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FuzzyBeam-Net: Fuzzy Logic-Enhanced Deep Learning for Adaptive Beamforming in 5G Massive MIMO Systems

Ajay Sonkesriya
Lecturer, Electronics and Communication Engineering, Kalaniketan polytechnic College Jabalpur, MP, India

Abstract-- **Adaptive beamforming in fifth-generation (5G) Massive Multiple-Input Multiple-Output (Massive MIMO) systems presents a fundamental challenge: real-time precoding weight optimisation in the presence of rapidly changing multipath propagation channels, uncertain angle-of-arrival (AoA) estimates, and hardware imperfections in large antenna arrays. Classical beamforming algorithms — including Zero-Forcing (ZF), Regularised ZF (RZF), and Minimum Mean Square Error (MMSE) precoding — rely on crisp channel state information (CSI) that in practice arrives with estimation errors, feedback quantisation noise, and latency. This paper proposes FuzzyBeam-Net, a novel hybrid beamforming architecture that couples a Fuzzy Logic Layer (FLL) with an Adaptive Attentive Neural Beamforming Module (AANBM), an Attention-Gated Self-Organising Cluster Mapper (AG-SOCM), and a Temporal Channel Drift Corrector (TCDC). The FLL maps noisy received signal strength indicators (RSSI), pilot-estimated CSI confidence scores, and AoA uncertainty measures to graded linguistic membership degrees — Low, Moderate, High — via trapezoidal membership functions, providing soft confidence-weighted inputs to all downstream modules in place of hard-thresholded binary decisions. The AANBM replaces the conventional linear precoding step with a self-attention mechanism over the concatenated user-beam interaction tensor followed by a three-layer MLP, enabling non-linear joint beam selection across spatially correlated user clusters. AG-SOCM introduces a sigmoid confidence gate into the SOM-based user clustering update rule, suppressing uncertain best-matching-unit (BMU) updates when pilot contamination is severe. TCDC applies exponential decay weighting over historical channel snapshots to account for Doppler-induced temporal correlation drift. Results on the DeepMIMO O1 and I3 ray-tracing datasets and the QuaDRiGa 3GPP 38.901 Urban Macro (UMa) channel model demonstrate that FuzzyBeam-Net achieves spectral efficiency of 47.8 bps/Hz at 64 antennas and SNR = 20 dB, surpassing Zero-Forcing (32.1 bps/Hz), MMSE (35.4 bps/Hz), FD-Net [21] (41.2 bps/Hz), and the direct predecessor HybridMIMO-Net [1] (43.6 bps/Hz) by statistically significant margins (paired t-test, $p < 0.05$). Ablation analysis confirms that the FLL contributes the second-largest individual gain (+2.4 bps/Hz), behind AG-SOCM (+3.1 bps/Hz) and ahead of AANBM attention mechanism (+1.8 bps/Hz), establishing cluster-quality-aware gating as the dominant architectural contributor.*****Keywords--*** **5G Massive MIMO; Adaptive Beamforming; Fuzzy Logic; Deep Learning; Self-Organising Maps; Spectral Efficiency; Channel Estimation; DeepMIMO; QuaDRiGa; Attention Mechanism**

I. Introduction

The deployment of fifth-generation (5G) New Radio (NR) networks worldwide has elevated Massive MIMO — base stations equipped with dozens to hundreds of antenna elements serving tens of simultaneous user equipment (UE) — from research prototype to commercial infrastructure [2, 3]. The defining performance promise of Massive MIMO is the ability to spatially multiplex a large number of users within the same time-frequency resource through highly directional beamforming, achieving spectral efficiency (SE) gains that scale nearly linearly with the number of base station antennas under ideal conditions [4].

In practice, however, three structural challenges erode this theoretical promise in deployed networks:

- *Imperfect Channel State Information (CSI):* Pilot-based channel estimation introduces estimation errors that grow with pilot sequence length, pilot contamination from neighbouring cells, and hardware non-idealities in RF chains. Classical linear precoders — ZF, RZF, MMSE — assume perfect CSI and degrade severely when this assumption fails [5, 6].
- *AoA Uncertainty:* Beamforming weights in hybrid analogue-digital architectures depend on accurate angle-of-arrival estimates. Multipath propagation in urban macro (UMa) environments produces angular spreads that cause beams to straddle cluster boundaries, leading to inter-beam interference [7].
- *Channel Non-Stationarity:* User mobility induces Doppler shifts that cause the channel to evolve across OFDM symbol intervals. Static beamforming weights computed at one time instant become progressively misaligned as the channel drifts, requiring periodic recomputation that consumes pilot overhead [8, 9].

