Learning Machine (SI-DELM), using the concept of swarm intelligence along with deep learning techniques. In SI-DELM, three distinct neural networks were employed. The process involved tuning parameters through a technique known as Assisted Mixture Ratio-based Cat Swarm Optimization (AIMR-CSO). The optimization method was employed to reduce both the Mean Square Error (MSE) and Bit Error Rate (BER).

In the year 2022, Song et al. [19] put forward a productive channel estimate technique that operates with a minimal subset of subcarriers. This approach formulates the challenge of channel estimation as a non-linear least squares optimization problem. Using consecutive subcarriers and a densely spaced antenna structure, the researchers managed to reduce ambiguity and effectively mitigate the impact of aliasing effects. The results of their study displayed promising achievements in addressing the complex, non-linear challenge of channel reconstruction. By strategically utilizing selected subcarriers and advanced antenna configurations, the proposed method demonstrated success in overcoming issues related to channel estimation and regeneration. Dai et al. [20] proposed a channel estimate model for the mmWave massive MIMO technique in 2021, based on the reduced size decomposition. To achieve higher estimate accuracy, experts broke down the channel estimation matrix. In order to get the sparse help collection, the "Sparse Signal Recover (SSR)" approach was utilized. "Least Squares Estimation (LSE)" was the model used to evaluate the route gain. Reducing training expenses and resources was a benefit of the suggested strategy. Crucially, experts used the matrix's NMSE functionality in channel assessment to assess the functionality, and they achieved improved functionality using different approaches. Gilbert and Bala [21] developed a "majorization minimization based fast non-convex (MM-FNC) algorithm" in 2021 to solve the non-convex regularization problem and estimate the channels. For huge-scale dimensional arrays with quicker convergence qualities, this model has assessed the low-rank channel. In 2021, Mostafa et al. [22] created the meta-heuristic-based clustering technique introduced to examine cloud workloads. Here, the fuzzy C-means technique and evolutionary algorithm have evolved the clustering strategy. For cloud workloads, the grey wolf optimizer (GWO) approach has been applied to determine the right scaling decision. Throughout the workload clustering process, the framework has been used to facilitate communication between users, cloud providers, and resource provisioning brokers. In 2022, Nallamothu et al. [23] introduced opposition-searched exploration-based Harris Hawks's optimization (OE-HHO) to enhance spectral efficiency by minimizing the normalized mean square error.

3. Method of System

Consider a downlink multi-user (MU) mmWave massive MIMO system. This system comprises user access (UA) endpoints and a base station (BS) equipped with a single antenna, as illustrated in Figure 1. The BS employs a uniform linear array (ULA) [24] for its antenna configuration. This approach can be adapted to different array structures. The BS possesses radio frequency (RF) chains and a certain number of antennas denoted as NRF and NAA respectively. In this context, hybrid precoding is employed, where the antenna count exceeds the number of RF chains, indicated as NAA ≫ NRF. The system employs orthogonal multiple access, which allows multiple users to transmit concurrently without interference. The number of active users denoted as U, is accommodated by the BS and is constrained to be less than or equal to the number of RF chains, i.e., U ≤ NRF. In scenarios where the number of active users (UA) is less than the number of RF chains (NRF), the BS allocates U-RF chains to simultaneously serve the U-users. The remaining RF chains, i.e., NRF − U, are deactivated to reduce power consumption. The collectively received signal for all U-users in the downlink scenario is denoted as z_{dl}, which can be mathematically expressed as:

$$Z_{dl} = H_{dl}.V_{RF}.F_{BB}.s + n_{dl} \quad (1)$$

Here, the additive white gaussian noise (AWGN) vector is shown as, $n_{dl} \epsilon \Re u$, which satisfies $n_{dl} \sim \alpha(0, \beta^2 I_U)$. The analog encoder and the digital pre-coder are pointed at V_{RF} and F_{BB}, respectively. Then, the signal vector is indicated as s $\in \omega^U$, and that should satisfy $E\{ss^h\} = I_U$. The entire user *BS* channel matrix is expressed in Eq. (2).

$$H = [h_1, h_2 \dots h_u]^T \in \omega^{U \times N_{AA}} \tag{2}$$

According to the *BS* via the "Saleh-Valenzuela mmWave" channel system the vector of the channel $h_u \in \omega^{N_{AA}}$ estimation is given in Eq. (3).

$$h_u = \sqrt{\frac{N_{AA}}{V_u}} \sum_{j=1}^{V_u} h_{u,j} = \sqrt{\frac{N_{AA}}{V_u}} \sum_{j=1}^{V_u} p_{u,j}\, \varepsilon\left(N_{AA}, \theta_{u,j}\right) \tag{3}$$

