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Using of Deep Learning in Beamforming Antenna Array

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Abstract

Beamforming (BF) is a critical technology for large antenna arrays, enabling precise control over beam steering. This research presents an innovative approach to enhance millimeter-wave transmission by integrating BF with a long short-term memory (LSTM)-based deep learning system. The system leverages digital signal processing and LSTM networks to optimize beamforming parameters, offering an alternative to traditional analog techniques and aiming for high spectral efficiency. Implemented in MATLAB, the methodology shows substantial improvements in performance metrics, underscoring the potential of combining BF with LSTM for advanced communication systems. To validate the approach, several illustrative examples are provided, guiding the beam pattern toward the desired direction. Initially, the model achieves a Mini-batch RMSE of 5.80 and a Validation RMSE of 4.19. By Epoch 40, these values improve significantly to a Mini-batch RMSE of 0.60 and a Validation RMSE of 2.14, highlighting the effectiveness of the LSTM-based BF method. Furthermore, the research compares this LSTM-based approach with artificial neural networks (ANN) and the least mean square (LMS) algorithm, confirming the robustness of the technique.

Keywords: Deep Learning” Beamforming” Artificial Neural Networks (ANN)” Least Mean Squares (LSM)” Long Short-Term Memory (LSTM)”.

الخلاصة:

تعد تقنية توجيه الشعاع تقنية أساسية لمصفوفات الهوائيات الكبيرة، حيث تتيح التحكم الدقيق في اتجاه الإشارات. يقدم هذا البحث نهجًا مبتكرًا لتعزيز نقل الموجات المليمترية من خلال دمج تقنية توجيه الشعاع مع نظام تعلم عميق يعتمد على الذاكرة طويلة وقصيرة المدى. يعتمد هذا النظام على معالجة الإشارات الرقمية وشبكات الذكاء الاصطناعي لتحسين معايير توجيه الشعاع، مما يوفر بديلاً للتقنيات التناظرية التقليدية، ويهدف إلى تحقيق كفاءة عالية في استخدام الطيف. تم تنفيذ هذه المنهجية باستخدام برنامجMATLAB ، وأظهرت النتائج تحسنًا كبيرًا في مؤشرات الأداء، مما يؤكد على إمكانية الجمع بين توجيه الشعاع والذاكرة طويلة وقصيرة المدى لتحقيق تقدم في أنظمة الاتصالات. للتحقق من فعالية النهج، تم تقديم عدة أمثلة توضيحية لتوجيه نمط الإشارة نحو الاتجاه المطلوب. في البداية، حقق النموذج متوسط خطأ قدره 5.80 للدفعات الصغيرة و4.19 للتحقق. بحلول المرحلة 40، تحسنت هذه القيم بشكل كبير لتصل إلى 0.60 للدفعات الصغيرة و2.14 للتحقق، مما يبرز فعالية طريقة توجيه الشعاع المعتمدة على الذكاء الاصطناعي. بالإضافة إلى ذلك، يقارن البحث بين هذا النهج المعتمد على الذاكرة طويلة وقصيرة المدى وتقنيات أخرى مثل الشبكات العصبية الاصطناعية وخوارزمية أقل متوسط تربيعي، مما يؤكد متانة هذه الطريقة.

1.INTRODUCTION

With the rising demand for enhanced capacity in mobile and personal communication systems, along with emerging applications in satellite and MIMO networks, researchers are actively developing algorithms to exploit spatial selectivity. These efforts extend to fields such as biomedical imaging, remote sensing, radio astronomy, and radar technology [1]. A crucial aspect in this context is determining the precise orientation of antennas to achieve the desired beam direction. Initially, mechanical phased arrays with motors were used in military applications; however, these systems presented limitations due to their size, weight, and vulnerability to weather conditions, alongside mechanical wear and failure. As a result, electronic beam steering systems have become preferred, eliminating the need for moving parts and enabling faster response times, particularly for dynamic environments [2].

Beamforming is an essential process in wireless communication and radar systems, concentrating the signal in a desired direction rather than dispersing it. This approach typically produces a main lobe oriented toward the target signal, while creating nulls that suppress interference signals, making it especially valuable in reducing the high propagation loss experienced in mm-wave communication systems. Popular adaptive beamforming techniques include minimum variance distortion-less response (MVDR) and null steering beamforming (NSB). While NSB aims to suppress interference while preserving the desired signal, MVDR minimizes interference and noise while maintaining signal quality [3].

