PARTICLE SWARM OPTIMIZATION–LONG SHORT-TERM MEMORY BASED CHANNEL ESTIMATION WITH HYBRID BEAM FORMING POWER TRANSFER IN WSN-IOT APPLICATIONS

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ABSTRACT

Non-Orthogonal Multiple Access (NOMA) helps to overcome various difficulties in future technology wireless communications. NOMA, when utilized with millimeter wave multiple-input multiple-output (MIMO) systems, channel estimation becomes extremely difficult. For reaping the benefits of the NOMA and mm-Wave combination, effective channel estimation is required. In this paper, we propose an enhanced particle swarm optimization based long short-term memory estimator network (PSO-LSTMEstNet), which is a neural network model that can be employed to forecast the bandwidth required in the mm-Wave MIMO network. The prime advantage of the LSTM is that it has the capability of dynamically adapting to the functioning pattern of fluctuating channel state. The LSTM stage with adaptive coding and modulation enhances the BER.PSO algorithm is employed to optimize input weights of LSTM network. The modified algorithm splits the power by channel condition of every single user. Participants will be first sorted into distinct groups depending upon respective channel conditions, using a hybrid beamforming approach. The network characteristics are fine-estimated using PSO-LSTMEstNet after a rough approximation of channels parameters derived from the received data

KEYWORDS

Signal to Noise Ratio (SNR), Bit Error Rate (BER),mm-Wave, MIMO, NOMA, deep learning, optimization.

1. INTRODUCTION

With the increase in the requirement of wireless spectrum, the underdeveloped mm-Wave has gained attention due to its enormous throughput as well as better signal economy [1]. Since the transponder could correct for considerable signal attenuation utilizing the combinational gain supplied mostly by Omni- directional antenna elements, it tends to be the most sought technology in 5G transceivers [2]. The mm-Wave technology helps to reduce computational burden and power utility. To eliminate the conflicts with some of the existing users, every radio wave link accommodates one user at a time. [3]. As the percentage of users expands, nonlinear operations classify the signals for every single user [4]. However, NOMA technologies could circumvent such fundamental constraints by employing coherence programming with successive interfering cancelation (SIC) at the receiver [5]. Multi-input signal identification is made possible mostly by the capabilities of neural networks rather than that of the classic interference cancellation method [6]. Transfer learning has currently gained popularity in the field of machine learning [7].

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Inter-symbol interference may occur due to wireless channels with multipath fading. the channel estimation techniques are classified into two namely, blind and pilot-based estimation [8]. Without the assistance of a preamble or pilot signal, the wavelet coefficients of the receiver side were used in fading channels [9]. To determine the performance indicators, a learning series containing existing data symbols are introduced at the beginning of broadcasting [10].

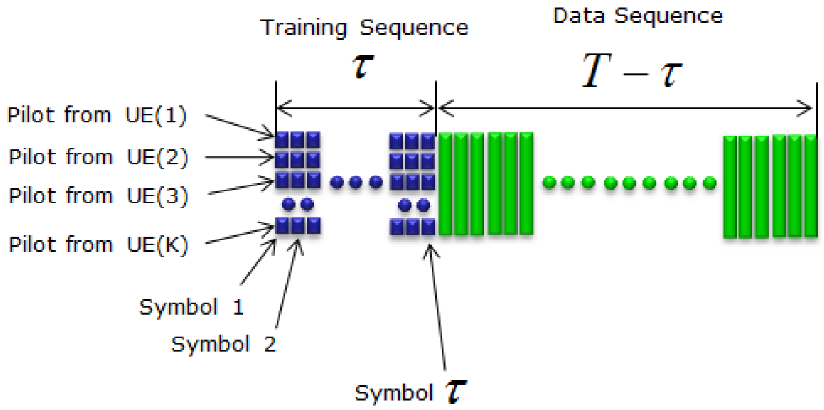

Figure 1. Sequencing the pilot data from user equipment

Figure 1 shows pilot signals from various user equipment. Block-type and comb-type are the basic categories of pilot-oriented channel estimation [11-13]. To achieve channel estimation, OFDM symbols are regularly sent with pilots across every subcarrier in block type. Since pilot frequencies were injected into every sub-channel of precoding over a specific period time, the frame pilot scheme is well adapted for intensity and slow multi-path fading [14]. Each symbol under these aforementioned categories contains more pilot symbols on the frequently distributed subcarriers. From the literature, it is inferred that the Comb-type pilot arrangements are better than block-type pilot arrangements. MMSE methods surpass LS algorithms in most cases, and they're more complicated [15].