The multi-channel path count, channel vector, and complex gain of the *ith* path are denoted as V_u, $h_{u,j}, p_{u,j}$, respectively, in Equation (3). The line-of-sight (LOS) path for the first channel path is included h_u, and the non-line-of-sight (NLOS) paths for *ith* path $2 \leq i \leq V_u$ have consisted of $V_u - 1$, and then the steering vector $\varepsilon(N, \theta)$ is derived in Equation (4).

$$\varepsilon(N,\theta) = \frac{1}{\sqrt{N}}\left[1, e^{h\pi\theta}, \dots e^{h\pi\theta(N-1)}\right]^T \tag{4}$$

The u^{th} candidate in the j^{th} way for the "Angle of Arrival (AOA)" is uniformly given in the interval of $[-\pi, \pi]$. Figure 1 illustrates the system model of a massive MIMO system operating in the mmWave frequency range. The proposed "channel evaluation approach in the mmWave massive MIMO model" is designed to address the limitations of conventional techniques by utilizing a metaheuristic algorithm. The primary focus of this system is to achieve channel evaluation through the utilization of a multi-objective function. For this, the D-LSTM model which is developed by the integration of DNN [25] and LSTM [26] was employed in this work, where the parameters were adjusted using the developed RSA [27] model. This model, incorporating RSA, obtains metrics including Spectral Efficiency (SE), Normalized Mean Squared Error (NMSE), Bit Error Rate (BER), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Ultimately, the research evaluation is conducted and compared against conventional models. As a result, the proposed model achieves superior channel estimation performance compared to other traditional techniques.

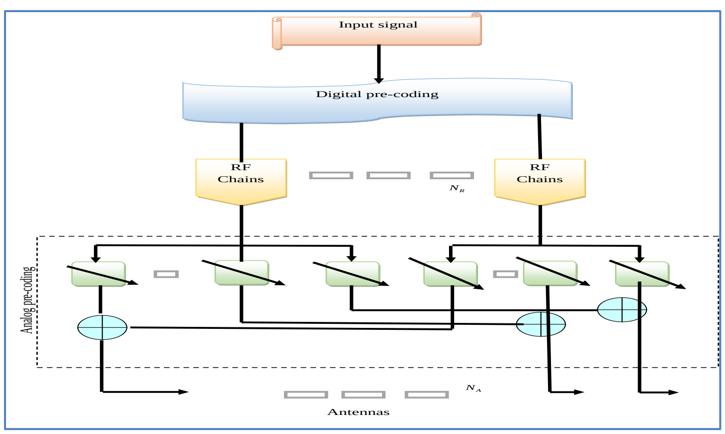


Figure 1. A model for mmWave MIMO communication system.

3.1. DNN

DNN [25] stands as a prominent deep learning algorithm, playing a crucial role in improving system efficiency and reducing the mmWave MIMO communication's complexity. The proposed method integrates both DNN and LSTM algorithms for channel estimation. DNN addresses the difficulties associated with "linear minimum mean square error (LMMSE)" and other traditional estimators. The structure of DNN consists of several levels like the initial level, intermediate level, and final level. Since this technique incorporates multiple intermediate levels, it is required to calculate the number of intermediate neurons within these levels. Each computational unit referred to as a "neuron" performs the following computations:

$$y = \sum_{j=1}^{m} w_j x_j + bi \tag{5}$$

Where y is the weighted computational unit, calculated from inputs and corresponding weights of each neuron denoted by $\{x_1, x_2, \ldots x_m\}$ and $\{w_1, w_2, \ldots w_m\}$ respectively, bias is given by bi. The neuron's output, denoted as a, is derived through a combination of linear and nonlinear transformations applied to the element y. This process can be expressed by equation (6).

$$a = f(y) = f\left(\sum_{j=1}^{m} w_j x_j + bi\right) \tag{6}$$

The commonly employed neuron functions include the logistic sigmoid, tanh, linear, and rectified linear unit (ReLU) functions, each defined as follows:

$$f_1(y) = \frac{1}{1 + e^{-y}} \tag{7}$$

$$f_2(y) = tanh(y) = \frac{e^z - e^{-z}}{e^z + e^{-z}} \tag{8}$$

$$f_3(y) = cy + d \tag{9}$$

$$f_4(y) = max(0, y) = \begin{cases} 0, & y \leq 0 \\ y, & y > 0 \end{cases} \qquad 10)$$

Using channel estimates obtained from the least squares estimation as its input, DNN is used to learn about the channel properties with the aim of minimizing errors. Reducing the average gap between the real and projected channels is the goal of using DNN for estimating. This is achieved by utilizing a specific loss function in the training process, as described in Equation (11).

$$Loss(W, \delta) = \frac{1}{NR} \sum_{nr=1}^{NR} \sum_{t=1}^{T} \|(f0_{va})^{nr}(t) - (ac_{va})^{nr}(t)\|_2^2 \tag{11}$$

In equation (11), weights and biases are given as W, δ correspondingly, the actual channel for $(f0_{va})^{nr}(t)$ is shown as $(ac_{va})^{nr}(t)$, and NR is the number of recognitions applied for the training process. Frequently, biases and weights used in DNN are iteratively adjusted from their beginning values by minimizing the loss function with the help of both prediction and error correction phases. Ultimately, the DNN methodology yields the predicted beam space channel amplitudes.