However, these methods are computationally intensive and less effective in dynamic environments, where continuously recalculating optimal weights can be challenging due to the large number of antenna elements. Recently, deep learning (DL) has shown considerable potential in applications like direction of arrival (DOA) estimation and adaptive beamforming, offering flexibility and efficiency in dynamic and complex environments.

2.Related works

Numerous studies have explored the development of antenna arrays using various optimization techniques. These include hybrid methods [5,8,13], genetic algorithms [9], particle swarm optimization [10,11], central force optimization [11,12], and gravitational search algorithms. However, as the number of antenna elements increases, the computational time to find optimal weights also grows. For time-sensitive applications, deep neural networks (DNNs) offer crucial computational efficiency.

Neural networks (NNs) have generated significant interest, with many studies examining their applications [5,6]. A robust adaptive beamforming approach based on NNs, for instance, has been used to address signal steering vector mismatches [7], while in DOA estimation, NNs have achieved low mean square errors [8]. In large MIMO systems, sum-rate maximization (SRM) remains a key challenge. To address this, a neural network-based algorithm was developed to maximize SRM by discarding less optimal users [9]. Deep learning (DL) applications have extended beyond just determining optimal weights [10] and estimating arrival angles [11,12], greatly enhancing MIMO beamforming performance and capacity [13]. It has also been applied in ultrasound beamforming and radiofrequency data processing to improve speed and accuracy in imaging tasks [15,16].

Research has demonstrated that combining forced-zero and maximum transmission ratio beamforming techniques significantly increases data transmission rates. Similarly, prior studies comparing interference cancellation methods in large-scale MIMO downlinks found that large-scale MIMO offers superior quality in small-scale fading environments compared to network MIMO, though the theory model remains complex. Other research has utilized antenna selection algorithms to optimize capacity transmission [10,15,18,19] and explored multi-cell coordinated beamforming to enhance cell-edge communication quality [17,20]. Finally, a hybrid large-scale MIMO beam assignment scheme was proposed to improve user spectrum usage and cater to multiple users, addressing a limitation in prior single-user schemes [20,22].

3.System model

Beamforming (BF) has been extensively studied in wireless communications for its ability to reduce interference and boost spectral efficiency. Researchers have explored various architectures and algorithms to optimize BF parameters, noting the simplicity and energy efficiency of analog beamformers [8,9]. However, as millimeter-wave systems become more prevalent, the limitations of analog BF such as hardware complexity and sensitivity to inaccurate Channel State Information (CSI) are increasingly apparent. To address these issues, recent research suggests integrating BF with digital signal processing, as digital BF offers added flexibility for advanced data processing and adaptation to changing channel conditions [10,11]. Replacing traditional analog components with field-programmable gate arrays (FPGAs) or digital signal processing (DSP) modules enables more efficient, compact, and programmable BF systems [18,19].

Ddeveloped a structured linear antenna array and compared its performance using three algorithms: Least Mean Square (LMS), Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM), incorporating adaptive beamforming components.

Functional Components:

  - **Algorithms**: LMS algorithm, deep learning with LSTM and artificial neural networks (ANN).
- **Visualization**:
  - A plot of the array factor based on the calculated weights.

