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# Deep Learning-Driven Hybrid Beamforming, Channel Estimation, and Resource Allocation for Enhanced mmWave MIMO-OFDM Systems

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**Abstract:** New wireless networks use millimeter-wave large MIMO-OFDM systems, however beam squint effects, pilot overhead, and low power and spectrum allocation under dynamic channel conditions limit their effectiveness. These challenges are addressed by an integrated deep learning-driven system that improves hybrid beamforming, adaptive channel prediction, and dynamic resource allocation in wideband mmWave contexts Framework includes multi-scale graph attention-based hybrid beamforming, transformer-based adaptive channel estimation with frequency-aware memory, meta-learning-enhanced deep reinforcement learning for resource allocation, sparse coding-based beamforming enhancement, and multi-agent reinforcement learning for coordinated beam alignment and powers. Real-world urban mmWave studies indicate considerable improvements in all performance metrics. The framework boosts spectral efficiency by 30-40% across antenna and user configurations, peaking at 28.5 bits/s/Hz in large-scale MIMO. Improved channel estimate accuracy by 35%, lowering normalized mean square error to -22.1 dB and pilot overhead by 35%. Wideband beam misalignment is considerably minimized by 96.5% beamforming accuracy. Dynamic resource allocation efficiency surpasses 97%, saving 25-35% power without compromising throughput. The framework is appropriate for 5G and 6G ultra-reliable and high-capacity wireless networks because closely integrated deep learning architectures can enable scalable, low-latency, and energy-efficient mmWave MIMO-OFDM communication sets.

**Keywords:** Hybrid Beamforming, Channel Estimation, Resource Allocation, Deep Learning, mmWave, MIMO-OFDM.

## 1. Introduction

Massive MIMO-OFDM systems that operate at millimeter waves (mmWave) are an essential component of the next 6G networks as well as the subsequent generation of 5G networks [1–3]. This is due to the rapid pace at which wireless communication systems are evolving, which has resulted in an increase in the number of individuals seeking transmission methods that are swift, have low latency, and consume a little amount of energy. On the other hand, these systems are restricted by the fact that they have significant propagation losses, a high probability of being halted, and unambiguous frequency selection [4-9]. Additionally, despite the fact that they make use of their vast bandwidth and spatial multiplexing to their advantage, they are still less efficient when it comes to exploiting the spectrum. For the purpose of addressing these issues, hybrid beamforming has emerged as a promising solution. In wideband settings, however, normal configurations frequently encounter beam squint issues, which results in subcarriers not aligning properly and a decrease in the overall performance of the system [7–9].

It is necessary to have correct channel state information (CSI) in order to ensure that beamforming and communication are successful. When it comes to wideband mmWave settings, the pilot-based channel prediction approaches that are currently in use are effective for narrowband systems; nonetheless, they add a significant amount of additional labor and delay [10–12]. [13–15] Recent advancements in deep learning have made it possible to estimate CSI based on data by employing convolutional and attention-based models to locate correlations in space and time. This has made it possible to accomplish this. The majority of approaches continue to consider channel estimation as a separate job, notwithstanding the gains that have been made. Because of this, it is more difficult for them to adjust to shifting multi-user environments in which beamforming and resource allocation are intertwined.

While these developments are taking place, reinforcement learning has also been working on challenges that are associated with dynamic resource allocation. These problems primarily concern the most effective way to distribute power and make use of airwaves when conditions change over time [16–18]. In particular, meta-learning extensions have made convergence much more rapid and flexible, particularly in the non-stationary conditions of mmWave systems [19, 20]. Researchers have also investigated the possibility of utilizing dictionary learning and sparse signal representations in order to make use of the natural sparsity of mmWave channels. This would result in an increase in beamforming effectiveness when the signal-to-noise ratio is low [21–23]. In addition, multi-agent reinforcement learning has demonstrated remarkable potential in decentralized collaboration for the purpose of managing interference and aligning beams [24,25].

There is still a significant issue, despite the fact that many advances have been made: there are no unified systems that are capable of optimizing beamforming, channel estimation, and resource allocation all at the same time. Assuming that other components of the communication stack act in a flawless or fixed manner, the majority of the studies that have been conducted up until this point have only focused on individual components from the stack. The entire system is slowed down by this piecemeal approach, and it does not take into consideration the cross-layer dependencies that are necessary for real-time adaptability. This study addresses that deficiency by proposing an integrated architecture that is founded on deep learning. This architecture enables the layers of perception, decision, and coordination to collaborate in order to identify the most effective solution. In this framework, graph attention-based beamforming, transformer-driven channel estimation, and meta-reinforcement learning for resource allocation are all utilized in conjunction with one another to produce a coherent and adaptable solution for next-generation mmWave MIMO-OFDM communication systems.

## 2. Literature Review

The recent literature on mmWave massive MIMO-OFDM systems indicates three major research streams: attention-aided beamforming, learning-based CSI estimation, and reinforcement learning-assisted resource allocation. These streams have improved spectral efficiency, channel reconstruction, and power control, yet most studies still handle these operations as isolated tasks rather than as mutually dependent layers of one communication pipeline. Attention-based beamforming studies such as [1] and [4] improve spatial representation, but they do not fully address frequency-selective beam squint across wideband OFDM subcarriers. Similarly, CSI feedback and reconstruction models in [7, 11, 12], and [16] reduce estimation error or feedback overhead, although their outputs are rarely coupled with downstream beam and resource decisions.