3.2. LSTM

LSTM [26] is employed in order to enhance performance of proposed estimation method. The LSTM network assists in monitoring the movement and beam direction by utilizing the received signals from beam training. In this context, LSTM has the capability to capture essential information while also filtering out redundant data. The fundamental RNN cell [28] considered as computational cell responsible for performing the computations described in the given equation (12).

$$hs_t = fn(w_{inhs} co_s + bi_{inhs} + w_{hshs} hs_{t-1} + bi_{hshs}) \tag{12}$$

$$fo_{va} = fn(w_{hsou} hs_t + bi_{hsou}) \tag{13}$$

In the above equation, bias for initial to intermediate level is denoted by bi_{inhs}, bias for intermediate level to next intermediate level is given as bi_{hshs}, bias for intermediate to final level is represented by bi_{hsou} and corresponding weights are w_{inhs}, w_{hshs}, w_{hsou} respectively. At the time step t the initial and final are mentioned as co_s and fo_{va} correspondingly. At time steps t and $t\text{-}1$, the intermediate states are given as hs_t and hs_{t-1} correspondingly. The activation function is mentioned as $fn(.)$ "The LSTM method is employed to perform the estimation of beam space channel amplitudes." The estimation of the downlink channel matrix H is achieved with reciprocity of channel and designing of A_{RF} and A_G is done by using H. Orthogonal pilot symbols are simultaneously sent by all users in the uplink channel for the purpose of distinguishing signals from multiple users, and this process is repeated multiple times *(f)* to improve signal differentiation. Each pilot symbol formed with length of U-orthogonal pilot symbols and the pilot matrix from U-user is represented by $R \in \Re^{u \times u}$.Moreover, various digital precoding and encoding matrices are represented by $A_{RF}^{f} \in \Re^{N_{AA} \times N_{RF}}$ and $A_G^{f} \in \Re^{N_{RF} \times N_{RF}}$ correspondingly.

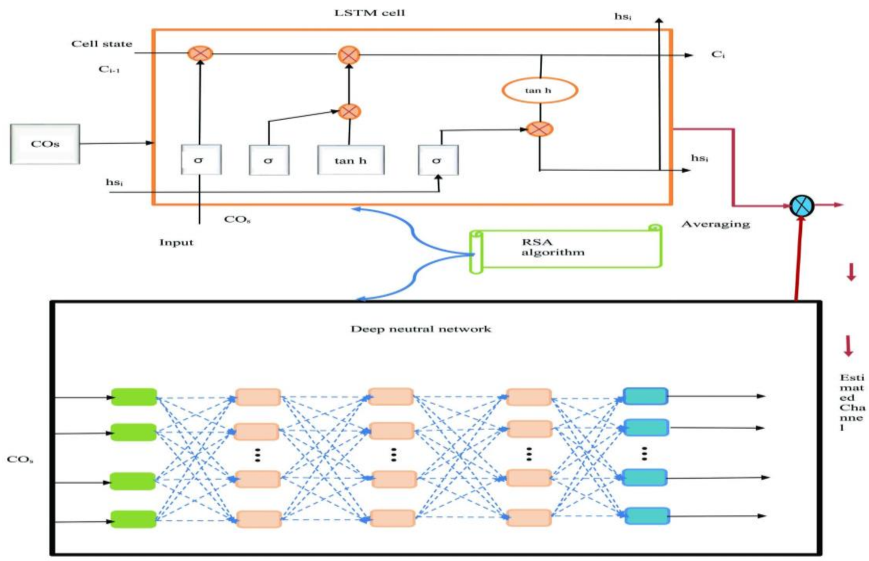


Figure 2. Channel estimation by using Hybrid deep learning.