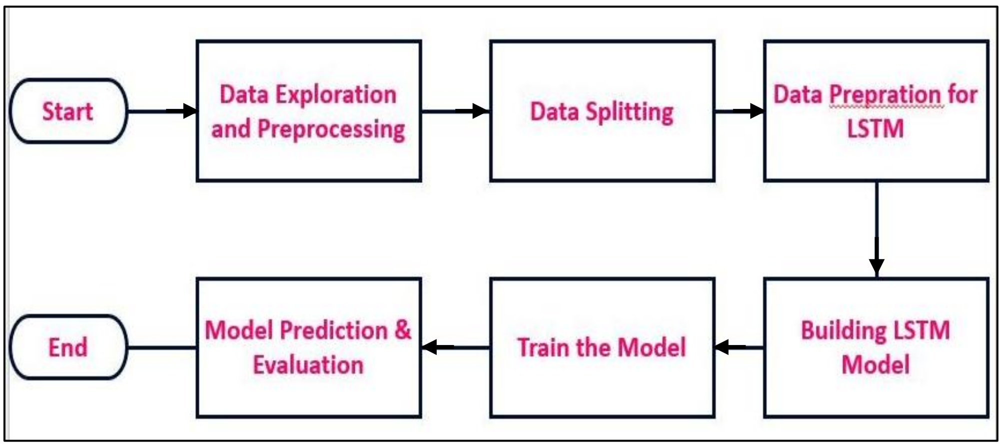

Fig.1 Data preprocessing until training the model steps

During the training phase, the LSTM model learns from the temporal dependencies inherent in the logged dataset, enabling it to capture complex patterns within the channel. The trained model subsequently plays a crucial role in the proposed adaptive beamforming system by effectively adjusting beamforming weights based on both current Channel State Information (CSI) and historical context derived from the dataset.

4.Research Methodology

Beamforming is a signal processing technique used in sensor arrays for directional signal transmission or reception. The study aims to explore and compare various machine learning algorithms, such as Least Mean Squares (LMS), Deep Learning using LSTM and Artificial Neural Networks (ANN), to enhance the performance of adaptive beamforming in uniform linear antenna arrays.

- **Design and Implementation of the MATLAB GUI Application**

Graphical User Interface (GUI) was developed to simulate and visualize the performance of different beamforming algorithms. The GUI consists of: "Uniform Linear Array". In tab allows to input parameters such as the number of antennas, distance between antennas, desired angle, and interference angle.

- **Algorithmic Approach**

Least Mean Squares (LMS) Algorithm: This algorithm adapts the weights of the antenna array to minimize the error between the desired and actual output. Deep Learning with LSTM: Long Short-Term Memory (LSTM) networks are employed to model the relationship between input parameters and the resulting beamforming patterns. Artificial Neural Networks (ANN): ANN is used to approximate the optimal weights for the antenna elements.

- **Simulation Process**

For each algorithm, the array factor (AF) is calculated based on the input parameters provided. The AF represents the radiation pattern of the antenna array.

The GUI plots the array factor, allowing a visual comparison of the effectiveness of each algorithm in steering the antenna beam toward the desired direction while minimizing interference.

- **Analysis and Evaluation**

The performance of each algorithm is evaluated based on the resulting beam patterns, particularly focusing on the ability to minimize interference and accurately target the desired direction.

Table 1: Beamforming Parameters and Their Impact.

Parameter	**Description**	**Impact on Beamforming**
Number of Antennas (N)	Total antennas in the array	Higher N improves resolution and reduces beamwidth
Distance Between Antennas (d)	Spacing between adjacent antennas	Affects grating lobes and array aperture
Desired Angle (θ_desired)	Target angle for beamforming	Determines main lobe direction
Interference Angle (θ_interf)	Angle of interfering signals	Determines null directions
Lambda (λ)	Wavelength of the signal	Affects the operational frequency and beamwidth

4.1.1 Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are AI models inspired by the human brain's structure, made up of interconnected nodes or neurons. These networks process information by receiving inputs, transforming them through weighted connections, and generating outputs. During training, the weights are adjusted, enabling the network to learn and improve [30].

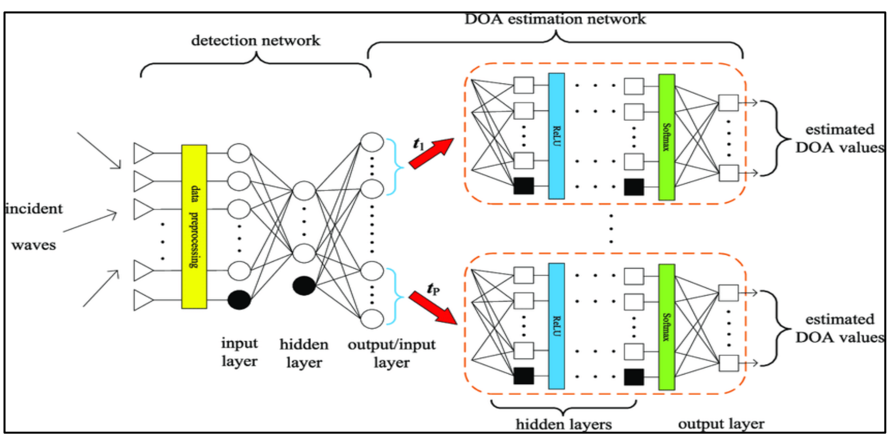

Fig.2 Beamforming Antenna Array [35].