Deep learning has gained a wide range of popularity due to its merit and the deep neural network embedded wireless communication system acts as a black box for the transmission and reception of the signal. Limited experimental and numerical results alone exist to justify the contribution of DL in studying major wireless system functional components methods seem to lack evident analytical sources to examine their advantages as well as limitations. A necessity arises to analyze the excellent performance of numerous tasks that are performed by DL method in order to still enhance its performance as well as to incorporate it for various scenarios. It is important to have complete cognizance about the limitations of DL in terms of wireless communication networks to have a better cognizance of suitable scenarios that are apt for DL-enabled communication systems. One of the prime concerns to be taken into consideration is the ability of the data-driven DL method to cope with the algorithms utilized in the field of wireless communication which are the due to outcome of human intervention. Signal and coding theories based on theoretical and practical approach helps to address the impairments such as channel fading, interference and noise in PHY communications. It seems to be uncertain that the black box DL method can outperform the white box DL approach. The DL methods have widely suppressed traditional signal processing techniques which contribute to optimum performance even without expertise.

The Motivation of this research work is briefed as follows, it seems to be a matter of concern that very sparse literature findings exists for earlier research that back deep neural networks (DNN) can outperform commonly used signal processing methods. The necessity arises to generate sufficient theoretical findings to justify the capability of DL-based communication systems. At present, more researches carried out suggest that DL methods are best suited for channel estimation due to its merit and frequent deployment of neural network with wireless communication system seem to be the recent trend which seems to be efficient though. Recent successful researches have proven DLL as an effective technique corresponding to channel estimation. This seems to be a major boost to rely upon and employ DL methods in order to perform effective channel estimation.

The following observations are considered to perform the pilot-based channel estimation by employing artificial intelligence.

The wireless communication model with appropriate hybrid beamforming employs the PSO-LSTMEstNet to achieve effective channel estimation (CE). Particle swarm optimization tunes the pilot impulses of the network, as opposed to a standard optimizer with a a specific learning rate. A multi-antenna downstream device is utilized in MIMO-NOMA mm-Wave broadcast architecture.

This paper is presented as follows: Section 2, illustrates the literature for optimization and neural network-based channel estimation with its limitations. Section 3 briefs the proposed PSO-LSTMEstNet model for efficient channel estimation. The empirical study is provided through figure representations in section 4. Finally, section 5 concludes the work by providing suitable concluding remarks.

2. RELATED WORKS

This research concentrates on improving the spectral efficiency of the mm-Wave MIMO–NOMA channel using a novel optimization technique hybrid beamforming scheme. The existing literature associated with the mm-Wave optimization method and artificial intelligence-based channel estimation methods were explained.

In comparison to traditional CE algorithms, the researchers in [16] presented a deep learning (DL) framework to enhance CE effectiveness and decrease computational costs. The researchers designed a convolutional neural network for MIMO (CNN-MIMO) that takes an incomplete channel matrix as input. The drawback is that it does not affect on either diversity increase or computation cost. The researchers designed a convolutional neural network for MIMO (CNN-MIMO) that considers an incomplete channel matrix as input. The drawback is that it has no effect on either diversity or computation cost. In [17], a generative adversarial network (GAN) is built for low-dimensional space using optimal digital and analog precoders. Through conceptualizing multimodal spatial multiplexing like a trans optical solution and instead arranging subsequent loop as a nodule, the investigators were keen to minimize search complexity. As a consequence, a unique model-based DNN with domain expertise is created. The major constraint is that, when the number of mobile terminals to BS antennae ratio is near to each other, it exhibits over CE performance. In [18], a Convolutional Deep Stacking Network (CDSN) is employed to remove the knowledge about the coherence, a rigorous method was provided to rebuild the scarce impulses first from measuring matrices. A deep fully connected neural network was employed in [19]. From the observations, it is inferred that such model is more effective than typical CS modeling techniques. A new LSTM system was proposed in [20], for solving an optimal control problem, and it justifies that the provided process surpasses standard dense overhaul techniques used for the investigation on actual statistics. The backpropagation (BP) approach was presented in [21] for constructing a multicellular feedforward neural network. A deep learning-based approach enabling intuitive channel quality can be estimated & rapid retrieval of broadcast signals were presented in [22]. The authors recommend an approximation message transmission structure for MIMO devices in [23]. This approach dramatically enhances the effectiveness of restoration as well as the reduction trade-off by instantly taking cognizance of spatial information immediately by merging sample covariance in MIMO carriers.

Table-1 comparison between various existing methods

Author	Method	**accuracy**	**BER**
Balevi et al. [16]	convolutional neural network	94.3%	32dB
Chen et al., [17]	generative adversarial network (GAN)	87.3%	-0.458
Palangi et al., [18]	Convolutional Deep Stacking Network (CDSN)	91.4%	-123
Mousavi et al., [19]	deep fully-connected neural network	90.3%	15 dB, 20 dB, 25 dB, and 30 db; MSE=10^{-5}
Rajendran et al., [20]	LSTM	87.2%	-0.432
Taspinar et al., [21]	multicellular feedforward neural network	90%	15 dB, BER=0.5
Ye et al., [22]	approximation message transmission structure	88.5%	15 dB, 20 dB, 25 dB, and 30 db; BER=10^{-2}
He et al., [23]	spatial information	84.5%	15 dB, 20 dB, 25 dB, and 30 db; MSE=10^{-3}