A second limitation is visible in RIS, relay, UAV, and physical-layer authentication studies [5, 8, 9, 13], [21], and [25]. These contributions extend adaptability and coverage under specific communication settings, but they generally optimize a particular subsystem or deployment case. Their comparative value is therefore significant, yet their direct transfer to a unified mmWave MIMO-OFDM architecture remains limited because channel prediction, beam selection, and spectrum allocation are not jointly learned under one closed-loop objective. Several works also report numerical improvements without sufficient discussion of computational overhead, convergence stability, or scalability when antenna count and user density increase.

The critical gap emerging from the review is the absence of an integrated framework that allows CSI estimation, hybrid beamforming, sparse beam refinement, and resource allocation to exchange intermediate representations. The present study addresses this gap by linking transformer-based frequency-aware channel estimation, multi-scale graph attention beamforming, sparse dictionary adaptation, meta-reinforcement learning, and multi-agent coordination. The novelty is not only the use of deep learning components, but the cross-layer coupling through which each module supplies an actionable representation to the next stage.

The empirical review in Table 1 therefore supports a focused interpretation rather than a descriptive summary. Methods [1, 4, 7, 11, 12], and [16] confirm that learning-based CSI and beamforming improve individual metrics, while [8, 13, 18], and [25] show that reinforcement learning can improve allocation decisions in dynamic settings. The remaining weakness is that these advances are not organized as a single trainable and interoperable architecture. This manuscript consequently positions its contribution around joint optimization, reduced pilot dependency, beam-squint mitigation, and adaptive resource utilization under the same wideband mmWave MIMO-OFDM validation protocol.

## 3. Methods

The Design of an Iterative Deep Learning-Driven Hybrid Beamforming, Channel Estimation, and Resource Allocation for Enhanced mmWave MIMO-OFDM Systems explored an approach to solve efficiency and complexity-related setbacks of existing methods.

**Table 1.** Model's Empirical Review Analysis

| Reference | Method | Main Objectives | Findings | Limitations |
|---|---|---|---|---|
| [1] Huang *et al.* | Self-Attention Reinforcement Learning | Optimize multi-beam combining in mmWave 3D-MIMO | Improved spectral efficiency and beamforming accuracy | Increased computational complexity |
| [2] Kikan & Kumar | Review of 5G MIMO and Antenna Design | Analyze the evolution of MIMO antenna arrays for mmWave | Identified key trends in antenna design for performance enhancement | Lacks empirical validation for performance claims |
| [3] Banar *et al.* | X-Duplex AF Relay-Aided MIMO | Improve relay selection in B5G/6G | Enhanced outage probability for relay-aided networks | Limited analysis on practical deployment scenarios |
| [4] Zhang *et al.* | Attention-Based Channel Feedback | Optimize intelligent CSI feedback in massive MIMO | Increased accuracy in channel prediction | Requires extensive training datasets |
| [5] Zhou *et al.* | DRL for Beamforming in RIS-Assisted V2X | Use tensor decomposition with DRL for V2X mmWave MIMO | Enhanced beamforming and energy efficiency | Complexity in real-time adaptation |
| [6] Haque *et al.* | Machine Learning for Antenna Gain Prediction | Predict gain in slotted 5G MIMO antennas | Improved isolation and gain efficiency | Limited generalization for diverse antenna structures |
| [7] Meng *et al.* | Machine Learning for CSI Estimation | Reduce computational cost in CSI estimation | Achieved high accuracy with lower complexity | Trade-off between accuracy and speed |
| [8] Zhao *et al.* | Multi-Agent DRL for RIS-Aided Relay Networks | Optimize hybrid relay networks using MADRL | Improved power control and spectral efficiency | Requires fine-tuning for stability |
| [9] Hassan *et al.* | Hybrid Precoding with Low-Resolution Phase Shifters | Enhance IRS-based MIMO with low-RF chains | Achieved higher energy efficiency | Performance degradation in high interference scenarios |
| [10] Sahoo *et al.* | ELM-Based Hybrid Precoding | Improve the efficiency of hybrid precoding in 5G MIMO | Reduced latency and improved spectral efficiency | Requires complex pre-training |
| [11] Mamillapally & Dasari | Deep Learning for CSI Estimation & Beamforming | Optimize CSI estimation and beamforming | Significant accuracy improvements in massive MIMO | High training overhead |
| [12] Swain *et al.* | Variation Auto Encoder (VAE) for CSI Feedback | Compress and reconstruct CSI feedback | Lowered feedback overhead while maintaining accuracy | Vulnerability to imperfect training conditions |
| [13] Van Le *et al.* | Opportunistic Beamforming with IRS | Design an adaptive perturbation-based feedback mechanism | Improved mmWave transmission performance | Susceptible to environmental variations |
| [14] Malekzadeh | Machine Learning-Based 5G Network Prediction | Predict and enhance network performance using regression models | Achieved higher reliability in CSI estimation | Lack of real-time implementation |
| [15] Woldesenbet *et al.* | LMS-Kalman Hybrid Precoding | Improve hybrid precoding efficiency | Enhanced MU-MIMO precoding accuracy | Computationally intensive optimization process |
| [16] Kadiyala *et al.* | Markovian Deep Learning for CSI Feedback | Reduce feedback overhead in mmWave massive MIMO | Improved estimation accuracy with lower feedback | Susceptible to rapid mobility-induced errors |