An algorithm was applied ANN as the figure (2), Artificial Neural Networks (ANNs) can be used in antenna design to address beamforming problems in communication networks. To clarify the parameters and settings used in the (ANN), it is important to understand the network configuration, including the number of hidden layers and neurons, the learning rate, and the number of training epochs. These settings play a critical role in defining the network's performance and tuning its learning process

- **Number of Layers:** The network has two hidden layers.
- **Number of Neurons**: Each of the two hidden layers has 7 neurons.
- **Learning Rate:** The learning rate used (0.01).
- **Number of Epochs:** The number of epochs for training ANNs is 1000 epochs.

Table 2: (ANN)Training parameters

Unit	Initial value	Stopped value	Target
epoch	0	376	1000
Elapsed time	-	00:01:39	-
performance	0.465	0.0138	0

4.1.2 Result and Discussion

The algorithm uses 16 antennas, with a distance of half the wavelength 0.5λ between each of element and interference angle (20 Deg.), to enhance beam accuracy and minimize interference. A higher number of antennas improves beam accuracy and the network's ability to train effectively, reducing error in beamforming. Broadcast power can be focused where it is most needed. and the Plot of Array Factor for ANN algorithm is shown in figure (3).

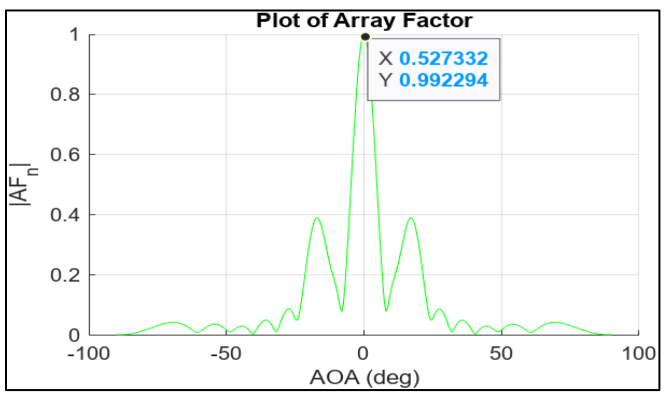

Fig.3 Array Factor for ANN algorithm

In Figure (4) shows: An Error Histogram is a graphical tool that displays the distribution of errors made by a predictive model, an (ANN). These errors represent the difference between the predicted outputs and the actual target values. It shows how prediction errors are spread, indicating whether they are centred around zero or biased.

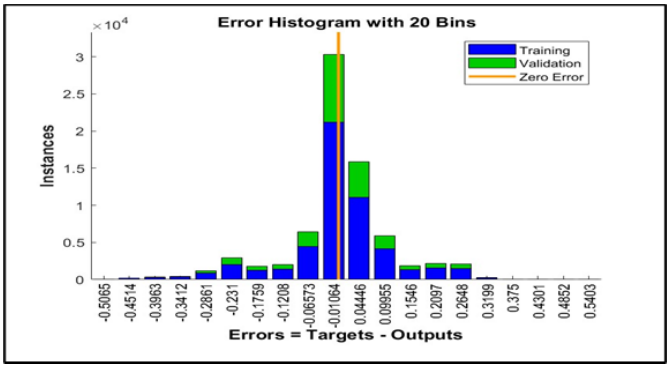

Fig.4 Error Histogram

The system's performance is evaluated by calculating the Root Mean Square Error (RMSE) to determine the accuracy of predictions made by the (ANN). RMSE measures the difference between actual and predicted values, with lower RMSE indicating better model performance.To optimize the ANN, the model is trained multiple times, adjusting weights to minimize RMSE. The training process includes dividing data into training (70%) and validation (30%) sets. The best model configuration or number of epochs is chosen based on the lowest RMSE observed during validation, ensuring accurate predictions.