Deep learning models can be employed to learn the mapping function, and also used to guess the mmWave channel characteristics with the advantage of reduced training overhead. In order to enhance the suggested design's performance, a hybrid deep learning method is adopted, which takes the input co_s, the correlation vector is rs_s and the estimation of beam space channel amplitude is referred to as ϕ.

$$\phi = \frac{N_{AA}}{Q} A^T A g^T \in \Re^{N_{RF} \times F \times Q} \tag{14}$$

The output expectation fo_{va} is obtained by taking the input as rs_s and ϕ for u = 1, 2, 3, ...U. The covariation array can be calculated using the equation (15)

$$co_s = \phi^H rs_s \tag{15}$$

The above covariation array is given as input to both LSTM and DNN to obtain results as estimated channel amplitude represented by h_s^g which is computed in equation (16).

$$q_s = \left[|h_s^g[1]|, |h_s^g[2]|, \dots, |h_s^g[Q]| \right]^T \in \Omega^Q \tag{16}$$

Ultimately, the result of hybrid deep learning denoted as $\widehat{q_s}$, what it is expected to be q_s.Moreover to enhance the performance in terms of efficiency, proposed mmWave MIMO model uses the RSA. The prime objective of this algorithm is to reduce the neuron count in the first and second intermediate levels of DNN as well as optimize the base training rate in LSTM. At the end, by taking the average of LSTM and DNN outputs final channel estimation is done, as shown in figure 2.

3.3. RSA

RSA is inspired by the encircling and hunting behavior exhibited by crocodiles. Crocodiles are semi-aquatic reptiles distinguished by their distinctive physical traits, including a streamlined physique, and capability to lift their legs to the sides while walking, a belly-crawling movement, and proficient swimming abilities. This part gives the exploration and exploitation attributes of RSA, which rely on the intelligent encirclement and pursuit of prey. Additionally, the mathematical operations and pseudo-code of RSA are included in this section.

3.3.1. Initialization stage

During this stage, initial candidate conclusions are created randomly in the search space, like other meta-heuristic algorithms. The initialization formula can be written as

$$Xik = rand\ (UB - LB) + LB, k = 1, 2..., n \tag{17}$$

X_{ik} indicates the i^{th} solution of the k^{th} search-agent position. The UB and LB are Upper and Lower boundaries of the search space respectively.

3.3.2. Exploration (Encircling stage)

During encircling stage, the exploratory nature of RSA is explored. During the encircling process, crocodiles perform two strategies. One is high walking and the other is belly walking. These movements pertain to various methodologies, each of which is dedicated to effectively conveying the algorithm's abilities for exploration. Crocodile motions, such as the high walk and belly walk, can avoid their ability to catch prey due to the noise they generate. Therefore, crocodiles may need to rely on alternative search mechanisms during an exploration phase in order to hunt successfully. Consequently, during this stage, the search process finds a better search, which require multiple search attempts before identifying a better location.

The RSA algorithm achieves coordination between exploration (encircling) and exploitation (hunting) by partitioning the total no. of iterations into four distinct phases based on specific conditions. The high walk movement is characterized by the condition t ≤ T/4, while the belly walk movement is explained by the conditions t > T/4 and t ≤ 2T/4 which implies that state for high walk movement will be satisfied nearly half of the exploration cycle, and the condition for the belly walk movement will also be met for the other half of the iterations, effectively dividing the exploration process evenly between the two strategies. The position upgrading formula for the exploration stage is described in Equation (18).

$$x_{(i,k)}(t+1) = \begin{cases} Best_k\ (t) \times -\eta_{(i,k)}(t) \\ \quad \times \beta - R_{(i,k)}(t) \times rand, & t \leq \frac{T}{4} \\ Best_k\ (t) \times x_{r1,k} \times ES(t) \times rand, & t \leq 2\,\frac{T}{4}\ and\ t > \frac{T}{4} \end{cases} \tag{18}$$

Here, t is the current iteration number, T is the maximum number of iterations, Best k (t) is the kth place in the best-yet-obtained solution, and rand is an integer that can have values between 0 and 1. The exploration operator of the *kth* point in the *ith* solution is identified by *η (i, k),* which is determined by applying Eq. (19). A crucial variable, denoted as *β*, governs the exploration precision for encircling (or high walking) repetitions, substituting the initial RSA, initially set at 0.1. As determined by Equation (20), *R (i, k)* is the amount used to decrease the search area. The letter *j* represents a random position of the *ith* solution, and r_1 is a random number between [1, N] and x_{r1}. The probability of decreasing values during the repetitions is given by Equation (21) and is represented by Evolutionary Sense ES (t), a random ratio between [2, −2].

$$\eta(i,k) = Bestk\ (t) \times P(i,k) \tag{19}$$

$$R(i,k) = \frac{Best_k\ (t) - x_{(r2,k)}}{Best_k\ (t) + \in} \tag{20}$$

$$ES\ (t) = 2 \times r3 \times \left(1 - \frac{1}{T}\right) \tag{21}$$

The random number *r2* in Eq. (20) ranges from [1, N] to a negligible sum. Since *r3* indicates that a random integer number falls between [1, −1], where *2* is the correlation value used to allocate values between *2* and 0. *Q(i,k)* is the difference, as determined by Eq. (22) between the *kth* position of the present solution and the *ith* position of the best-obtained solution.