The fundamental issue of hybrid detection in MIMO is to develop an equipment stage with low volatility, perceived control, outstanding performance, and maximum throughput. At present, very few methods are analyzed which can combat the issue with its own limitations corresponding to complexity and real time execution. ML identification is regarded as the best technique to combat BER through exhaustive search irrespective of its complexity which is exponentially larger than the number of transmission and reception radio lines. Direct approximations such as, zero-forcing (ZF) as well as MMSE, on the other hand, have a lesser intricacy but a large execution tragedy. The utilization of mm Wave in wireless communication systems facilitates the need for interconnectivity. Most of the researches carried out suggest an unrealistic approach to employ multiple users with a requirement of single antenna per user. In order to design channel estimation algorithms, the multiple access technique that is employed must be taken into account. Therefore, additional work must be devoted to the pilot contamination challenge that has the potential to restrict the number of scheduled users while degrading channel forecast accuracy.

3. SYSTEM MODEL

The input data is first passed to a converter block, which converts serial data to parallel data. The data is then passed via a 64-QAM block, which uses a single radio wave to indicate six bits of data by altering parallel data, where K symbols form a modulated data block [24]. A MIMO encoder/decoder block is shown, with a prefix included to counteracting multipath fading. The modulator is linked to the sub carrier block, which comprises of numerous pilot blocks. The Particle swarm optimization approach is used to identify the best pilot. The input for PSO is set of pilot signals coming from a 64-QAM modulators [25]. The optimal pilot signals are given to the LSTM network for efficient channel estimation as shown in figure-2. The optimal pilot signals can be denoted as {opt(pi1),opt(pi2),…..opt(pin)} which is the input for LSTM.

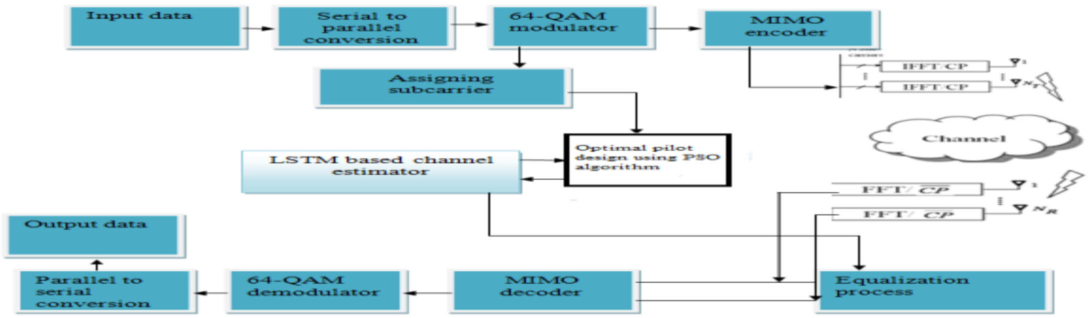

Figure-2 Particle swarm optimised LSTM channel estimator network block diagram (PSO-LSTMEstNet)

3.1. Pilot signals arrangement with sparsity in MIMO-NOMA

Data transmission results from a base station (BS) on M transmitters that use MIMO systems to broadcast the input messages, with each radio transmitter's duration being N cycles, within W(0 < W < K) which W(0 < W < K) signals and the channel width L have been selected as the data transmission pilot. The i the transmission directional antennas pilot design pio_(k), k = 1, 2, ..., N, where pio(k)∩pio(l) = ∅, If k ≤ l.

The impact of channel estimation by utilising the fragmented properties of the channels and minimal pilot symbols, thus improves bandwidth consumption.

$$\left\{\frac{p}{2}, piseven; p+\frac{1}{2}pisodd\right\} \tag{1}$$

As a result, researchers evaluate the sparsity first and then choose those components that fall inside that region. Because the amplification factors of the network tapping were larger than just the background signal at greater signal-to-noise ratios, the recovered scalar components were organized on highest to the lowest. The disparity between entities that interact is being used to measure the number of components chosen for such repetition as well as to approximate the sparseness progressively. Since they may contain data signal, the items preceding the highest divergence were chosen for such an extended version.

3.2. Optimal pilot design using Particle Swarm optimization method

Training symbols are sent to aid pilot-aided channel estimation (PACE). The transmit vector $x[k]$ can be expressed as $X \in C^{N_t \times N_t}$ when stacked in a matrix. To ensure a full rank, a minimum of N_t training symbols must be conveyed. The training matrix is made up of orthogonal sequences that have been subjected to $XX^t = \mu I_{NT}$ where µ is the signal strength assigned to the training matrix. Since the optimization problem (P1) is non-convex, traditional convex optimization methods cannot be applied. Therefore, in this paper, we leverage the IPSO mechanism to solve it.