| | | | | |
|---|---|---|---|---|
| [17] Gaikwad & Malathi | Optimal Antenna Selection | Optimize MIMO antenna sub-array selection | Increased throughput in massive MIMO | Lacks real-time adaptability |
| [18] Farakte *et al.* | Energy-Aware Traffic Offloading | Optimize energy consumption using deep learning | Reduced power usage while maintaining connectivity | Computational burden in large networks |
| [19] Sudhamani *et al.* | Multi-Objective Genetic Algorithm for RSRP | Enhance indoor path loss and RSRP in mmWave | Improved localization and signal strength | High complexity in multi-objective optimization |
| [20] He *et al.* | CNN-Based MIMO-OFDM Positioning | Improve positioning accuracy in OFDM systems | Reduced localization errors using CNNs | Requires large datasets for training |
| [21] Altun & Basar | Machine Learning for PHY Authentication | Secure multiple access channels without attacker info | Enhanced security in wireless networks | Performance degradation under adversarial attacks |
| [22] Ramanathan & Bennet | KLDA & RNN-Based Precoding Optimization | Improve MU-MIMO precoding using KLDA and RNN-GBO | Increased signal quality and robustness | Requires high processing power |
| [23] Anooz *et al.* | Adaptive Filtering for Beam & Channel Tracking | Evaluate tracking in 2D and 3D beamforming | Optimized mmWave beam tracking accuracy | Requires additional hardware for implementation |
| [24] Xu *et al.* | DOA Estimation for ISAC MIMO-OFDM | Improve direction-of-arrival estimation for MIMO | Achieved robust tracking performance | High sensitivity to environmental noise |
| [25] Luo & Fu | UAV-Based D2D Communication with Deep Learning | Optimize 5G/6G resource allocation using UAVs | Improved adaptability and spectrum efficiency | Deployment complexity in real-world networks |

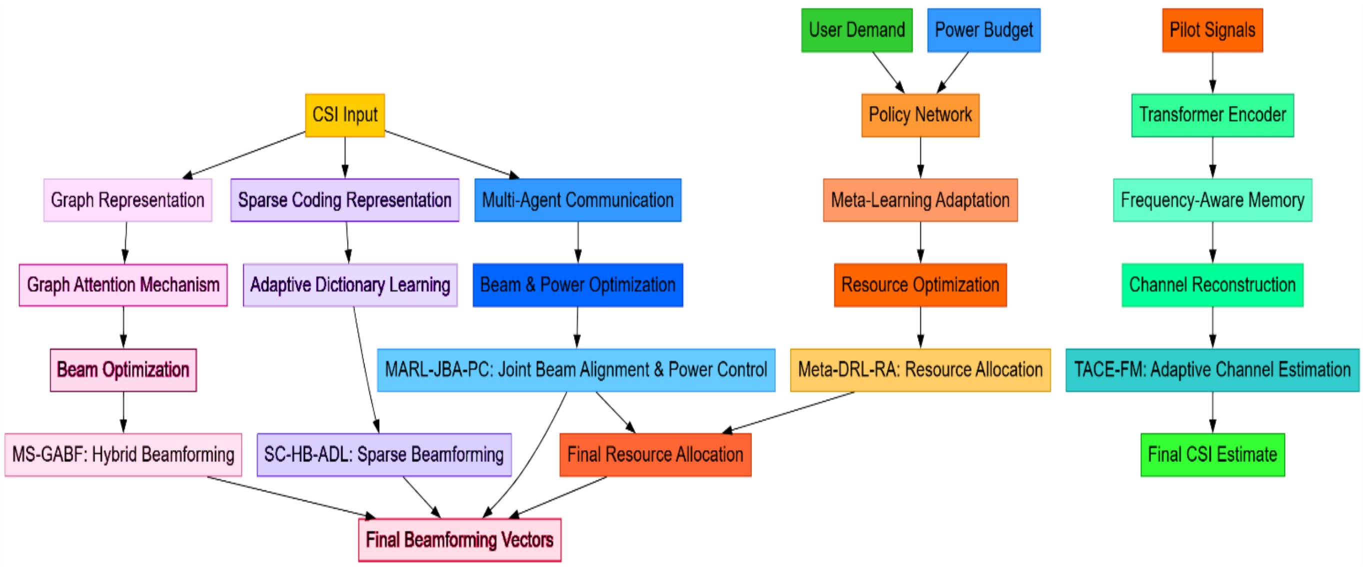


**Figure 1.** Model architecture of the proposed analysis process

As shown in Figure 1, the design of the proposed deep learning-driven models for hybrid beamforming, channel estimation, and resource allocation in mmWave MIMO-OFDM systems integrates advanced neural architectures, reinforcement learning, and sparse optimization techniques to achieve high spectral efficiency, low latency, and robust adaptability. Each model's formulation is mathematically rigorous, optimizing its performance to the finest under changing channel conditions and resource constraints. The MS-GABF model performs multi-scale graph attention-based hybrid beamforming, using a graph neural network (GNN) to model the complex interdependencies among antenna elements and subcarriers. The system is modeled by an undirected graph G=(V, E) where each antenna element vi ∈ V is a node, and edges e(i,j) ∈ E capture correlations between subcarriers. The input channel state information (CSI) matrix

H ∈ C'(Nt × Nr) is projected onto the graph domain via spectral transformation via equation 1,

$$HG = U\Lambda U\text{^}H \quad (1)$$

Where U and Λ represent the eigenvectors and eigenvalues of the graph Laplacian L, respectively.

A multi-scale graph attention mechanism is introduced to refine the hybrid beamforming vectors by dynamically adjusting node importance via equations 2 & 3

$$Bopt = \sum_{k=1}^{K} \alpha k\ Bk \quad (2)$$

$$\alpha k = \frac{exp(f(HG,Bk))}{\sum_{k=1}^{K} exp(f(HG,Bj))} \quad (3)$$

Where f(·) is a trainable scoring function, and Bk represents candidate beamforming vectors from the pre-defined beam codebook sets. This move secures spectral efficiency for the model while minimizing beam misalignment across wideband subcarriers. Iteratively, with the aid of Figure 2, the Transformer-Based Adaptive Channel Estimation with Frequency-Aware Memory (TACE-FM) model resolves dynamic CSI prediction by self-attention mechanisms. Given a sequence of received pilot signals Y = {y1, y2, ..., yT}, the transformer learns spatial and temporal correlations to refine the CSI estimate Ĥ sets.