$$Q_{(i,k)} = \beta + \frac{(x_{(i,k)} - N(x_i))}{Best_k(t) \times (UB_{(k)} - LB_{(k)}) + \in} \tag{22}$$

Where $N(x_i)$, as determined by Eq. (23), related to the average locations of the *ith* solution. The upper and lower bounds of the *kth* position are denoted, respectively, as $UB_{(k)}$ and $LB_{(k)}$. is a crucial parameter, set at 0.1 in this study, that directs the exploration accuracy for hunting cooperation during the course of iterations.

$$N(x_i) = \frac{1}{n} \sum_{k=1}^{n} x_{(i,k)} \tag{23}$$

3.3.3. Exploitation (hunting) stage

During this stage, RSA incorporates exploitative behavior, specifically hunting. Coordination and collaboration are two different tactics that crocodiles use when hunting. These tactics resemble the exploitation search procedure, which is expressed as given in Equation (24). The hunting coordination tactic is employed when the condition $t \leq 3T/4$ is met or when $t > 2T/4$. Alternatively, the cooperative hunting approach is used. The position update approach is developed by equation (24), which is applied throughout the exploitation phase.

$$X_{(I,k)}\ (t+1) = \begin{cases} Best_k\,(t) \times Q_{(i,k)}(t) \times rand, & t \leq 3\frac{T}{4} and\ t > 2\frac{T}{4} \\ Best_k\,(t) - \eta_{(i,k)}(t) \times \epsilon & \\ -R_{(i,k)}(t) \times rand, & t \leq T\ and\ t > 3\frac{T}{4} \end{cases} \tag{24}$$

The kth location in the best-found solution at time t is referred to as *"$Best_k\,(t)$"* in this context. Equation (19) is used to determine the hunting parameter for the *kth* point in the *ith* solution, which is represented by the symbol *"$\eta_{(I,k)}$"*. Equation (20) calculates the term $R_{(I,k)}(t)$,which denotes the amount employed in order to narrow down the search space for this iteration.

(1) Create the beginning population at random and set the RSA parameters to initial values.
(2) When t < T
(3) Evaluate each solution's fitness.
(4) Determine the best option available thus far.
(5) Use equation (21) to update the ES.
(6) Xi do
(7) Update the η, R, and Q values for every crocodile by applying equations (19), (20), and (22).
(8) Should t be less than 0.25T
(9) Apply equation (6) to ascertain the new position Xi.
(10) If t > 0.25T and t < 0.5T, then
(11) Apply equation (18) to find the new location Xi.
(12) If t > 0.5T and t < 0.75T, then
(13) Use equation (24). To find the new location Xi.
(14) Else
(15) Use equation (24). Determine the new position Xi.
(16) Come to an end if
(17) Assess the level of fitness and choose the most fit option.
(18) Complete while
(19) t = t + 1
(20) Return to the optimal position and fitness
(17) Assess the fitness and choose the best position

Deep MIMO data was used in MATLAB 2020a to implement the suggested approach. In this regard, spectral efficiency over existing heuristic algorithms and NMSE (Normalized Mean Square Error) were two metrics used to assess and compare the performance of the suggested system with traditional models.

Following data presents the simulation restrictions for mmWave large MIMO communication system design.
Ten populations are included; there are around 1024 OFDMs.
Maximum iterations: 10; Channel length: 4; Active base station: [1, 2, 3, 4, 5].
There are 32 antennas on the Y-axis; 8 antennas on the Z-axis; 4 on the X-axis; Bandwidth of 0.5000.
Factor of sampling for OFDM1with OFDM limit of 64; the base station's number is 5.
Five paths and 500,000,000 Hz of bandwidth; 724 users are listed; between antennas: 0.5000.

3.4. Performance metrics

1. MEP: "MEP" stands for "Mean Error Percentage." Which is the average of percentage errors between forecasts made by a model and the actual values of the quantity being forecast.

$$MEP = \frac{1}{n}\sum_{i=1}^{n}\frac{ac_i - fo_i}{fo_i} \times 100 \tag{25}$$

2. SMAPE: It stands for Symmetric Mean Absolute Percentage Error, is indeed an accuracy measure commonly used to assess the accuracy of forecasts or predictions. It is based on percentage errors.

$$SMAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|fo_i - ac_i|}{\frac{(|ac_i| + |fo_i|)}{2}} \times 100 \tag{26}$$

3. MASE: It stands for Mean Absolute Scaled Error, which compares the Mean Absolute Error (MAE) of estimated values to the MAE of a simple in-sample one-step naive forecast.