Lets start by periodically making a series of x_p i.e., $X = \{x_{p,i}\}$, i=1,2,....K, where another component $x_{p,i}$ indicates an approximate solutions in (P1) while K is the predetermined overall density $f(x_{p,i}) = \mu avg(x_{p,i})$.. The metaheuristic optimization adjusts the component $x_{p,i}$placement pbesti and the optimal solutions resolution gbest fitness evaluation value. In the t[th] repetition, the trajectories of components $x_{p,i}$ are changed as follows:

$$v_i^t = wv_i^{t-1} + c_1r_1\left(pbest_i - x_{p,i}^{t-1}\right) + c_2r_2\left(gbest_i - x_{p,i}^{t-1}\right) \quad (2)$$

$$x_{p,i}^t = x_{p,i}^{t-1} + v_i^t \quad (3)$$

where v_i^{t-1} and $x_{p,i}^{t-1}$ indicates the particle's position and speed. $x_{p,i}$ in the (t − 1)-th iteration. w is the weight vector, which would be employed to keep the particle's movement reluctance constant since it can increase the subspace. In generally, the parameter is dynamically modified within every know prior on the optimisation findings. The training parameters c1 and c2 refer to the quantum state stride length as it moves more toward the ideal place. When [0,1], r1 & r2 are equally dispersed. Each variable is $(x_1, x_2, \ldots . x_{Mvar})$ floating number, fitness widow is determined using fitness function f in widow $(x_1, x_2, \ldots . x_{Mvar})$ so,

$$Fitness = f(widow) \quad (4)$$

The widow denotes the portion of data received across the channel, while M_{var} denotes the total number of pilots assigned to the channel, the $x_1, x_2, \ldots . x_{Mvar}$are used to tally the overall number of channels. The optimization technique begins with the size $M_{pop} \times M_{var}$ candidate widow matrix generated by the spider's first population. The parents are chosen at random to carry out the procreation process through mating.

- Procreate- This step reproduces the array with alpha named as widow array of random numbers, that contains the offspring as shown in the equation where x_1 and $x_2$denotes parents and the offspring refers by $y_1$and y_2

$$y_1 = \propto \times\, x_1 + (1 - \propto) \times x_2 \quad (5)$$

$$y_2 = \propto \times\, x_2 + (1 - \propto) \times x_1 \quad (6)$$

The process is repeated for $\frac{M_{var}}{2}$ times, in randomly manner.

- Cannibalism- The first sort of cannibalism in the algorithm is sexual cannibalism, in which a black widow spider eats her spouse during mating. The fitness values of women and males are used to identify them in this method. The second type of cannibalism is sibling cannibalism, in which stronger particles eat their weaker siblings. This method establishes a cannibalism rating depending on the number of survivors and uses the fitness value to determine if the spider hatchlings are robust or feeble.
- Mutation- At this point, choose an arbitrary number of individuals to represent the mutation population. At the array, each of the chosen solutions replaces approximately two elements.
- Convergence- Three stopping conditions are assumed, as with every evolutionary algorithm: Predetermined repetitions (A). (B) The Observation that the fitness value of the better widow employed for varied repeats does not change. (C) Attain a specified level of precision.

- Parameter setting- Procreation Rate (PR), Cannibalism Rate (CR), and Mutation Rate (MR) are the variables specified in the PSO algorithm. To improve the algorithm's performance and achieve greater results, parameters must be altered appropriately.

3.3. LSTM network-based channel estimation

Pilot pattern is the foundation for further examination in pilot-aided channel estimate algorithms for OFDM systems. The block pilot pattern effectively overcomes frequency-selective fading by inserting pilot symbols into all subcarriers in an OFDM signal,

Step-1 Initialize the weights (w) and bias (b)

$W = \{w_1, w_2, w_3, .. w_n\}$
$B = \{b_1, b_2, b_3, b_n\}$
Epochs (E)→ $e_1, e_2, .. e_n$

Step-2 Update the training sets- $\{(x_1, t_1), (x_2, t_2), .. (x_m, t_m)\}$

Step-3 Include the pilot signals- $X_i = (i = 1,2,3 \ldots m) and\ t_i = (i = 1,2,3 \ldots m)$

Repeat the above steps-1 to step-3

Step-4 Calculate the output layer $o' = \{(o_1 x_1, t_1), (o_2 x_2, t_2), \ldots . (o_m x_m, t_m)\}$

Step-5 Compute the cost function

E= $\sum_{k=j}^{n} \mathrm{f}(x_i, t_i)$

Step-6 compute the partial derivation for weight and bias

Until reach iteration =I(c)
Return the training samples calculation
If

Step-7 I(c)>x_iElse

Step-8 Restart the training process

endif

3.3.1. Structure of LSTM network

A MIMO wireless communication system has been considered. The signal that is delivered at the receiver's end is written as,

$$y = Hx + n$$

While n represents AWGN, H is the network error signal, and x represents the incoming signal. The encoder, hidden units, and output vector make up the LSTM network model. The input is accepted by the encoder. The LSTM cells make up the buried layer. The predictive performance are shown in the output layer. Input, forget, and output gates are all present

