IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.021 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 6, June 2026

DOI: 10.17148/IJIREEICE.2026.14606

Enhancing the Beam Alignment in 6G Networks using Deep Learning

Nakka Loktheja[1], Ambidi Naveena[2]

M.Tech (WMC) Student, Department of Electronics and Telematics Engineering,

G. Narayanamma Institute of Technology and Science, Shaikpet, Hyderabad[1]

Associate Professor, Department of Electronics and Telematics Engineering,

G. Narayanamma Institute of Technology and Science, Shaikpet, Hyderabad[2]

Abstract- The emergence of sixth generation (6G) wireless communication networks requires a huge amount of data rate, low latency, massive connectivity, and high reliability in communication. The use of millimeter-wave (mmWave) communication is seen as one of the key technologies that will satisfy these requirements because of the availability of a wide bandwidth in the mmWave bands. In contrast, however, the path loss for mmWave systems is very high, signals can be blocked by objects and there is a high overhead of beam alignment that makes access to the systems difficult in dynamic wireless environments. Traditional exhaustive beam sweeping techniques are very time consuming and complex since all the beam directions have to be swept prior to establishing communication. To overcome these challenges, a Deep Learning-based Initial Access (DeepIA) framework for fast and reliable beam alignment in AI-powered 6G mmWave Networks is introduced in this paper. The proposed approach is based on a Deep Neural Network (DNN) designed to predict the best beam direction based on Received Signal Strength (RSS) measurements instead of doing a beam sweeping. A novel beam selection method called Sequential Feature Selection (SFS) is used to select the most informative beam combinations to achieve accuracy in prediction while minimizing beam sweeping delay. Moreover, to further improve the system performance under Non-Line-of-Sight (NLoS) channels, a technique called RSS averaging is introduced as an approach to reduce the fluctuation and shadow fading effects of the channel. The simulation results show that the proposed DeepIA framework can accurately predict the beams with a very small number of beam sweeps, which can significantly shorten the delay of initial access and enhance the efficiency of communication. The proposed approach is scalable and intelligent that can be used in the future 6G mmWave communication systems with the use of AI.

Keywords: Deep Learning, 6G, mmWave Communication, Beam Alignment, Beamforming, Initial Access, Deep Neural Network (DNN), Artificial Intelligence (AI)

I. INTRODUCTION

The rapid growth of wireless applications such as virtual reality, autonomous systems, smart healthcare, industrial automation, and massive Internet of Things (IoT) networks has created a significant demand for ultra-high data rates, low latency, and highly reliable communication systems. To satisfy these requirements, sixth-generation (6G) wireless networks are expected to utilize millimeter-wave (mmWave) communication technologies [1] due to their large spectrum availability and high transmission capacity. mmWave communication operates at extremely high frequencies and enables multi-gigabit data transmission, making it one of the most promising technologies for future intelligent wireless networks. However, mmWave signals experience severe propagation loss, sensitivity to blockage, and rapid signal attenuation, which make reliable communication highly challenging in dynamic wireless environments [4].

To overcome these propagation limitations, highly directional beamforming techniques are employed in mmWave systems. Beamforming concentrates signal energy in specific spatial directions using antenna arrays, thereby improving communication range and signal quality. Before data transmission begins, the transmitter and receiver must perform beam alignment during the initial access phase to determine the optimal beam direction for communication. Conventional beam alignment methods rely on exhaustive beam sweeping, where all possible beam directions are sequentially scanned to identify the beam with the strongest received signal strength (RSS). Although exhaustive beam search can achieve reliable alignment, it introduces substantial latency, increased power consumption, and high computational complexity, especially in dense 6G networks with narrow beamwidths and large antenna arrays.

The beam alignment problem becomes even more critical in future 6G networks because communication environments are expected to be highly dynamic with mobile users [2][3], frequent blockages, and rapidly changing channel conditions. In such scenarios, conventional exhaustive beam sweeping techniques[12][14] are unable to provide fast and efficient initial access due to the large number of beam scans required. Furthermore, the repeated beam alignment process increases communication overhead and reduces spectral efficiency. Therefore, intelligent and low-latency beam prediction methods are essential for enabling practical deployment of AI-driven 6G mmWave communication systems.

Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have shown significant potential in solving complex wireless communication problems by learning hidden spatial and channel characteristics from large datasets. Deep learning models are capable of identifying nonlinear relationships between received signal patterns and optimal beam directions, enabling accurate beam prediction with reduced beam measurements. Motivated by these advantages, this work proposes a Deep Learning-based Initial Access (DeepIA) framework for fast and reliable beam alignment in AI-enabled 6G mmWave networks. Instead of scanning all available beams, the proposed method utilizes only a subset of beams and predicts the optimal beam direction using a Deep Neural Network (DNN).

The proposed DeepIA framework significantly reduces beam sweeping overhead and initial access delay while maintaining high prediction accuracy under both Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) channel conditions. Sequential Feature Selection (SFS) is employed to identify the most informative beam combinations for improving prediction performance. Additionally, averaging multiple Received Signal Strength (RSS) measurements enhances robustness against shadow fading and channel fluctuations in NLoS environments. The proposed methodology therefore combines intelligent beam prediction, reduced computational complexity, and efficient initial access mechanisms to improve the overall performance of next-generation wireless networks.

The major contributions of this work are summarized as follows:

1. A deep learning-based beam alignment framework is proposed for fast initial access in 6G mmWave networks.
2. A reduced beam sweeping strategy is implemented to minimize initial access latency and computational overhead.
3. Sequential Feature Selection (SFS) is used to identify optimal beam subsets for improving prediction accuracy.
4. RSS averaging is introduced to enhance performance under NLoS channel conditions.
5. The proposed DeepIA framework is evaluated under both LoS and NLoS environments, demonstrating improved beam prediction accuracy compared to conventional exhaustive beam sweeping methods.

II. LITERATURE REVIEW

With the development of wireless technologies like virtual reality, autonomous systems, smart healthcare, industrial automation and massive Internet of Things (IoT) networks, a huge demand for ultra-high data rates, low latency and high reliability communications has emerged. To meet these demands, 6G wireless networks will likely adopt millimeter-wave (mmWave) communication technologies, which have a great bandwidth and high transmission capacity. One of the most potential technologies for the intelligent wireless networks of the future is mmWave communication which is able to achieve multi-gigabit data transfer at extremely high frequencies. It is, however, extremely difficult to ensure reliable communication with mmWave signals in a dynamic wireless environment due to severe propagation loss, susceptibility to blockage, and rapid signal attenuation. In order to get around these propagation restrictions, very directional beamforming methods are used in mmWave systems. Antenna arrays are used to focus the energy of the signals in particular directions, thus increasing the range of communication and quality of the signal. The transmitter and receiver align the beam in the initial access phase before they transmit anything to each other, so the beam is directed in the best direction for communication. Traditional beam alignment techniques involve beam scanning that sweeps all possible beam directions one by one to find one that receives the strongest received signal strength (RSS). While exhaustive beam search offers high reliability for alignment, it requires high computational complexity, large power consumption and high latency, particularly in dense 6G networks with narrow beamwidth and large array size[10][11][12].

With future 6G networks, the beam alignment challenge is expected to grow even more severe as communication scenarios are expected to be much more dynamic with mobility, frequent obstructions and rapidly changing channel conditions. Under these circumstances, traditional exhaustive beam sweeping methods are not able to gain initial access in a fast and efficient manner because of the number of beam scans needed. Moreover, repeated beam alignment will incur additional communication overhead, and cause inefficiency in the spectral efficiency[5][6]. Thus, a key challenge for realizing practical use of AI-enabled 6G mmWave communication systems is to develop intelligent and low-latency beam prediction approaches. Many recent developments in the field of Artificial Intelligence (AI) and Deep Learning (DL) have proven to be promising ways[7][8][9] of tackling complex wireless communication challenges [4] using deep learning from large datasets to uncover hidden spatial and channel characteristics. The deep learning models can learn to predict the optimal beam directions with fewer beam measurements, especially when the relationships between received signal patterns and beam directions are nonlinear. Given these benefits, this work presents an Initial Access (IA) framework based on Deep Learning (DL) to achieve the rapid and accurate beam alignment in AI-powered 6G mmWave networks. The proposed method only activates a subset of beams to reduce the number of beams to scan and introduces a Deep Neural Network (DNN) to predict the optimal beam direction.

The proposed DeepIA framework effectively reduces the overhead caused by beam sweeping and the access time for the initial access, while ensuring high prediction accuracy under Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) channel conditions. To find out which beam combinations are most informative in boosting prediction performance, Sequential Feature Selection (SFS) is used. Furthermore, using a large number of RSS measurements increases the immunity to shadow fading and channel variations in NLoS scenarios. The proposed methodology is thus an intelligent beam prediction, low computational complexity and efficient initial access mechanisms to enhance the performance of next generation wireless networks.