$$MAPE = mean\left(\frac{|fo_i|}{\frac{1}{n-1}\sum_{i=2}^{n}|(ac_i)_n - (fo_i)_n|}\right) \tag{27}$$

4. MAE: It stands for Mean Absolute Error, is a commonly used metric for evaluating the accuracy of a predictive model, particularly in regression analysis. It measures the average absolute difference between the predicted values and the actual values in a dataset.

$$MAE = \frac{\sum_{i=1}^{n}|(ac_i)_n - (fo_i)_n|}{n} \tag{28}$$

5. RMSE: Root Mean Square Error is a commonly used metric in statistics and machine learning for evaluating the accuracy of a predictive model. It measures the average magnitude of the errors between predicted values and actual values.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}((fo_i)_n - (ac_i)_n)^2}{n}} \tag{29}$$

6. BER: Bit Error Rate measures the rate at which bits of data are erroneously received or decoded compared to the total number of bits transmitted.

$$BER = \frac{1}{2} erfc\sqrt{\frac{Eb_r}{Nb_o}} \tag{30}$$

7. L1-NORM: The L1-norm represents the cumulative sum of the absolute values of vector components within a given space.

$$l1 = \sum_i |l_i| \tag{31}$$

8. L2-NORM: It corresponds to the minimum distance required to travel between two points.

$$l2 = \left(\sum_{i=1}^{i} l_i^2\right)^{\frac{1}{2}} \tag{32}$$

9. L-INFINITY NORM: The length of a vector can be determined using the maximum norm.

$$l_\infty = \max_{1 \le i \le n} |l_i| \tag{33}$$

4. Results and Discussion

The suggested "mmWave massive MIMO communication system" channel estimate was implemented using Deep MIMO data in MATLAB 2020a. Here, the suggested model's performance was evaluated against the conventional models using a variety of metrics, including spectral efficiency and NMSE, in comparison to other heuristic algorithms such as the Direction of Arrival (DOA) [27], the Deer Hunting Optimization Algorithm (DHOA) [28], and Harris Hawks Optimization (HHO) [29]. Figure 3 presents the results of evaluating the performance of suggested channel estimation using an RSA-D-LSTM-based technique by adjusting the learning percentages. In order to determine the efficiency of the suggested channel estimation technique, different performance metrics like MEP, SMAPE, MASE,

MAE, RMSE, L1-NORM, L2-NORM, L-INFINITY NORM are evaluated. In terms of MEP shown in Fifure 3 (a) the RSA-D-LSTM secures 16.66%, 25%, and 31% better compared to DOA-D-LSTM, DHOA-D-LSTM, and HHO-D-LSTM respectively at 40 learning percentage rates. In terms of L-INFINITY NORM shown in figure 3 (h) the RSA-D-LSTM secures 26.15%, 31.42%, and 40% better compared to DOA-D-LSTM, DHOA-D-LSTM, and HHO-D-LSTM respectively at 35 learning percentage rates. Similarly, in remaining all parameters, proposed method shows better performance compared to other algorithms.