The control signal determines when fresh data may be recorded in the current block as well as keeps undesired data out of the main memory. The update gate ft checks its prior statec_{i-1}has been forgotten (i-1). After that the memory is updated (i.e) $c_i$to the forget gate and the input gate function together. The resultant gate determines what data will be sent out. The information of these gates in an LSTM network matches the equations beneath.

$$f_t = \sigma(w_f x_t + R_f h_{t-1} + b_f) \quad (7)$$

$$g_t = \tanh\,(w_g x_t + R_g h_{t-1} + b_g) \tag{8}$$

$$i_t = \sigma\,(w_i x_t + R_i h_{t-1} + b_i) \tag{9}$$

$$o_t = \sigma\,(w_o x_t + R_o h_{t-1} + b_o) \tag{10}$$

Where R_f, R_g, R_i, R_o denotes the weights matrices for the previous short-term stateh_{t-1}. w_f, w_g, w_i, w_o are the weight matrices in the current input statex_t, and b_f, b_g, b_i, and b_o are the bias terms. The current long-term state of the network$c_t$can be calculated as

$$c_t = f \times c_{t-1} + i_t \times g_t \tag{11}$$

And the output y of the network is

$$y = h_t = +o_t \times \tanh\,(c_t) \tag{12}$$

Upon that output side, a converter is required to transform the codeword containing the received signal onto concurrent data feeds. The Inverse Fourier Transform will then be used to transfer the waveform into the time-frequency domain. A coding scheme must be used to lessen the effects of cross-functional and cross-interference. The width of the CP should be bigger than just the maximum propagation latency of the stream. It is designated the spread spectrum network of a sampling region bounded by sophisticated randomized variables $\{h(n)\} \sum_{n=0}^{n-1} k$. Following that, the impulse response can indeed be analyzed as follows:

$$y(n) = x(n) \oplus h(n) \oplus w(n) \tag{13}$$

wherein $x(n) \oplus h(n)$seems to be the control input, $\oplus$convolution is cyclic, $w(n)$ and $y(n)$seems to be the integral gain. Inside the fourier transform, the impulse response could be described:

$$Y(K) = X(K)H(K) + W(K) \tag{14}$$

where, the FFT of $x(n)$, $h(n)$, $y(n)$and $w(n)$ are $X(K)$, $H(K)$, $Y(K)$and $W(K)$, respectively. The output (o_t) of LSTM network can be expressed as

$$o_t = LSTM(l_{t-1}, l'_{t-1,} x_t, x'_{t,} \theta_{bi}) \tag{15}$$

Whereas $l'_{t-1,}$ represents the LSTM channel's downstream hidden column during schedule t-1, whereas $x'_{t,}$represents the LSTM channel's backwards inputs at prime time t. θ_{bi}& LSTM(•) signify together all parameters and transformations functions of the LSTM network, correspondingly.

The initial stage in LSTM-based predictions would be to calculate the carrier for such currently obtained OFDM signal employing originally expected performance indicators, with the i-th Memory system supply marked as x'_i.

This early phase in LSTM-based forecasting is to guess the network again for present receiving OFDM signal employing originally expected performance indicators, with the i-th LSTM unit output marked by x'_i.

$$x_i' = \begin{cases} h_{(lstm)}[k], \; where \; k \epsilon k_d \\ h_{i-1}[k] \; where \; k \epsilon k_p \end{cases} \tag{16}$$

x_i' is generated by converting a complex value to a real value and stacking the real and imaginary values in a single vector. After that, using the i[th] received OFDM signal, pilot aided estimation is performed in the LSTM estimated channel. To get the optimum performance, the suggested LSTM training is carried out with SNR = 40 dB. This is because when the training is carried out with a high SNR value, the LSTM is capable of learning the channel statistics better and has a good generalization capacity.

3.3.2. Construction of PSO-LSTMEstNet

The number of OFDM symbols is used as the time sequence number since the LSTM network requires symbols as input. The data is sent into a 1D CNN network after pre-processing, and feature vectors are retrieved using 1D-CNN. Because the continuous response is directly estimated in time-domain channel estimation, when contrasted to modifications that occur estimate, the source data does have an additional latency element. Channels estimate in the frequency response is not the same as fading channels in the temporal domain, the variables to be estimated are compressed using a 1D Maxpooling layer. The information is moved to the LSTM model post background subtraction & attribute dimensionality minimization, as well as the optimized pilot information, is delivered right to the LSTM model like illustrated in figure 3.

The carrier configuration information matrix is used as training dataset to the training stage throughout this study. The CSI matrices are represented by $H \in C^{T\times N}$ as time-frequency fading channels as well as as $G \in C^{T\times NL}$as transfer function data transmission. Least Squares (LS) is used to compute the CSI at precoding, whereas the CSI at information bits is set to 0. As a result, $H \in C^{T\times N}$ for bandwidth fading channels and $G \in C^{T\times NL} + 0$for time and frequency domains channel model can be used as the output to the training stage. The LSTM unit requires a temporal relationship, result, the CSI is represented as such and turned into a series.