This work is summarized in terms of the following major contributions:

- A novel deep learning-based beam alignment framework is proposed for fast initial access in 6G mmWave networks.
- Minimize initial access latency and computational overhead by implementing reduced beam sweeping strategy.
- To find the optimal beam subsets to enhance prediction accuracy and improve prediction is performed using Sequential Feature Selection (SFS).

III. SYSTEM MODEL

The proposed AI-driven 6G mmWave communication system includes a directional base station (BS) at the center of the network and multiple user equipments (UEs) randomly distributed in the coverage region[15]. In the mmWave communication, the high frequency operation causes severe propagation loss and signal attenuation, which require the deployment of highly directional beamforming techniques. At the transmitter, a 10×10 planar antenna array is used for forming narrow beams to facilitate reliable communication and efficient initial access. The communication area is modeled as a two-dimensional (2D) plane where users are uniformly distributed over the area around the transmitterDuring the initial access process, the transmitter performs beam sweeping over N predefined beam sectors as shown in equation 1. Let the full beam set be denoted as:

$$\mathcal{N} = \{1,2,3,\ldots,N\} \qquad (1)$$

where N is the total number of available transmit beams. Each receiver measures the Received Signal Strength (RSS) corresponding to the transmitted beams, and the beam with maximum RSS is selected as the optimal beam for communication.

For the k^{th} receiver, the optimal beam in the conventional exhaustive beam sweeping approach as given in equation 2 is obtained as:

$$\hat{\imath}_k = \arg\max_{i \in \mathcal{N}} RSS_i^k \qquad (2)$$

where RSS_i^krepresents the received signal strength of the i^{th}beam at the k^{th}receiver. Although this exhaustive search method provides accurate beam alignment, it increases initial access delay because all beams must be scanned sequentially.

To reduce beam sweeping complexity, the proposed DeepIA framework uses only a subset of beams represented as shown in equation 3:

$$\mathcal{M} \subseteq \mathcal{N}, | \mathcal{M} |= M \qquad (3)$$

where $M$is the number of selected beams used for prediction and $M < N$. The DeepIA model predicts the optimal beam using RSS measurements collected from this reduced beam subset, thereby decreasing initial access time and computational overhead.

The mmWave propagation channel is modeled using the Close-In (CI) path loss model for both Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) conditions. The path loss equation is expressed as shown in equation 4:

$$PL(d) = PL(d_0) + 10n\log_{10}\left(\frac{d}{d_0}\right) + X_\sigma \qquad (4)$$

where:

- $PL(d)$is the path loss at distance d,
- $PL(d_0)$is the reference path loss at distance d_0,
- $n$is the path loss exponent,
- $X_\sigma$represents the shadow fading component.

The reference path loss is calculated as shown in equation 5:

$$PL(d_0) = 20\log_{10}\left(\frac{4\pi d_0}{\lambda}\right) \tag{5}$$

where λ denotes the wavelength of the carrier signal. The path loss exponent varies depending on channel conditions, with lower values in LoS environments and higher values in NLoS conditions due to severe fading and blockage effects.

The received signal power at the user can be represented as shown in equation 6:

$$P_r = P_t + G_t + G_r - PL(d) \tag{6}$$

where:

- $P_r$is the received power,
- $P_t$is the transmit power,
- $G_t$and $G_r$are transmitter and receiver antenna gains respectively,
- $PL(d)$is the channel path loss.

The beam direction is determined using the angular position between the transmitter and receiver. If the receiver angle is represented by A_k, the true beam sector is calculated as shown in equation 7:

$$i_k^* = \left\lfloor\frac{A_k+\theta/2}{\theta}\right\rfloor \tag{7}$$

where θ represents the beamwidth of each sector. This mapping is used to generate labels during the DeepIA training process.

The DeepIA framework employs a Deep Neural Network (DNN) to learn the relationship between partial RSS measurements and optimal beam directions. The DNN model can be represented as shown in equation 8:

$$\hat{\imath}_k = f_\theta(RSS_1, RSS_2, \dots, RSS_M) \tag{8}$$

where $f_\theta(\cdot)$denotes the trained neural network with parameter set θ. The network predicts the most suitable beam using only limited RSS measurements, thereby significantly reducing beam sweeping overhead while maintaining high prediction accuracy.