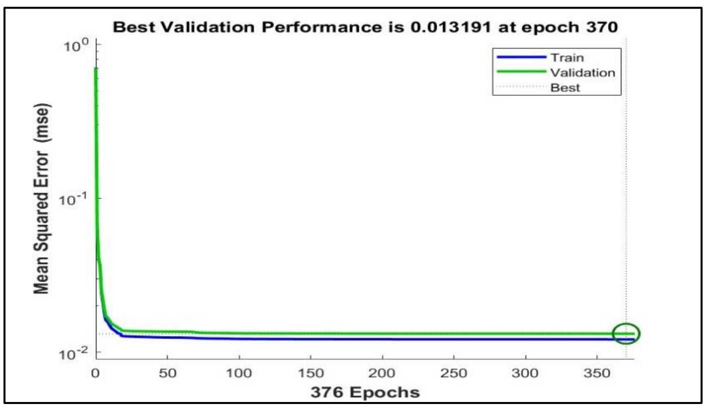

Fig.5 Mean Squared Error (MSE)

4.2.1 Least Mean Square (LMS)

Least Mean Squares (LMS) algorithm for adaptive beamforming. The LMS algorithm is typically used for adaptive filter design, where the goal is to minimize the error between a desired signal and the actual output signal. In the context of beamforming, it helps to adjust the weights of the antenna array to steer the beam towards the desired direction while minimizing interference.

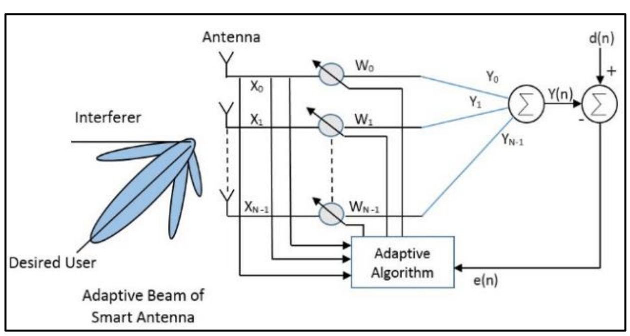

Fig.6 Least Mean Square (LMS)Algorithm [35]

Weights Calculation

The weights (w) updated iteratively using the LMS algorithm :

$$w(n+1) = w(n) + \mu \cdot X \cdot (d(n) - X' \cdot w(n))$$

Where:

- w(n) is the weight vector at step n.
- μ is the learning rate.
- X is the input vector.
- d(n) is the desired output at step n.
- X′ is the transpose of the input vector X.
- w(n+1) is the updated weight vector after step n.

4.2.2 Result and Discussion

LMS algorithm can be employed to enhance signal reception and optimize beam direction, thereby improving the overall performance of wireless communication and data transmission. In the figure below we used the algorithm LMS. Figure (7) provides information about the antennas used. The number of antennas is specified as the total number of elements, which is 16 in this case. The distance between the antennas is indicated as 0.5 λ, and the desired antenna angle, interference angle, and desired wavelength are all provided. We used to direct the beam at zero angle, as show at the table below, to illustrate the direction of the beam.

Table 3: The information for Plot of Array Factor for LMS (case1)

Number of antennas	Distance between antennas	Desired angle of antenna	Interference angle of antenna	Desired lambda
16 elements	0.5λ	0 Deg.	30 Deg .	1

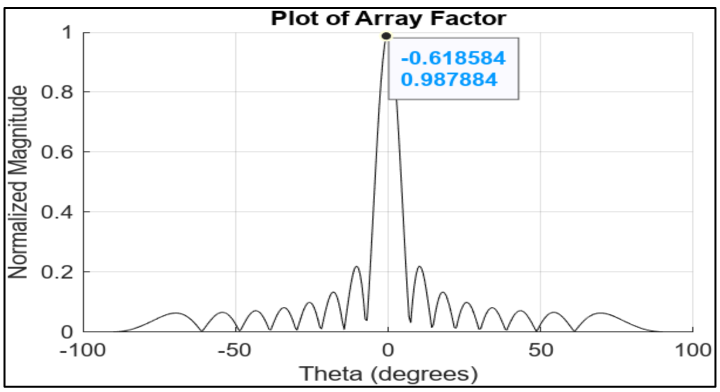

Fig.7 Plot of Array Factor for LMS algorithm (case1).

Figure (8) showcases a reduced number of antennas to depict the shape and direction of the beam. Use fewer antennas to clarify the beam's shape and direction. The greater the number of antennas, the greater the accuracy and direction of the wave. As shown in Figure 11, we notice that the beam routing is less accurate.