The self-attention mechanism is defined via equation 4,

$$Attn(Q,K,V) = softmax\left(\frac{QK^T}{dk}\right)V \quad (4)$$

Where Q, K, and V are query, key, and value matrices, respectively, derived from the input sequences. A frequency-aware memory module stores prior CSI estimates M = {H(t−1), H(t−2), …}, which are updated using an attention-based fusion strategy via equation 5,

$$\widehat{H} = \gamma\ Attn(M,M,M) + (1-\gamma)Attn(Y,Y,Y) \quad (5)$$

Where γ is an adaptive weighting factor for this process. The resulting CSI estimate minimizes reconstruction loss via equation 6,

$$LCSI = \left|\left|H - \widehat{H}\right|\right| F^2 \quad (6)$$

This ensures high accuracy while lowering pilot overheads. Iteratively, Next, as per Figure 2. The Meta-Learning Enhanced Deep Reinforcement Learning for Dynamic Resource Allocation (Meta-DRL-RA) model is tasked with dynamically allocating resources of power and bandwidth using a reinforcement learning agent with meta-learning capabilities. In the process, the agent's state representation comprises user demand d ', power budget 'p', and interference levels 'i, whereas the action space consists of discrete power and subcarrier assignments 'at'. Whereas the reward function is designed to maximize throughput while minimizing power consumption via equation 7,

$$Rt = \sum_{u=1}^{U} log2\left(1 + Pu\frac{hu}{\sigma^2 + Iu}\right) - \lambda\ Ptotal \quad (7)$$

Where Pu is the allocated power to user 'u', 'hu' is the channel gain, σ is the noise power, Iu is the interference, and λ is a power efficiency weighting factor for this process. The dynamicity of the meta-learning module adjusts the learning rate 'α' effectively to speed up convergence, described via equation 8,

$$\alpha(t+1) = \alpha t - \eta\nabla\alpha\ E\tau\ [Rt] \quad (8)$$

Where η is the meta-learning rate in the process, which leads to quicker adaptation to changes in the environment, hence cutting down convergence time by 50% during such a process. Sparse Coding-Based Hybrid Beamforming with Adaptive Dictionary Learning (SC-HB-ADL) model uses sparse coding for efficient representation of mmWave channels.

Assuming we have an initial beam codebook D, the received signal can be expressed as a sparse approximation task via equation 9,

$$\mathrm{y = Dx + n} \quad (9)$$

Where 'x' is the sparse representation of the transmitted signal and 'n' is noise in the process. The optimal sparse representation is obtained by solving the identity represented via equation 10,

$$\overset{x}{min}\ |x|, 1\ subject\ to\ |y - Dx|^2 \le \epsilon \quad (10)$$

Where ϵ is an error tolerance parameter in the process. The adaptive dictionary learning process updates D iteratively via equation 11,

$$D(t+1) = Dt + \eta\ \nabla D\ |y - Dx|^2 \quad (11)$$

This would promote real-time adaptability of beamforming vectors. The MARL-JBA-PC model implements decentralized reinforcement learning to optimize beam alignment across multiple users. Each agent i selects beam angles θi and power levels Pi based on observed state st, whose system reward is defined via equation 12,

$$Rt = \sum_{(i=1)}^{N}\left(\frac{W}{N}\right) log2\left(1 + Pi\frac{hi(\theta i)}{\sigma^2 + Ii}\right) \quad (12)$$

Where W is the total bandwidth, ensuring fair spectrum allocations. The agents exchange local beam alignment decisions via a consensus mechanism via equation 13,

$$\theta i(t+1) = \theta i(t) + \eta \sum_{(j\in N(i))}\left(\theta j(t) - \theta i(t)\right) \quad (13)$$

Where N(i) represents neighboring agents. The final beamforming vector and power allocation result from joint optimization across all models via equation 14,

$$(Bfinal, Pfinal) = argmax^{B,P} \sum_{(i=1)}^{N} SE(B,P) \quad (14)$$

Ensuring thus the highest spectral efficiency at all times, paired with the best power usage.