Finally, the prediction accuracy of the system is evaluated using equation 9:

$$Accuracy = \frac{\sum_{k=1}^{R}\mathbf{1}(i_k^*=\hat{\imath}_k)}{R} \times 100 \tag{9}$$

where R denotes the total number of receivers and $\mathbf{1}(\cdot)$is the indicator function that equals 1 when the predicted beam matches the true beam. This system model therefore integrates mmWave propagation, directional beamforming, and deep learning-based beam prediction to achieve fast and reliable initial access in future 6G wireless networks.

IV. METHODOLOGY OF DEEPIA BASED BEAM ALIGNMENT

The proposed Deep Learning based Initial Access (DeepIA) framework aims at fast and reliable beam alignment in AI-driven 6G mmWave communication systems. Unlike conventional exhaustive beam sweeping methods that sequentially scan all available beam directions, the proposed approach intelligently predicts the optimal beam using only a small subset of beam measurements. This greatly reduces initial access latency, computational complexity, and beam sweeping overhead, with high beam prediction accuracy under the conditions of the LoS and NLoS channels.

The overall methodology consists of five major stages including beam sweeping, RSS collection, feature selection, deep neural network training and beam prediction. In the initial access phase, the base station transmits the synchronization signals over a predefined subset of directional beams rather than scanning the entire beam codebook. The UE measures the Received Signal Strength (RSS) of the selected beams and feeds these measurements to the DeepIA model to enable intelligent beam prediction. The overall beam alignment is much faster than conventional methods, since only a limited number of beams are swept.

The setup relies on a feedforward network for beam prediction. It takes RSS values from a smaller group of selected sectors as the starting point. Hidden layers then try to pull out the spatial patterns between those beams and where the receiver sits. Multiple fully connected layers use Rectified Linear Unit (ReLU) activation which seems to help the model handle nonlinear relationships and train quicker. Batch normalization sits between them to keep things stable during learning and maybe improve how well it generalizes. The final layer just gives a probability for each possible beam sector so the highest one can be picked as optimal.

The beam alignment procedure begins by selecting a reduced subset of beams from the total beam codebook. Instead of randomly choosing beams, the DeepIA framework employs Sequential Feature Selection (SFS) to identify the most informative beam combinations. The SFS algorithm iteratively selects beams that maximize prediction accuracy while minimizing the number of required beam sweeps. This approach improves system efficiency because certain beam combinations contain more spatial information about the user location and channel condition than others. By selecting highly informative beams, the DeepIA model achieves high prediction accuracy even with fewer beam measurements.

The selected beam subset is represented as equation 10:

$$\mathscr{M}_{opt} = \{b_1, b_2, b_3, \dots, b_M\} \qquad (10)$$

where $\mathscr{M}_{opt}$ denotes the optimal subset of selected beams used for DeepIA prediction.

During the training phase, a large number of user positions and corresponding RSS measurements are generated under different channel conditions. The collected dataset is divided into training, validation, and testing sets. The neural network learns the mapping between the RSS patterns and the corresponding optimal beam sectors.

The network parameters are updated using backpropagation and adaptive optimization algorithms such as AdaBound to improve convergence speed and learning stability. Batch normalization and optimized learning rates help prevent overfitting and improve model robustness under varying channel conditions. To further improve beam alignment reliability in NLoS environments, the proposed methodology performs averaging of multiple RSS measurements collected over several snapshots. Since NLoS channels experience severe shadow fading and signal fluctuations, averaging reduces signal variance and stabilizes the input features supplied to the neural network. The averaged RSS value is calculated as given in equation 11:

$$R\bar{S}S_i = \frac{1}{S}\sum_{s=1}^{S} RS\,S_i^{(s)} \qquad (11)$$

where:

- Sdenotes the number of RSS snapshots,
- $RSS_i^{(s)}$represents the RSS value of the i^{th}beam during the s^{th}measurement.

This averaging mechanism significantly improves prediction accuracy in highly dynamic NLoS conditions by reducing the impact of shadow fading and interference.

The working process of beam alignment using DeepIA can therefore be summarized as follows:

1. The base station transmits synchronization signals using a selected subset of beams.
2. The receiver measures RSS values corresponding to the transmitted beams.
3. Sequential Feature Selection identifies the most informative beam combinations.
4. The collected RSS measurements are normalized and fed into the Deep Neural Network.