Deep learning approaches to beamforming have attracted considerable research attention in the past five years. El Ayach et al. [10] introduced the hybrid precoding paradigm; Huang et al. [11] applied deep neural networks for mmWave beamforming; Elbir and Coleri [12] proposed CNN-based hybrid precoding. More recently, transformer-based architectures have been applied to beam selection [13, 14], and recurrent models have been used for temporal channel tracking [15, 16].

However, a consistent limitation across all prior deep learning beamforming systems is the treatment of CSI inputs as crisp, high-confidence observations rather than as soft, uncertainty-bearing estimates. This mismatch between the assumed input quality and the real-world measurement environment is a root cause of performance degradation under pilot contamination and rapid fading.

Fuzzy logic [17], originally developed by Zadeh as a formal framework for reasoning under uncertainty, provides an elegant solution to this mismatch: trapezoidal membership functions can replace binary decisions over RSSI strength, CSI estimation quality, and AoA confidence with graded membership degrees that propagate calibrated uncertainty signals throughout the beamforming pipeline. Despite the demonstrated value of fuzzy inference in classical signal processing [18, 19], no prior work has systematically integrated fuzzy logic with deep learning beamforming architectures for 5G Massive MIMO.

This paper proposes FuzzyBeam-Net, a hybrid beamforming architecture that addresses all three structural challenges through four mutually reinforcing components:

- *C1. Fuzzy Logic Layer (FLL):* Trapezoidal membership functions map received signal quality indicators to graded confidence signals (Equations 1–5).
- *C2. Adaptive Attentive Neural Beamforming Module (AANBM):* Self-attention over the fuzzy-weighted user-beam interaction tensor followed by a three-layer MLP replaces linear precoding (Equations 6–9).
- *C3. Attention-Gated Self-Organising Cluster Mapper (AG-SOCM):* A sigmoid confidence gate scales each SOM weight update by the reliability of the corresponding BMU assignment, suppressing updates under high pilot contamination (Equations 10–12).
- *C4. Temporal Channel Drift Corrector (TCDC):* Exponential decay weighting over historical channel snapshots corrects for Doppler-induced channel evolution (Equations 13–14).

The contributions of this paper are summarised as follows:

- *Fuzzy-neural integration for beamforming:* We propose the first systematic integration of fuzzy membership functions into a deep learning beamforming pipeline, enabling uncertainty-aware signal processing at the front end of a Massive MIMO precoder.
- *AG-SOCM gated clustering:* We introduce a sigmoid confidence gate into the SOM-based spatial user clustering update rule, demonstrating via ablation that cluster quality is the dominant training-environment bottleneck constraining beamforming accuracy.
- *Temporal drift correction:* TCDC applies exponential decay weighting to historical channel observations, providing the first fuzzy-deep learning beamformer with explicit Doppler compensation.
- *Comprehensive evaluation:* We evaluate FuzzyBeam-Net on three publicly available channel simulation datasets (DeepMIMO O1, DeepMIMO I3, QuaDRiGa UMa) with five baseline comparisons, ablation analysis, and paired statistical significance testing.

II. Related Work

2.1 Classical Beamforming in Massive MIMO

Linear precoders form the foundation of Massive MIMO beamforming. Zero-Forcing (ZF) precoding inverts the channel matrix to null inter-user interference at the cost of noise enhancement when the channel is ill-conditioned [5]. Regularised ZF (RZF) and MMSE precoding introduce diagonal regularisation to balance interference suppression against noise amplification [6]. Both require knowledge of the full channel matrix, which is available only through pilot-based estimation. Marzetta [4] established the theoretical justification for Massive MIMO: as the number of antennas M grows large, the effects of fast fading and uncorrelated noise vanish. However, pilot contamination — the reuse of orthogonal pilot sequences across cells — remains an irreducible performance ceiling [5].

2.2 Deep Learning for Beamforming

El Ayach et al. [10] demonstrated that the hybrid precoding problem — jointly designing the analogue phase-shifter matrix and digital baseband precoder — can be reformulated as a sparse signal recovery problem, enabling efficient solutions via OMP. Subsequent deep learning approaches replaced the iterative solver with feed-forward networks: Elbir and Coleri [12] trained a CNN to predict analogue precoder codebook indices from quantised CSI; Huang et al. [11] applied deep networks to mmWave beam selection with compressed feedback.

Transformer architectures have recently entered the beamforming literature. Lin et al. [13] applied multi-head self-attention to joint beam selection across users, exploiting inter-user spatial correlation.

Chen et al. [14] proposed a BeamFormer architecture that treats subcarrier beamforming weights as a sequence and models cross-subcarrier dependencies via attention. For temporal channel evolution, Jiang et al. [15] trained a bidirectional LSTM to predict future channel states from historical measurements; Ma et al. [16] applied a convolutional-recurrent hybrid.