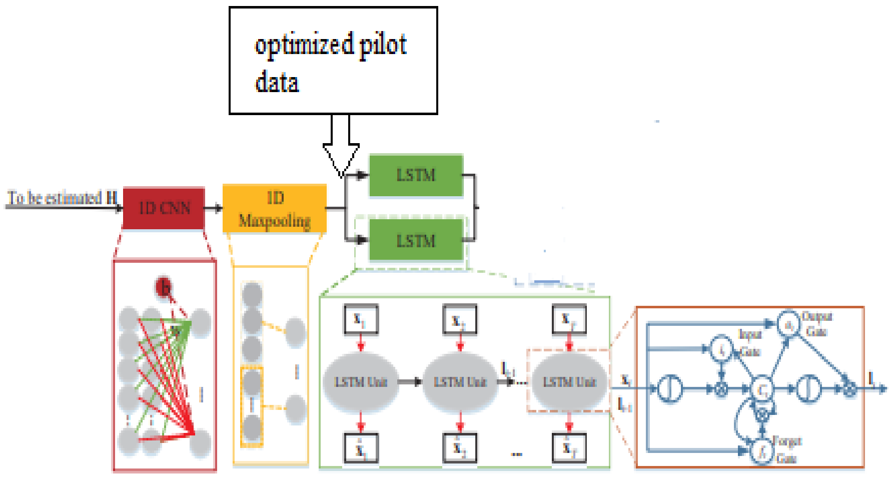

Figure 3. Architecture of PSO-LSTMEstNet

$$G = \{g_1, g_2, \ldots . g_t\} \tag{17}$$

where $g_t \in C^{1\times NL}$ denotes the CSI at the T^{th} OFDM symbol. Because multichannel data collected is a complicated waveform, it must be pre-processed before ever being fed into the knowledge construction structure. The received information is transformed by distinguishing the complex numbers $G^i \in R^{T\times 2NL}$ and $g'_t \in R^{1\times 2NL}$

The incoming data is pre-processed before being sent to CNN for extraction of the frequencies feature space. The main purpose of CNN is to extract then select a periodic feature representation. To retrieve the feature representation, the Deep network uses filters to perform a linear transformation on G'. As once evaluation is complete by the Deep cnn, the calculated results remain unchanged, and it is presented as $G'' \in R^{T\times 2NL}$.The output dimensions of the CNN will be decreased by the Maxplooing network for time-domain channel estimation. When the Maxpooling network's pooling window size is set to as $1 \times L$ the data dimension after pooling becomes $G'' \in R^{T\times 2N(1\times L)}$

Channel estimation- Based on historical and current input as well as future data, the proposed PSO-LSTMEstNet learning network seeks to anticipate the current CSI. Because the LSTM network excels at learning sequence data, it is employed to predict the current CSI in this study. The CSI at the later instant is anticipated by the CSI at the prior moment in forwarding prediction. The CSI at the prior time is anticipated by the CSI at the later moment in the backward prediction, and the forward and backward pilot information is completely utilized to increase the accuracy of the channel estimation. Each time step of the LSTM network includes an output for channel estimation. In order to train the PSO-LSTMEstNet, we use the end-to-end approach to obtain all the weights and biases in the PSO-LSTMEstNet. We use Particle Swarm Optimization (PSO) algorithm to update the set of pilot design parameters for the PSO-LSTMEstNet network. This algorithm is different from the traditional optimization algorithm with fixed learning rate. Through training, can to adaptively update the learning rate.

3.4. Algorithm- PSO-LSTMEstNet

Step-1 Initialize the weights (w) and bias (b)

$W = \{w_1, w_2, w_3, ..w_n\}$
$B = \{b_1, b_2, b_3, b_n\}$
Epochs (E)→ $e_1, e_2, ..e_n$

Step-2 Update the training sets- $\{(x_1, t_1), (x_2, t_2), ..(x_m, t_m)\}$
Step-3 Include the pilot signals- $X_i = (i = 1,2,3 \dots m) and\ t_i = (i = 1,2,3 \dots m)$

Repeat the above steps-1 to step-3

Step-4 Calculate the output layer $o' = \{(o_1 x_1, t_1), (o_2 x_2, t_2), \dots .(o_m x_m, t_m)\}$
Step-5 Compute the cost function

E= $\sum_{k=j}^{n} \mathrm{f}(x_i, t_i)$

Step-6 compute the partial derivation for weight and bias
Until reach iteration =I(c)

Return the training samples calculation
If

Step-7 I(c)> x_iElse
Step-8 Restart the training process

endif

4. EXPERIMENTAL ANALYSIS

The experimental analysis were carried out using MATLAB software and the parameters used for analysis are Bit Error Rate (BER), Computational time, Signal to Noise Ratio (SNR) Symbol Error Rate (SER). Three common techniques—the Convolutional Deep Stacking Network (CDSN), the Multi-layered Perceptron (MLP) neural network, and the Generative Adversarial Network—are used to compare the results obtained for these factors (GAN). The simulation parameter for channel estimation is displayed in Table 1.