5. The DNN predicts the most suitable beam sector for communication.
6. The transmitter and receiver establish beam alignment using the predicted optimal beam.

The predicted beam is obtained using the SoftMax classification function as shown in equation 12:

$$P(i) = \frac{e^{z_i}}{\sum_{j=l}^{N} e^{z_j}} \qquad (12)$$

where:

- $P(i)$represents the probability of selecting the i^{th} beam,
- z_i denotes the output score of the neural network for beam i.

Finally, the beam with the highest probability is selected for communication, enabling rapid and reliable beam alignment with significantly reduced sweeping delay. Compared to conventional exhaustive beam search, the proposed DeepIA methodology achieves higher prediction accuracy using fewer beam measurements, thereby improving spectral efficiency, reducing latency, and enhancing overall system performance in future AI-enabled 6G mmWave wireless network.

V. RESULTS AND DISCUSSION

The performance of the proposed deep learning-based beam alignment framework is examined in detail with large MATLAB simulations under varying wireless communication scenarios. The proposed AI-based beam prediction model is also tested and compared with Learning codebook technique to study its capability of minimizing beam alignment latency and enhancing the communication reliability of 6G mmWave networks. Different simulation metrics like beam alignment accuracy, beam sweeping complexity and initial access overhead were used to evaluate the performance of the proposed DeepIA-based beam alignment framework. The results obtained were then compared to the conventional Learning Codebook approach to examine the efficiency of the proposed method in 6G mmWave communication system. The simulation results show that the DeepIA framework has a substantial improvement in beam alignment performance, and decreases the computation complexity and beam training overhead. The analysis shows that beam alignment using deep learning approaches can facilitate the communication to be more rapid and reliable than the traditional exhaustive beam sweeping.