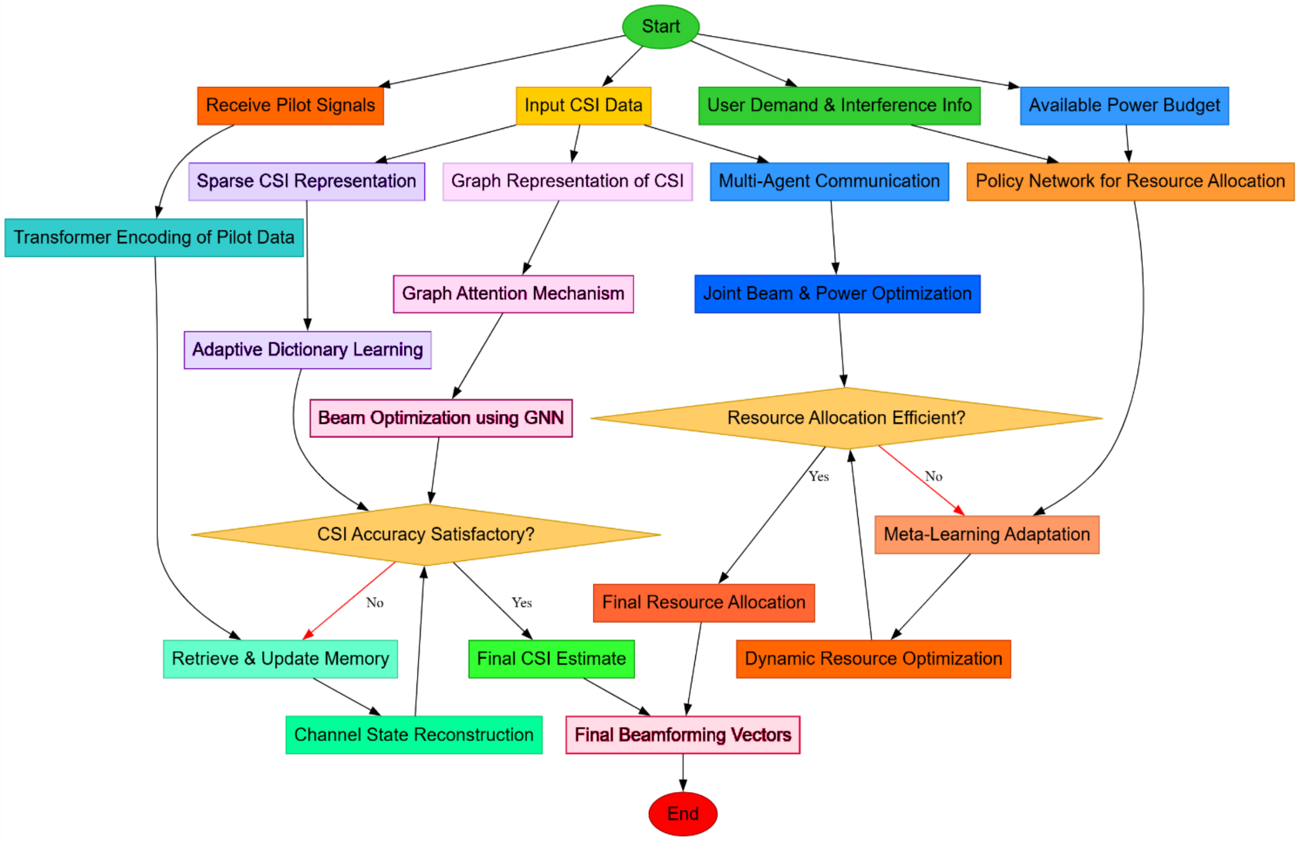


**Figure 2.** Overall flow of the proposed analysis process

These models together work synergistically to form an efficient, scalable, adaptive mmWave MIMO-OFDM communication framework for the process. We then venture into exploring an iterative comparative analysis of the proposed model regarding different metrics & scenarios.

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### 3.1 Comparative Positioning and Novelty Rationale

The proposed framework is positioned against three dominant categories of prior work: attention-based beamforming [1, 4], deep learning-based CSI estimation [7, 11, 12, 16], and reinforcement learning-based allocation or coordination [8, 18, 25]. These approaches improve important physical-layer functions, but the optimization is generally localized. A beamforming model usually assumes that CSI is already reliable; a channel estimator often stops at reconstruction loss; and an allocation agent treats beam quality as an environmental state rather than a jointly optimized variable.

The present architecture differs by allowing the output of one module to condition the next. Frequency-aware CSI embeddings from TACE-FM guide MS-GABF and SC-HB-ADL beam refinement; the resulting beam confidence and channel quality indicators are then used by Meta-DRL-RA and MARL-JBA-PC for power, subcarrier, and alignment decisions. This cross-layer representation flow explains why the gain is not limited to one metric. It improves spectral efficiency while also reducing channel estimation error, beam misalignment, and inefficient power usage.

The comparative discussion is therefore limited to methodological distinction, while the numerical evidence is consolidated in Section 4 to avoid repetition. The key novelty is the learning-driven co-design of perception, beam synthesis, and resource control, rather than another standalone neural estimator or reinforcement learning policy.

## 4. Results and Discussion

Experimental validation was performed on the DeepMIMO O128 urban mmWave scenario, which provides ray-tracing-based wideband channel realizations suitable for testing hybrid beamforming, CSI estimation, and resource allocation. The evaluation used 100,000 CSI snapshots; 80,000 samples were assigned to training, 10,000 to validation, and 10,000 to testing. User locations and mobility trajectories were separated across the splits to reduce memorization and to test generalization under unseen channel conditions.