Table 2. Simulation parameters

Parameters	Values
The overall amount of sub - carriers	1543
Type of modulation	BPSK, QPSK, 16-QAM, 64-QAM
Pilot inserting sort	Convolution
Intermittent sort of guard	Cyclic prefix
Guard frequency duration	432
Noise form	White Gaussian noise

Signal to Noise Ratio (SNR)

The signal-to-noise ratio (SNR) is frequently given in dB, and is characterized as the proportion of transmit strength to signal strength. A signal-to-noise proportion larger than 1:1 (more than 0 dB) shows there's more transmission over interference.

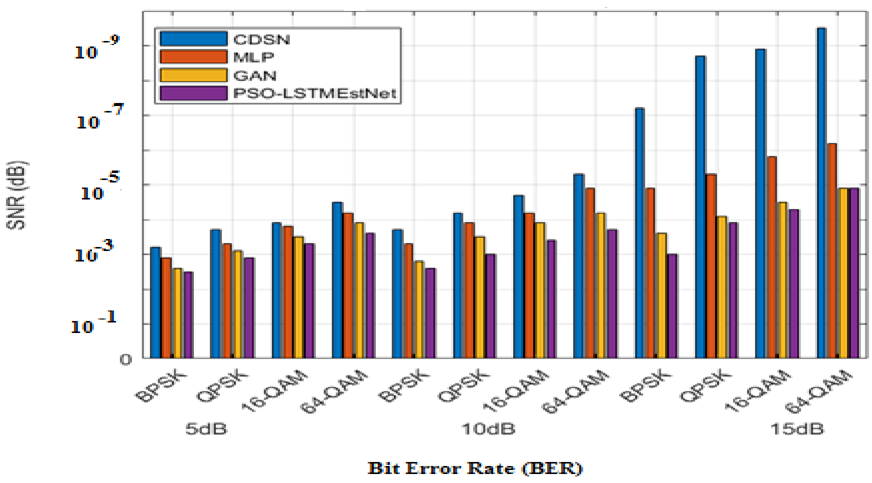

Figure 4. Analysis of Signal to Noise Ratio (SNR)

Figure 4, represents the analysis of Signal to Noise Ratio (SNR) between PSO-LSTMEstNet and various corresponding neural networks. In this analysis, the comparison is performed concerning different modulation schemes to perfectly examine the effectiveness of SNR with corresponding BER. The modulation technique 64 QAM employed here is taken as the reference for comparing SNR for the specified neural networks. The simulated findings, incur that on an average of 10dB of BER, SNR of 10^{-2} is achieved by the suggested PSO-LSTMEstNet. From the analysis, it is evident that the suggested model is more efficient than the rest of the neural network models.

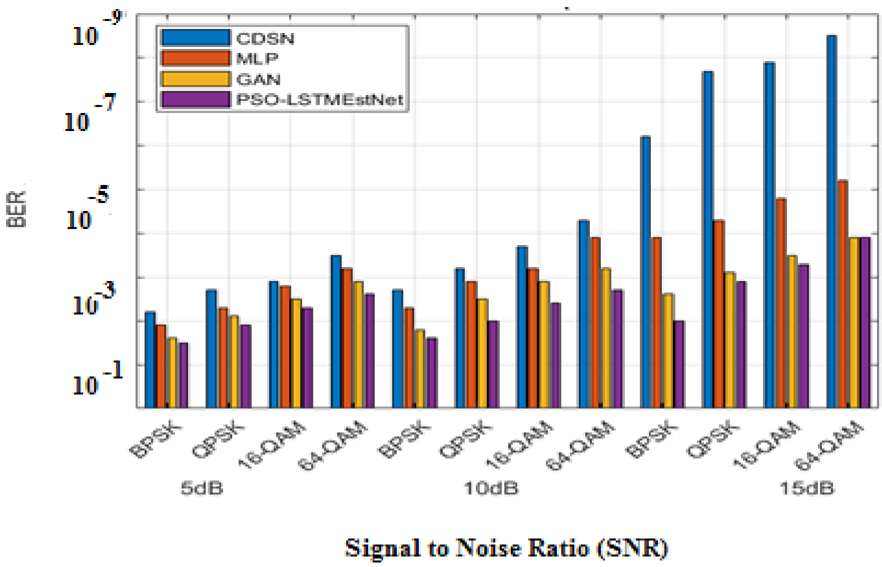

Figure 5. Analysis of Bit Error Rate (BER)

The comparative analysis of bit error rate, between suggested PSO-LSTMEstNet and various networks such as Convolutional Deep Stacking Network (CDSN), Multi-layered perceptron (MLP) neural network, Generative Adversarial Network (GAN) is performed. The various modulation techniques along with their corresponding SNR is taken into consideration for analysis. In order to observe the outcome of simulated findings, 64 QAM is fixed as a reference index. On an average, it is observed that BER of 10^{-2} is obtained at 10db.The above findings ensure that the suggested network is efficient.