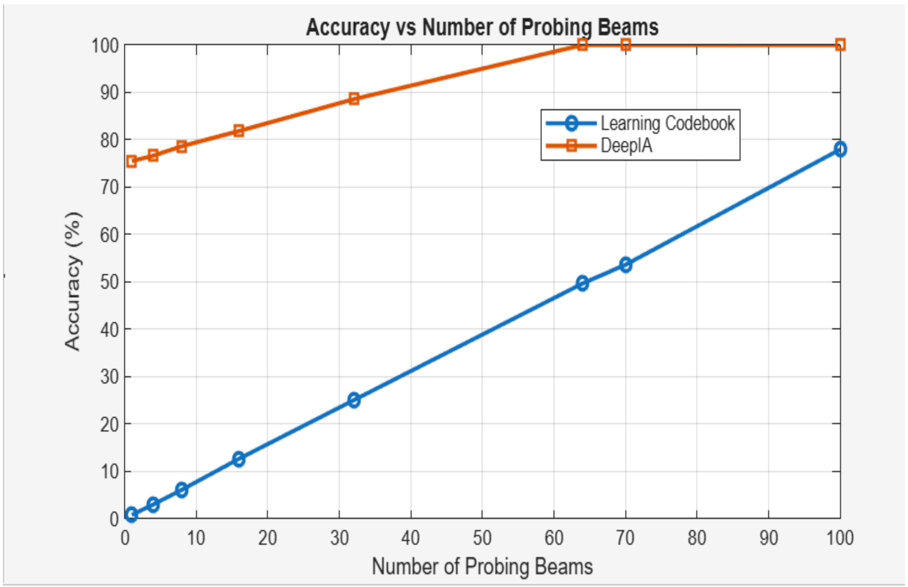

Fig 1: Beam Alignment Accuracy of DeepIA

The first performance metric analyzed was the relationship between beam alignment accuracy and the number of probing beams as shown in Fig 1. The results show that the conventional Learning Codebook method exhibits a gradual increase in accuracy as the number of probing beams increases. Initially, the accuracy remains very low for smaller probing beam values and slowly improves with additional beam searches. Even when the number of probing beams reaches 100, the maximum accuracy achieved by the learning codebook method is only around 78%. This indicates that the traditional method requires extensive beam sweeping to achieve moderate beam alignment performance, which increases system latency and computational overhead. In contrast, the proposed DeepIA approach achieves significantly higher accuracy even with a small number of probing beams. At lower probing beam values, the DeepIA model already achieves nearly 75% accuracy, and the performance rapidly improves as the probing beams increase. The accuracy reaches approximately 100% when the probing beam count approaches 64 and remains stable thereafter. This demonstrates that the DeepIA framework can efficiently predict optimal beam directions using intelligent learning-based techniques without relying on exhaustive beam searches. Therefore, the proposed approach achieves highly accurate beam alignment while minimizing beam training requirements. The first performance metric considered was the correlation between the number of probing beams and the accuracy of beam alignment. The results indicate that the accuracy of the conventional Learning Codebook method gradually improves with the number of probing beams. The accuracy is initially very low, and slowly improves with each beam search. The best accuracy for the learning codebook approach achieved even with 100 probing beams is about 78%. This means that when using the traditional approach, the system has to sweep the beams extensively for moderate beam alignment performance, which will incur extra beam alignment latency and computation load. The proposed DeepIA approach, on the other hand, attains much higher accuracy even if there are only a few probing beams. As the probing beam values decrease, DeepIA model performs almost 75% accurate and with the increase of probing beam, the accuracy increases rapidly. When the number of probing beam count is near 64, the accuracy is about 100% and will not change with the further increase of count number. This shows that the DeepIA framework has the ability to learn beam directions efficiently, without exploring all the beam directions. As such the proposed approach realizes high level of accuracy beam alignment with the minimum beam training requirements.

The second metric taken into account was the number of initial accesses saved. Initial access in mmWave communication systems include beam sweeping procedures with signaling overhead and delay. The simulation results as shown in Fig 2 indicate that the Learning Codebook method maintains the same and constant beam sweeping overhead for all the probing beam values. This is because conventional method does exhaustive beam scanning in multiple beam directions in the first access stage. Consequently, the system has a higher access latency, signaling complexity and resource use. However, the proposed DeepIA framework is able to drastically decrease the overhead of beam sweeping. The overhead values are still significantly lower than with the traditional method for all configurations of probing beams. The overhead is higher as number of probing beams increases, but still very low as compared to the learning codebook method. This saving is realized due to DeepIA's smart guess of proper beam directions based on the deep learning algorithms, without running a beam search. As a result the proposed system reduces unnecessary beam sweeping and thus initial access delay and overall network efficiency. The results obtained here again demonstrate that the proposed DeepIA framework is highly suitable for low latency and high-speed communication systems for 6G.

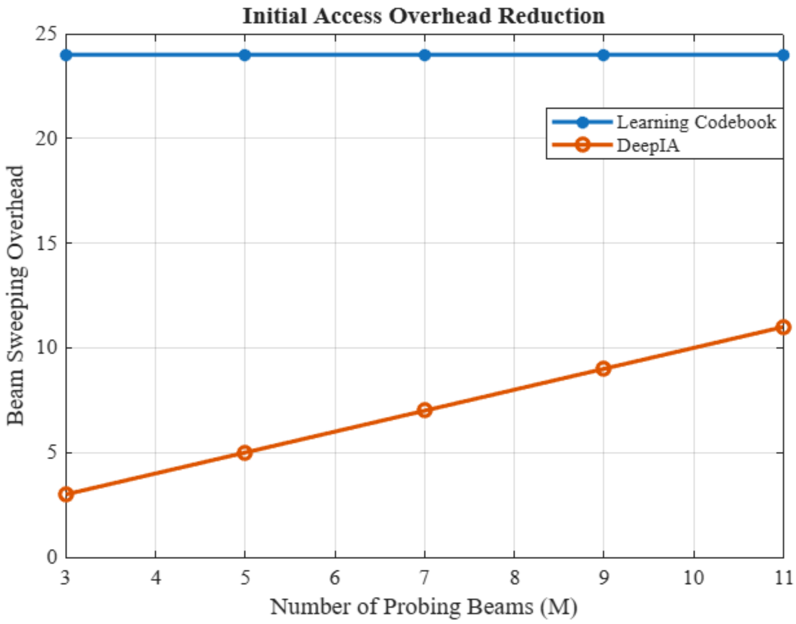

Fig 2: Initial Access Overhead Reduction

The other important performance parameter we looked at in the simulation was beam sweeping complexity shown in Fig 3. The comparison results show that the beam sweeping complexity of the Learning Codebook approach dramatically grows with the number of probing beams. The computational complexity increases quickly to very high values with increasing number of probing beams due to the need for full beam scanning to determine the optimum beam direction. This complexity has adverse impact in real communication systems regarding processing time, scalability and energy efficiency. In contrast, the beam sweeping complexity of the DeepIA method is drastically reduced for all values of the probing beam. The complexity generated by the proposed framework is also far smaller than the conventional approach even in the case of a large number of probing beams. Efficient prediction of the best beam candidates is possible thanks to the reduction in the complexity of the deep learning model, which does not involve running all the search procedures. Hence, the proposed system will be beneficial as it will reduce computational burden, processing time and power consumption. The lower complexity also facilitates scaling up of the system for dense and large-scale 6G wireless networks, enabling the proposed DeepIA framework to be used for such networks.