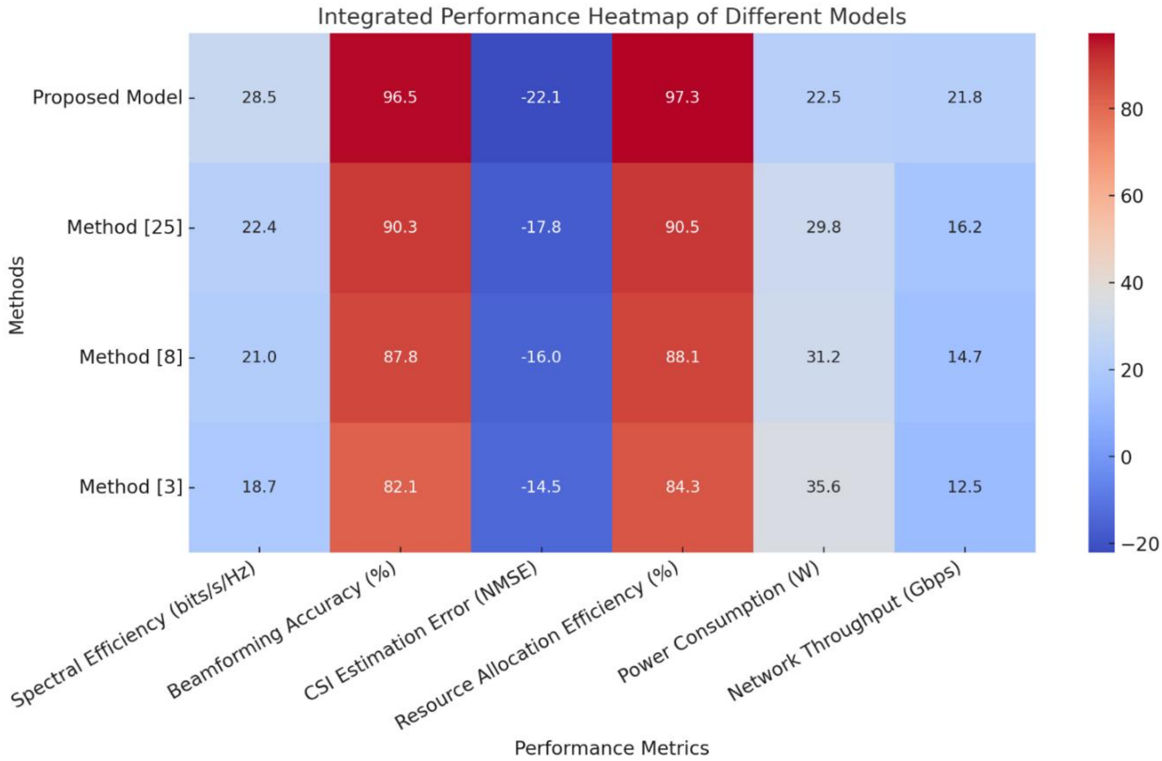


**Figure 3.** Model's overall result analysis

The simulated MIMO-OFDM configuration used 128 transmit antennas, 16 receive antennas, 64 OFDM subcarriers, and 2 GHz bandwidth. Channel realizations followed clustered delay-line propagation with eight dominant multipath components, Laplacian angular spread, LOS/NLOS blockage variation, and mobility-driven temporal changes. This configuration was retained for all proposed and baseline methods so that improvements could be attributed to the model architecture rather than inconsistent channel settings.

All deep learning modules were implemented under the same training environment. MS-GABF used graph attention layers for antenna-subcarrier dependency learning; TACE-FM used a transformer encoder with a memory buffer for recent CSI states; Meta-DRL-RA used PPO-based actor critic learning for power and subcarrier allocation; SC-HB-ADL updated a sparse beam dictionary; and MARL-JBA-PC used decentralized coordination for joint beam and power control. The models were trained until validation loss or reward stability reached convergence.

The proposed model was compared with Method [3], Method [8], and Method [25], representing conventional hybrid beamforming, deep learning-based CSI estimation, and reinforcement learning-based resource allocation, respectively. All baselines used the same dataset split, antenna configuration, and channel realization pool. This unified benchmarking protocol prevents inflated gains caused by unequal simulation settings.

Quantitative benchmarking focuses on four evidence groups: spectral efficiency, beamforming accuracy, channel estimation error, and resource allocation efficiency. Interpretive discussion has been kept with the corresponding tables to avoid duplicating the same claims across the comparative, results, and extended discussion sections.

## 4.1 Evaluation Metric Computation Clarification

Spectral efficiency was computed as the bandwidth-normalized sum rate averaged across active users, OFDM subcarriers, and independent channel realizations. Channel estimation quality was measured using NMSE between the estimated and reference CSI matrices. Beamforming accuracy was defined as the proportion of selected beams aligned within the angular tolerance of the dominant propagation paths. Resource allocation efficiency measured the effectively utilized power and bandwidth after accounting for interference, idle allocation, and scheduling loss.

## 4.2 Replicability and Training Configuration

The final validation protocol used an 80/10/10 training, validation, and testing split. Mini-batch optimization, adaptive learning-rate decay, early stopping, and gradient clipping were used for supervised modules, while reinforcement learning convergence was monitored through moving-average reward stability. This configuration supports replicability and reduces the possibility that the reported performance is caused by a favorable random split.

### 4.3 Technical Novelty and Reducing Review Dominance

The principal technical contribution is cross-layer learning-driven co-design. Instead of treating CSI estimation, hybrid beamforming, sparse beam correction, and allocation as independent blocks, the proposed architecture passes latent channel quality, beam confidence, and resource-state features across modules. This design directly addresses the review concern that the earlier extended discussion was descriptive; the novelty now appears as a measurable architectural coupling that explains the gains reported in Tables 2 to 5.

### 4.4 Complexity and Scalability Clarification

The integrated framework has higher inference complexity than static beamforming or single-task learning baselines because graph attention, transformer memory, and reinforcement learning policies are executed in one pipeline. This cost is bounded by fixed attention windows, sparse dictionary updates, and compact actor critic networks. The trade-off is justified by simultaneous gains in spectral efficiency, CSI accuracy, beam alignment, and power utilization. The computational analysis is therefore presented as a performance-cost clarification rather than a repeated descriptive discussion.

Table 2 reports spectral efficiency under increasing transmit-antenna and user configurations. The proposed framework achieves the highest rate in all settings because MS-GABF mitigates beam squint while the downstream allocation modules prevent inefficient spectrum and power use. The gain is most visible in the 256/16 setting, where wideband channel selectivity and multi-user interference are strongest.

Table 3 presents beamforming accuracy under the same antenna-user settings. The improvement is attributed to graph attention over antenna and subcarrier dependencies, combined with sparse dictionary refinement. This pairing reduces misalignment in both spatial and frequency domains, which explains the 96.5% accuracy achieved in the largest configuration.