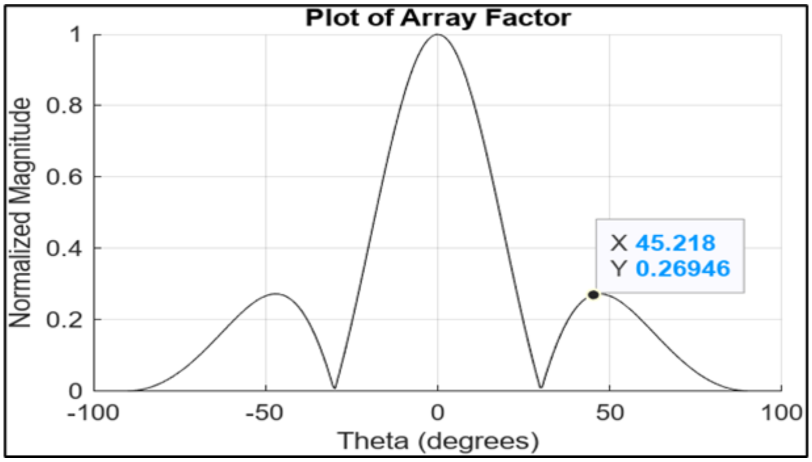

Fig.8 Array Factor for LMS algorithm with four element antennas (case2)

4.3.1 Long Short-Term Memory (LSTM)

LSTM is an advanced type of recurrent neural network (RNN) designed to process sequential data and overcome the challenges of long-term dependencies. LSTMs are particularly effective for tasks such as language translation, speech recognition, and time series forecasting [31].

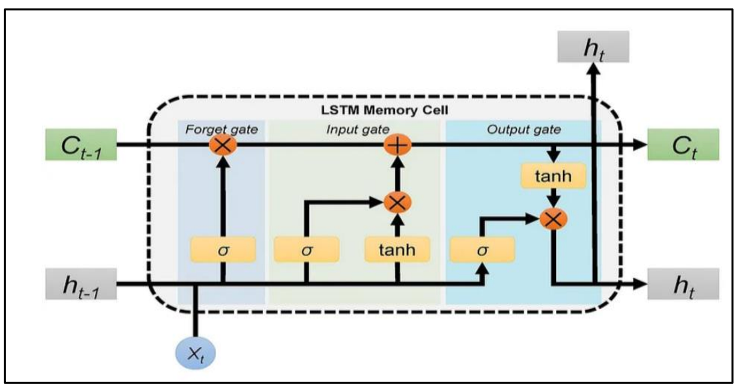

Fig.9 LSTM (long short-term memory) Algorithm [33]

LSTM cells are designed to capture long-term dependencies in sequences. Each LSTM cell uses several gates to update its cell state [32].

4.3.2 LSTM model

The following details outline the configuration and parameters of the LSTM model used. This includes the number of layers, neurons in each LSTM cell, learning rate, number of epochs, and the structure of the training instances. Understanding these parameters is crucial for evaluating the model's performance and optimizing its application in beamforming tasks for antenna systems. The specific details from regarding the LSTM model:

- **Number of Layers:** The LSTM model includes the following layers:
  - Sequence Input Layer
  - Batch Normalization Layer
  - LSTM Layer
  - Fully Connected Layer
  - Regression Layer

- **Number of Neurons in Each LSTM Cell:** The LSTM layer (LSTM Layer) has 100 hidden units (neurons).
- **Learning Rate:** Learning rate is set to 0.01.
- **Number of Epochs:** The model is trained for 40 epochs.
- **Number of LSTM Cells:** The LSTM layer consists of 100 LSTM cells.

4.3.3 Results and Discussion

To direct the beam more accurately, use a linear array consisting of 16 antennas arranged in a straight line, and the distance between each antenna is 0.5 λ half the wavelength. In this case, we chose the required angle of (0deg.) zero to direct the beam and an interference angle (20 deg.). The figure (10) shows the beamforming more precisely using the LSTM algorithm.