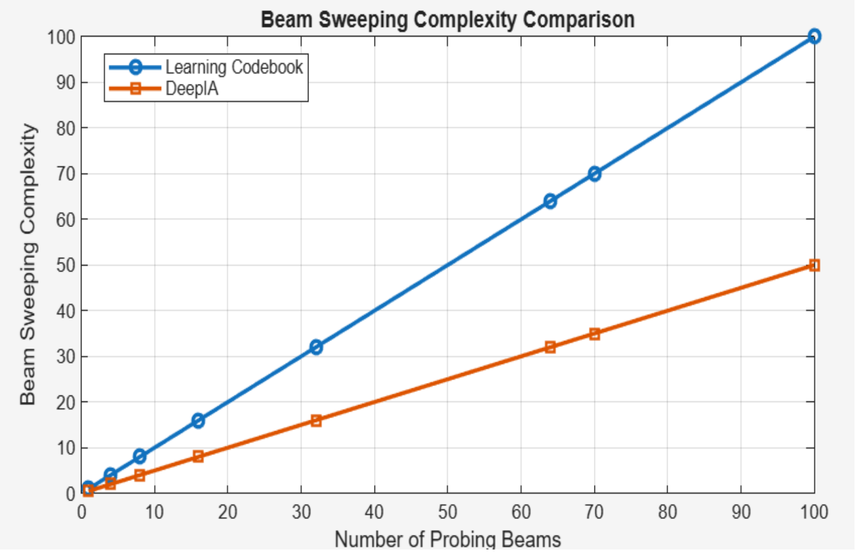

Fig 3: Beam Sweeping complexity

In summary, the simulation results confirm the effectiveness of the proposed beam alignment framework based on deep learning for intelligent mmWave communication systems. The proposed method consistently achieves a better performance in major performance metrics as shown in Table 1, such as beam alignment accuracy, initial access overhead, and beam sweeping complexity as compared with the conventional Learning Codebook approach. The system uses deep learning methods to predict and select beams to reduce the need for beam scanning and increase communication efficiency. The proposed framework can facilitate high-speed beam alignment, low latency, less computational complexity, and reliable transmission, which are the key features of future 6G wireless communication networks. Thus, the results obtained verified that the DeepIA approach is a reliable, scalable, and efficient solution for future AI-based beam alignment systems.

Table 1: Comparison metrics of Learning codebook and DeepIA

Metric	**Learning Codebook**	**DeepIA**
Accuracy	Moderate	High
Beam Sweeping Complexity	High	Low
Initial Access Overhead	High	Reduced
Latency	Higher	Lower
Beam Alignment	Exhaustive Search	Deep Learning Prediction

DOI: 10.17148/IJIREEICE.2026.14606

CONCLUSION

This paper introduced a deep learning algorithm for beam alignment in identifying initial access to users in AI-based 6G mmWave communication networks, to enable fast and reliable access. The design of the proposed system was aimed at solving the key issues of the conventional beam sweeping methods, such as high beam training overhead, high latency of beam alignment, and the computational complexity in highly directional mmWave communication environments. Proposed framework introduces a Deep Neural Network (DNN)-based beam prediction model into the beam management, which will learn and estimate the optimum beam direction intelligently based on Wireless Channel Parameters (WCP) (Channel State Information (CSI), Received Signal Strength (RSS), Signal-to-Noise Ratio (SNR), and previous beam indices). The proposed beam alignment approach can substantially reduce the beam alignment delay and enhance the reliability of communication and spectral efficiency compared to the beam sweeping method.