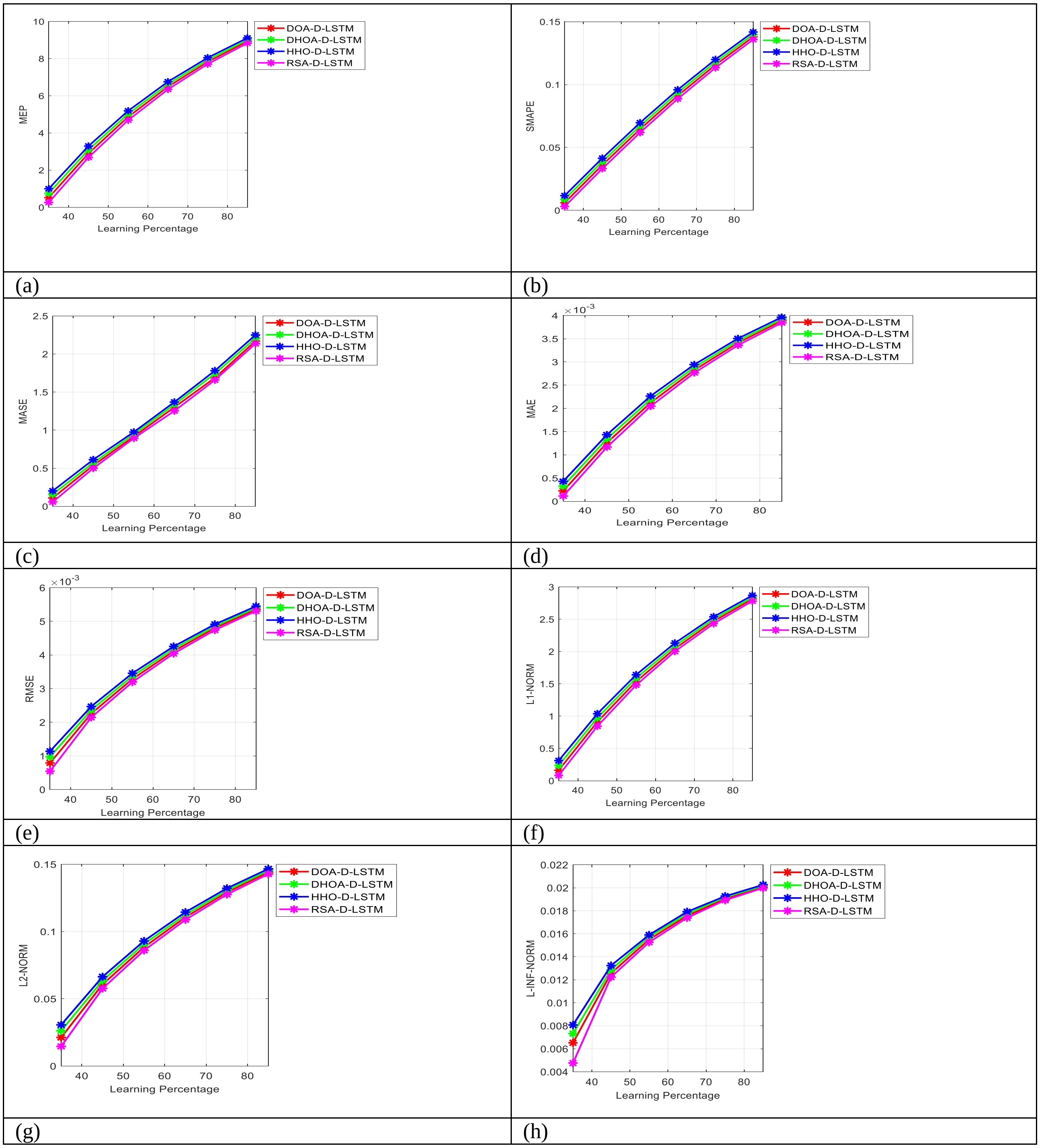
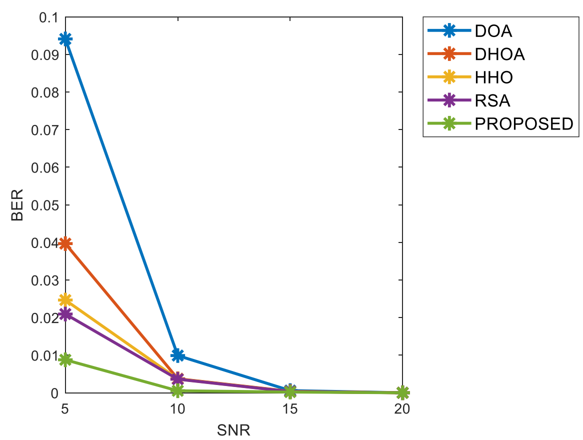
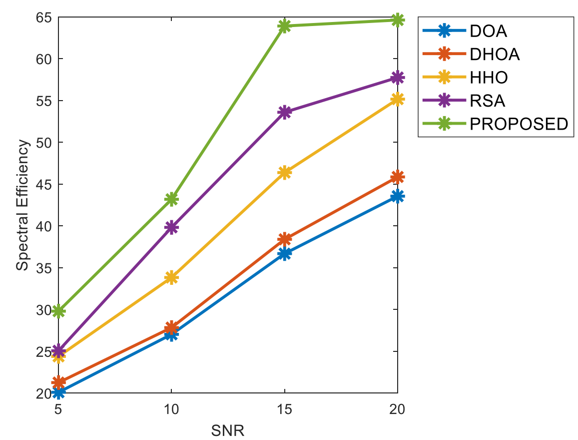


Figure 3. Analysis of the suggested system's channel estimate performance using heuristic methods expressed in terms of (a) MEP, (b) SMAPE, (c) MASE, (d) MAE, (e) RMSE, (f) L1-NORM (g) L2-NORM and (h) -INF-NORM.