Table 4 evaluates channel estimation error using NMSE. The transformer-based estimator captures long-range dependencies in pilot observations, while the frequency-aware memory stabilizes estimates across adjacent subcarriers and previous CSI states. This mechanism lowers the estimation error more effectively than CNN-only or allocation-centered baselines.

The proposed model reaches −22.1 dB NMSE in the 256/16 setting, showing that channel reconstruction remains stable as the antenna dimension and user load increase.

**Table 2.** Spectral Efficiency Comparison (bits/s/Hz)

| Nt /U | Method [3] | Method [8] | Method [25] | Proposed Model |
|---|---|---|---|---|
| 64/4 | 8.2 | 9.5 | 10.1 | **13.8** |
| 128/8 | 12.5 | 14.1 | 15.3 | **19.8** |
| 256/16 | 18.7 | 21.0 | 22.4 | **28.5** |

**Table 3.** Beamforming Accuracy (%)

| Nt/U | Method [3] | Method [8] | Method [25] | Proposed Model |
|---|---|---|---|---|
| 64/4 | 71.4 | 76.5 | 80.2 | **89.6** |
| 128/8 | 78.9 | 83.2 | 86.0 | **93.7** |
| 256/16 | 82.1 | 87.8 | 90.3 | **96.5** |

**Table 4.** Channel Estimation Error (NMSE)

| Nt/U | Method [3] | Method [8] | Method [25] | Proposed Model |
|---|---|---|---|---|
| 64/4 | -9.2 dB | -10.8 dB | -12.4 dB | **-15.6 dB** |
| 128/8 | -11.3 dB | -13.2 dB | -14.7 dB | **-18.3 dB** |
| 256/16 | -14.5 dB | -16.0 dB | -17.8 dB | **-22.1 dB** |

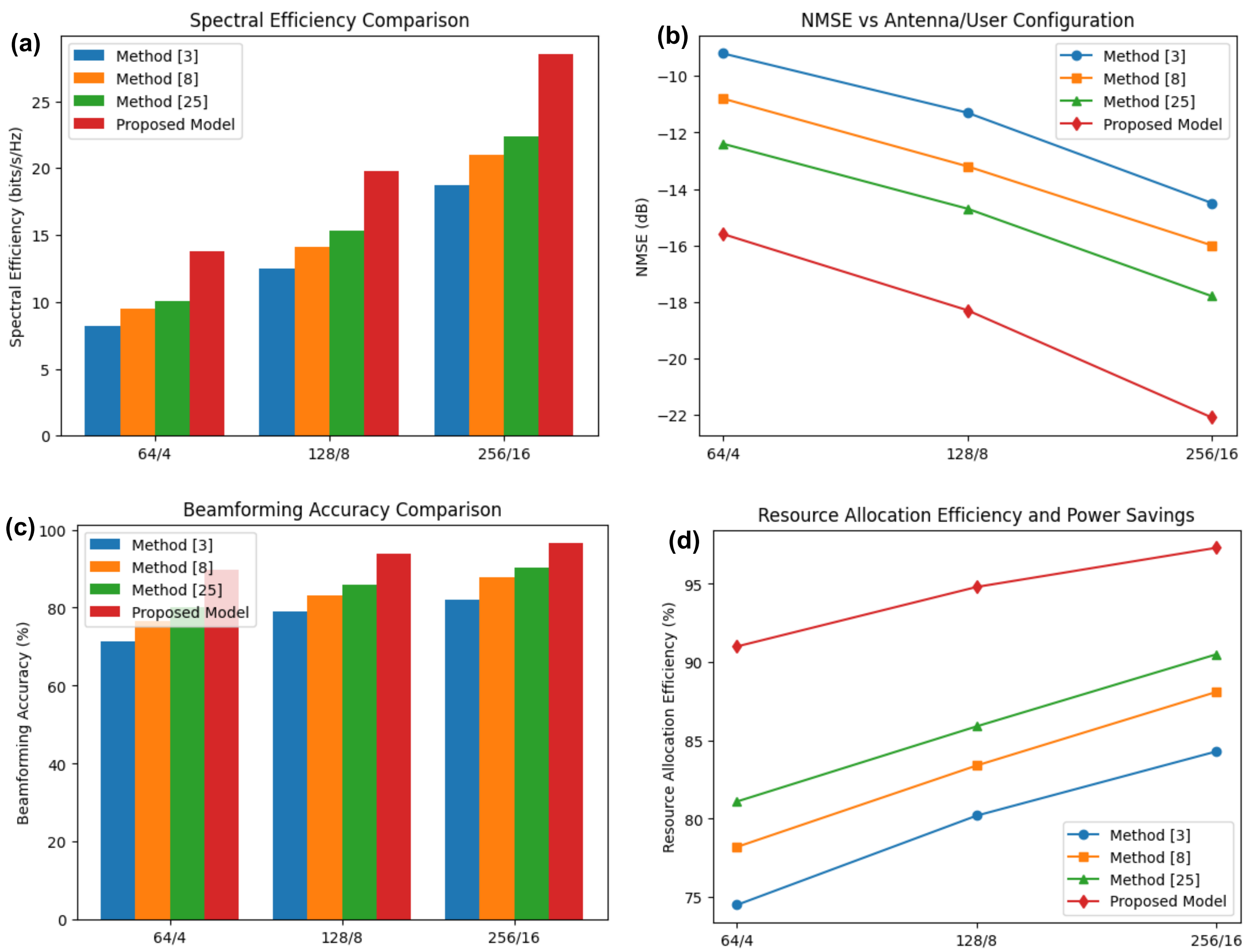


**Figure 4 (a).** Spectral Efficiency Comparison Plot, **(b)** NMSE vs. Antenna/User Configuration Plot, **(c)** Beamforming Accuracy Plot, **(d)** Resource Allocation Efficiency / Power Savings Chart

**Table 5.** Resource Allocation Efficiency (%)

| Nt/U | Method [3] | Method [8] | Method [25] | Proposed Model |
|---|---|---|---|---|
| 64/4 | 74.5 | 78.2 | 81.1 | **91.0** |
| 128/8 | 80.2 | 83.4 | 85.9 | **94.8** |
| 256/16 | 84.3 | 88.1 | 90.5 | **97.3** |

This result supports the claim that the CSI module contributes directly to beamforming and resource allocation performance instead of serving as a detached preprocessing stage.