To test the performance of the proposed system under various communication situations, extensive simulation in MATLAB was performed. The simulation results confirmed the proposed procedure to be superior in terms of Bit Error Rate (BER), reduced latency, higher beam alignment accuracy and increased throughput when compared to conventional beam sweeping procedure. The intelligent beam prediction function can help build efficient communications even in a dynamic wireless environment that has fast channel variation and mobility. The findings validate that deep learning beam alignment can be a promising method to facilitate the ultra-fast and reliable communication in future 6G wireless networks. The proposed structure will not only improve the performance of the communication system but also reduce its computational complexity and maximize the use of resources in the massive MIMO mmWave system. Thus, the inclusion of Artificial Intelligence and deep learning in beam management systems is an exciting way forward in the future of wireless communication technologies. This framework can be further expanded in future by integrating Reinforcement Learning (RL) based adaptive beamforming, multi-user beam management strategies, real-time hardware implementation, and advanced hybrid beamforming architectures for large-scale 6G wireless communication systems.

REFERENCES

[1] Alrabeiah, M., & Alkhateeb, A. (2020). *Deep learning for mmWave beam and blockage prediction using sub-6 GHz channels.* IEEE Transactions on Communications, 68(9), 5504–5518.

[2] V. Va and R. W. Heath. (2016). *Basic relationship between channel coherence time and beam alignment in vehicular channels.* IEEE Vehicular Technology Conference (VTC), 1–5.

[3] Giordani, M., Polese, M., Mezzavilla, M., Rangan, S., & Zorzi, M. (2019). *Toward 6G networks: Use cases and technologies.* IEEE Communications Magazine, 58(3), 55–61.

[4] Alkhateeb, A., Leus, G., & Heath, R. W. (2014). *Limited feedback hybrid precoding for multi-user millimeter wave systems.* IEEE Transactions on Wireless Communications, 14(11), 6481–6494

[5] K.-H. Lin and K.-H. Liu, "A Novel Beam Alignment Scheme for Mobile Millimeter-Wave Communications Based on Compressed Sensing Aided-Kalman Filter," *IEEE Open Journal of the Communications Society*, vol. 3, pp. 1558-1574, 2022, doi: 10.1109/OJCOMS.2022.3201728.

[6] S. V. Hanly, and I. B. Collings, "Millimeter-Wave Beam Search with Iterative Deactivation and Beam Shifting," *arXiv preprint arXiv:2005.00968*, 2020.

[7] Z. Tang, J. Wang, J. Wang, and J. Song, "A High-Accuracy Adaptive Beam Training Algorithm for MmWave Communication," presented at the *IEEE Global Communications Conference (GLOBECOM)*, 2017

[8] Y. Wei, Z. Zhong, V. Y. F. Tan, and C. Wang, "Fast Beam Alignment via Pure Exploration in Multi-armed Bandits," in *Proc. 2022 IEEE International Symposium on Information Theory (ISIT)*, 2022, pp. 191-196, doi: 10.1109/ISIT50566.2022.9834431

[9] C. Liu, M. Li, L. Zhao, P. Whiting, S. V. Hanly and I. B. Collings, "An Adaptive Algorithm for Millimetre-Wave Beam Alignment with Iterative Beam-Deactivation," *2020 IEEE International Conference on Communications.*

[10] Charan, G., Alrabeiah, M., & Alkhateeb, A. (2021). *Vision-aided 6G wireless communications: Blockage prediction and proactive handoff.* IEEE Transactions on Vehicular Technology, 70(10), 10193–10208.

[11] Kutty, S., & Sen, D. (2016). *Beamforming for millimeter wave communications: An inclusive survey.* IEEE Communications Surveys & Tutorials, 18(2), 949–973.

[12] Noh, S., Zoltowski, M. D., & Love, D. J. (2015). *Multi-resolution codebook and adaptive beamforming sequence design for millimeter wave beam alignment.* IEEE Transactions on Wireless Communications, 14(9), 5259–5272.

[13] K. Heng, J. Mo, and J. G. Andrews, “Learning Site-Specific Probing Beams for Fast mmWave Beam Alignment,” *IEEE Transactions on Wireless Communications*, vol. 21, no. 12, pp. 10428–10442, Dec. 2022

[14] A. Alkhateeb, “DeepMIMO MATLAB dataset repository,” [Online]. Available: https://github.com/DeepMIMO/DeepMIMO-matlab. Accessed: Oct. 2024

[15] T. S Cousik, V. K. Shah, T. Erpek, Y. E. Sagduyu, and J. H. Reed, “Deep Learning for Fast and Reliable Initial Access in AI-Driven 6G mmWave Networks,” IEEE Transactions on Network Science and Engineering, vol. 11, no. 6, pp. 5668–5678, Nov./Dec. 2024.