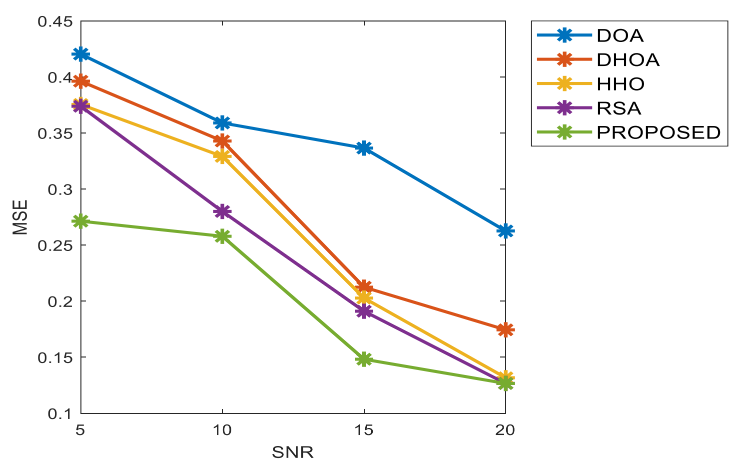
The effectiveness of the suggested channel estimation method designed with RSA-D-LSTM is evaluated, based on various performance metrics across different Signal-to-Noise Ratios (SNR) in comparison to heuristic techniques. The results of this evaluation are presented in Figure 4. The BER of the RSA-D-LSTM is 89.47%, 75%, 60% and 50% minimized than DOA, DHOA, HHO, and RSA respectively for SNR = 10 dB which is shown in figure 4 (a). Likewise, the spectral efficiency of the RSA-D-LSTM is 68.62%, 62.26%, 30.3%, and 19.77% higher than DOA, DHOA, HHO, and RSA respectively for SNR = 10 dB as shown in figure 4 (b). The MSE of the RSA-D-LSTM is 40%, 36.25%, 23.88%, and 28.16% reduced compared to DOA, DHOA, HHO, and RSA respectively for SNR = 5 dB which is shown in figure (c).



(a)



(b)



(c)

Figure 4. Analysis of proposed method for estimating the channel using heuristic techniques over (a) BER (b) Spectral Efficiency (c) MSE.

4.1. Channel Estimation - Algorithm Comparison

The statistical analysis of the proposed RSA_D_LSTM by comparing with different meta heuristic algorithms like DOA_D_LSTM, DHOA_D_LSTM and HHO_D_LSTM is as shown in table 1. From the analysis it is observed that the proposed method achieves good spectral efficiency by minimizing the errors compared with other techniques. The MEP of the RSA-D-LSTM is 1.5%, 2.9%, and 4.23% reduced compared to DOA_D_LSTM, DHOA_D_LSTM and HHO_D_LSTM respectively.

Table1: Performance comparison with different algorithms

TERMS	DOA_D_LSTM	DHOA_D_LSTM	HHO_D_LSTM	RSA_D_LSTM
MEP	7.826	7.9371	8.0478	7.7069
SMAPE	0.11569	0.11784	0.12001	0.11341
MASE	1.6881	1.7428	1.7815	1.6589
MAE	0.0034111	0.0034589	0.0035058	0.0033594
RMSE	0.0047999	0.0048565	0.0049117	0.0047395
L1-NORM	2.4696	2.5043	2.5382	2.4322
L2-NORM	0.12915	0.13067	0.13216	0.12753
L-INF-NORM	0.019031	0.019178	0.01927	0.018923

4.2. Channel Estimation - Classifier Comparison

The statistical analysis among various classifiers like CNN, DNN, D_LSTM and RSA_D_LSTM in terms of different errors is observed in table2. The proposed method minimizes normalized mean square error (NMSE) compared other techniques.

Table 2: Performance comparison with different Classifier

TERMS	CNN	DNN	D_LSTM	RSA_D_LSTM
MEP	8.3909	8.5063	8.6201	7.7069
SMAPE	0.12683	0.12917	0.1315	0.11341
MASE	1.9259	1.974	2.0134	1.6589
MAE	0.0036536	0.003703	0.0037519	0.0033594
RMSE	0.0050836	0.005141	0.0051993	0.0047395
L1-NORM	2.6452	2.681	2.7164	2.4322
L2-NORM	0.13679	0.13833	0.1399	0.12753
L-INF-NORM	0.019527	0.019647	0.019782	0.018923

5. Conclusion

In this research, a novel estimation of channels model with integrated D-LSTM classifier and improved hybrid deep learning technique is presented for mmWave MIMO systems of communication. The RSA technique has increased the channel estimation model's efficiency. Enhancing spectral efficiency while lowering the Normalized Mean Squared errors (NMSE) rate was the important aim of the developed system. According to the performance analysis, the RSA-D-LSTM minimizes MAE compared to CNN, DNN, and D-LSTM by 8%, 9.27%, and 10.46%, respectively. Comparing the suggested model to other methods, data indicate that it performs effectively in channel estimation. In terms of future work, it is possible to improve and assess how well the suggested RSA-D-LSTM model performs when channel coding and multiple-input multiple-output setups are in place.

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