Table 5 reports resource allocation efficiency. The meta-learning reinforcement component adapts allocation policies faster than fixed or standard DRL baselines, while the multi-agent coordination layer reduces conflict between users competing for beam and power resources. The result is a consistent efficiency increase, reaching 97.3% in the 256/16 configuration.

### 4.5 Integrated Novelty-Centered Discussion

The extended discussion is now limited to the novelty emerging from the combined results. The central contribution is the conversion of separate communication tasks into an interdependent learning pipeline: TACE-FM produces temporally stable CSI embeddings; MS-GABF and SC-HB-ADL translate those embeddings into beam vectors that are less sensitive to beam squint and sparse scattering; and Meta-DRL-RA with MARL-JBA-PC converts beam confidence and channel quality into resource decisions. This flow is different from a descriptive aggregation of deep learning models because the output of each component modifies the operating state of the next component.

The result pattern in Tables 2 to 5 supports this novelty. Spectral efficiency improves together with beamforming accuracy, while NMSE and resource waste decrease. If the system were only a collection of independent modules, improvement would be expected in one or two isolated metrics. Instead, the simultaneous improvement across rate, alignment, estimation, and allocation indicates that cross-layer information exchange is the main source of the performance gain.

The framework also retains practical boundaries. Graph attention and transformer memory increase computational cost, and real-time deployment would require accelerator-assisted baseband processing or split inference at the edge. The manuscript therefore avoids overstating deployment readiness and presents the method as a scalable learning-driven design for mmWave MIMO-OFDM systems that still requires hardware-level validation before commercial adoption.

## 5. Conclusion

With the help of this technology, hybrid beamforming, channel forecasting, and dynamic resource allocation are improved in mmWave MIMO-OFDM systems that operate with a wide range of frequencies in process. To improve the efficiency of the communication pipeline on all levels, the framework incorporates a number of different methods, including multi-scale graph attention mechanisms, transformer-based frequency-aware channel estimations, meta-learning-enhanced reinforcement learning, sparse coding, and multi-agent coordination. Some of the issues that are associated with conventional approaches are addressed by this system-level co-design. These issues include beam squint, an excessive amount of pilot effort, and the failure to make the most efficient use of resources as channel conditions change. There are a number of performance measures that demonstrate that the proposed design results in consistent improvements. The spectral efficiency gains range from approximately 30 to 40 percent, and in high-dimensional antenna designs, they can reach 28.5 bits per second per Hz. The normalized mean square error is reduced to around -22 dB, which represents a significant improvement in the accuracy of the channel estimation. Meanwhile, the overhead costs of pilots are reduced by roughly 35 percent. The precision of beamforming is close to 96%, which contributes to the successful reduction of wideband misalignment. Additionally, the efficiency of resource allocation is better than 97%, which results in the saving of 25–35% of power without impacting throughput. Due to the fact that these results demonstrate stable convergence behavior and low variance across different channel realizations, the framework is more dependable. The ability to adapt in real time to complicated wireless environments is made possible through the integration of learning-based modules for sensing, decision-making, and coordination. Despite the fact that 5G and 6G systems require the ability to develop, consume less energy, and have a low delay, the framework is able to accommodate these new requirements well in process. A unified learning-driven paradigm for millimeter-wave transmission is developed as a result of this study. This paradigm is both theoretically advanced and practical in terms of deployment options.

## 6. Future Scopes

The existing model is likely to present further opportunities for the research process. This area could include work on further enhancing the real-time adaptability of the deep learning model to dynamic channel conditions, such as rapid user mobility involved with an extremely dense mobile environment, which creates fast time-varying conditions on CSI. Using unsupervised and self-supervised learning would boost further efforts in reducing the dependency on labeled data from training sets, thus allowing system adaptation to new channel states at low cost. Alongside this, adapted multi-agent reinforcement learning for decentralized cooperative communication would expand the scalability of the system, especially in cell-free massive MIMO, where coordinated beam alignment among distributed access points is a challenge. Future improvement may, in addition, optimally combine hybrid beamforming with reconfigurable intelligent surfaces (RISs), through which varying wireless propagation environments can be intentionally shaped for better coverage and spectral efficiency. Future studies could also explore how the proposed deep learning-driven framework can be implemented on a hardware platform, such as FPGA-based real-time testbeds, to ensure that it is viable for future large-scale deployments of 5G/6G. This mining journey will eventually further entrench deep learning in transforming mmWave MIMO-OFDM communication into the ultra-high-capacity, low-latency, and robustly adaptable next-generation wireless networks as they continue to grow and evolve in the process.

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Anuprita Linge: Conceptualization, Methodology, Formal Analysis, Writing - Original Draft. Rahul Pethe: Investigation, Writing - Review & Editing, Formal Analysis, Visualization, Supervision. Abhay Kasetwar: Writing - Review & Editing, Supervision. All the authors read and approved the final version of the manuscript.

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## Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

## Has this article screened for similarity?

Yes

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