Time complexity is a type of computational effort that specifies how the amount of time is required by a system to a execute particular operation. Table 4 depicts the comparison of computational time between proposed PSO-LSTMEstNet and existing Convolutional Deep Stacking Network (CDSN), Multi-layered perceptron (MLP) neural network, Generative Adversarial Network (GAN).

Table 4. Comparison of computational time

Modulation techniques	**CDSN**	**MLP**	**GAN**	**PSO-LSTMEstNet**
BPSK	53	52	49	45
QPSK	61	58	55	52
16-QAM	67	63	59	55
64-QAM	72	69	65	61

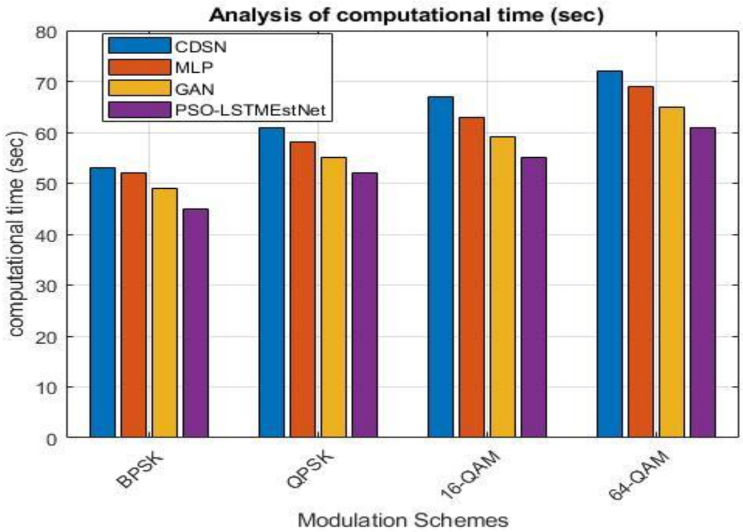

Figure 6. Analysis of computational time

The analysis of computational time between PSO-LSTMEstNet and various networks such as Convolutional Deep Stacking Network (CDSN), Multi-layered perceptron (MLP) neural network, and Generative Adversarial Network (GAN) is depicted in figure 6. Various modulation schemes are taken into consideration for comparison that includes BPSK, QPSK, 16-QAM and 64-QAM. From the observation based on simulated findings, the computational time of PSO-LSTMEstNet is found to be minimal, the rest of the networks that were subjected to comparison. Thus, with reduced computational time which is a major feature, the PSO-LSTMEstNet is proved to be efficient.

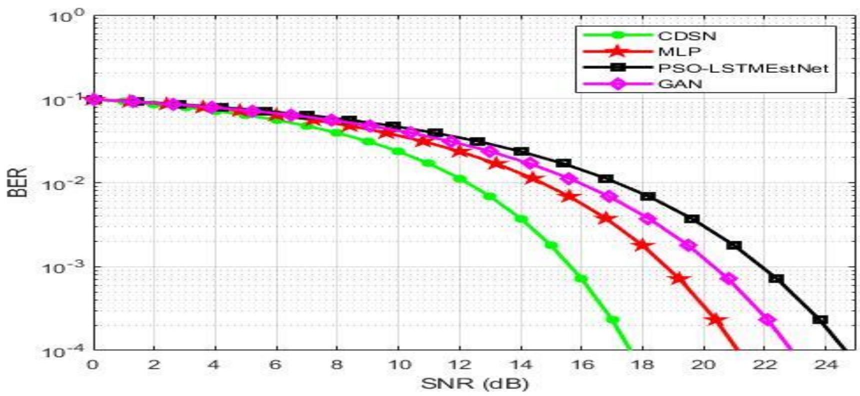

Figure 7. Comparison between SNR vs BER

Gathering information through wireless transmission is not a major challenge. The prime concern is whether the proposed method is capable of predicting mm Wave channel as well as received signal. .With the current massive developments in the field of deep learning that comprises of efficient techniques such a Bayesian neural networks, deep convolutional neural networks and recurrent neural networks which seem to be promising and is widely employed due its exceptional performance.

5. Conclusion

In this paper, The PSO-LSTMEstNet model is proposed to enhance the spectral efficiency of the MIMO- NOMA for mm-Wave applications. The model enhances performance by combining a deep learning technique with an optimization strategy to improve system performance. The optimization method paved the way for LSTMEstNet approach in the mm-Wave channel system and hybrid beam formation with large-scale antennas. The LSTM model is employed where the channel conditions vary frequently at different stages, particularly in the training stage. For enhanced spectral efficiency and reduced hardware complexity, hybrid beamforming approaches are employed. From the simulated findings, the outcome of comparative analysis signifies that PSO-LSTMEstNet exhibits enhanced performance with corresponding parameters such as SNR, BER and computational time. The computational time is observed to be minimal which terms the network to be efficient.

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Conflicts of Interest

The authors declare no conflict of interest.

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