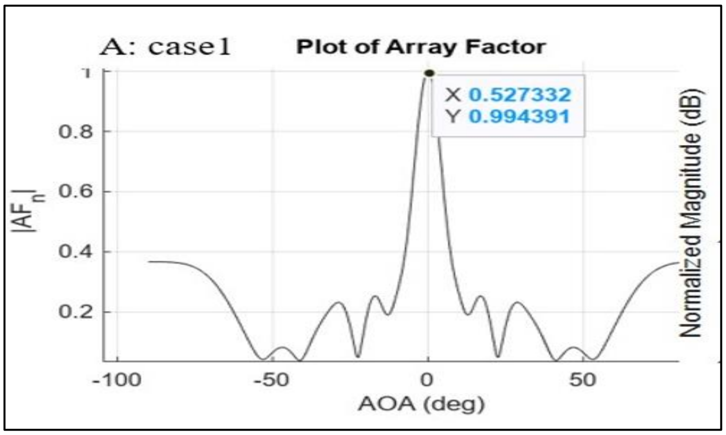

Fig.10 Plot of Array Factor for LSTM algorithm

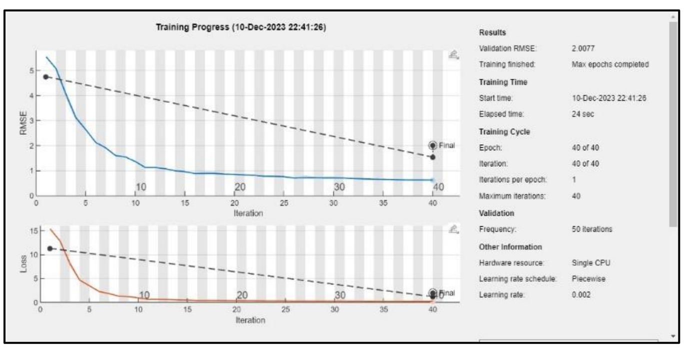

Fig.11 Training Progress (trained LSTM Model)

TABLE 4: Training on LSTM Model.

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch RMSE	Validation RMSE	Mini-batch Loss	Validation Loss	Learning Rate
1	1	00:00:05	5.80	4.19	16.8290	8.7952	0.0100
40	40	00:00:24	0.60	2.14	0.1779	2.2949	0.0020

• Epoch 1, Iteration 1: At the initial stage, the model shows a Mini-batch Root Mean square Error RMSE of 5.80 and a Validation RMSE of 4.19, indicating a rough start in model accuracy.

• Epoch 40, Iteration 40: After training, the model significantly improves with a Mini-batch RMSE of 0.60 and a Validation RMSE of 2.14, demonstrating the effectiveness of the LSTM-based DBF method.

• Loss Reduction: The Mini-batch and Validation Losses also decrease substantially from 16.829 and 8.7952 to 0.1779 and 2.2949, respectively, highlighting the model's learning efficiency.

• Learning Rate: The base learning rate is adjusted from 0.0100 initially to 0.0020 by the end, reflecting the fine-tuning of the learning process as the model progresses.

The results from training the LSTM model indicate significant improvement in performance over the training epochs. Initially, the RMSE and loss values for both mini-batch and validation were high, suggesting a considerable discrepancy between the predictions and actual data. As training progressed, these values decreased markedly, indicating that the model became more accurate in its predictions.

5. CONCLUSION

This work presents a detailed approach to enhancing millimeter-wave transmission by combining Long Short-Term Memory (LSTM) deep learning with Beamforming (BF). To address challenges from imprecise Channel State Information (CSI), the proposed system leverages digital signal processing and LSTM’s memory capabilities to optimize beamforming parameters. Implemented in MATLAB, the results show improved spectral efficiency and resilience to channel variations. Analyzing the beam patterns reveals the spatial properties and directionality the LSTM-based BF algorithm achieves. While current findings demonstrate the system’s feasibility, future research could explore deployment scenarios, expand training features, and experiment with alternative deep learning architectures. Integrating BF with LSTM is a promising strategy for advancing communication systems. Our results validate this method’s potential to enhance spectral efficiency and robustness, making a valuable contribution to wireless communication. Comparative analysis of beamforming algorithms highlights that the LSTM-based approach achieves the best side lobe suppression, suitable for precision-critical applications, despite its slower computation time. The LMS algorithm offers a balance of main lobe sharpness and efficiency but lacks in side lobe suppression. At the same time, ANN provides the fastest computation with a balanced main lobe and side lobe performance, ideal for speed-sensitive scenarios.

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