HybridMIMO-Net [1], the direct predecessor to FuzzyBeam-Net, proposed a four-component architecture combining SVD-based precoder initialisation, content-driven KNN user clustering, SOM-based spatial mapping, and K-Means++ partitioning with Silhouette cluster selection. It achieved spectral efficiency of 43.6 bps/Hz at 64 antennas and SNR = 20 dB on DeepMIMO O1, surpassing ZF (32.1) and MMSE (35.4) substantially. However, [1] retains four structural limitations: linear SVD precoding, overconfident SOM updates under pilot contamination, temporal stationarity, and uncalibrated fusion of multi-stream scores — motivating FuzzyBeam-Net.

2.3 Fuzzy Logic in Signal Processing

Fuzzy logic [17] has been applied to wireless communications in several contexts. Samad et al. [18] used fuzzy inference for adaptive power control in CDMA systems, demonstrating 8–12% improvement in SINR over hard-threshold controllers. Liang et al. [19] applied fuzzy clustering to channel estimation, replacing crisp pilot groupings with soft cluster memberships to reduce estimation error by 6.3% in frequency-selective fading channels. Mishra et al. [20] proposed a fuzzy-MIMO antenna selection criterion based on graded RSSI membership functions.

Despite these precedents, no prior work has integrated fuzzy membership functions into the input representation of a deep learning beamforming network, nor applied them to modulate the cluster update dynamics of a SOM-based spatial user mapper. FuzzyBeam-Net addresses both gaps simultaneously.

2.4 Research Gaps

A systematic survey of 35 papers in neural beamforming, fuzzy signal processing, and Massive MIMO channel estimation reveals four specific gaps that FuzzyBeam-Net closes:

- **G1:** No published deep learning beamformer applies fuzzy membership functions as an uncertainty-aware front end, replacing crisp CSI with graded confidence signals.
- **G2:** All existing SOM-based spatial user clustering algorithms in beamforming apply weight updates uniformly regardless of BMU assignment reliability.
- **G3:** Temporal channel drift correction via exponential Doppler-weighting has not been combined with fuzzy-attentive neural precoding in a single pipeline.
- **G4:** Heterogeneous multi-stream score calibration prior to beamforming weight fusion has not been studied in the neural Massive MIMO literature.

III. SYSTEM MODEL

We consider a single-cell 5G NR Massive MIMO downlink scenario with one base station (BS) equipped with M antenna elements arranged in a Uniform Linear Array (ULA) and K single-antenna user equipment (UE) simultaneously served in the same time-frequency resource block. The number of RF chains R satisfies $K \le R \le M$, enabling hybrid analogue-digital precoding.

3.1 Channel Model

The M×K downlink channel matrix $H \in \mathbb{C}^{M\times K}$ is generated according to the DeepMIMO ray-tracing framework [22] and the QuaDRiGa 3GPP 38.901 Urban Macro (UMa) geometry-based stochastic model [23]. Each column $h_k \in \mathbb{C}^M$ represents the channel vector between the BS and the k-th UE, modelled as a superposition of L multipath components:

$$h_k = \sqrt{M/L} \cdot \Sigma_{l=1}^{L} \alpha_{k,l} \cdot a(\theta_{k,l}) \quad (1)$$

where $\alpha_{k,l} \in \mathbb{C}$ is the complex gain of the l-th path, $\theta_{k,l}$ is the angle-of-arrival (AoA), and $a(\theta) \in \mathbb{C}^M$ is the ULA steering vector:

$$a(\theta) = (1/\sqrt{M}) [1, e^{j\pi\sin\theta}, e^{j2\pi\sin\theta}, ..., e^{j(M-1)\pi\sin\theta}]^T \quad (2)$$

3.2 Pilot-Based Channel Estimation

During the uplink pilot phase, each UE transmits a pilot sequence of length τ_p symbols. The estimated channel $\hat{H}_k$ is modelled as:

$$\hat{H}_k = h_k + \varepsilon_k, \quad \varepsilon_k \sim KN(0, \sigma^2_e \cdot I_M) \quad (3)$$

where $\sigma^2_e = \sigma^2_n / (K \cdot \rho_p)$ is the estimation error variance, σ^2_n is the noise power, and ρ_p is the pilot transmit SNR. The CSI confidence score for user k is defined as:

$$c_k = \exp(-\sigma^2_e / \|\hat{H}_k\|^2) \in [0, 1] \quad (4)$$

A confidence score near 1 indicates reliable CSI; near 0 indicates high estimation noise relative to signal strength.

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3.3 Spectral Efficiency

Under matched-filter (MF) precoding with weights $W = H^H(HH^H)^{-1}$, the downlink spectral efficiency for user k is:

$$SE_k = \log_2\left(1 + \frac{p_k |h_k^H w_k|^2}{\sum_{j\neq k} p_j |h_k^H w_j|^2 + \sigma^2_n}\right) \quad (5)$$

The aggregate system SE (bps/Hz) = $\sum_{k=1}^{K} SE_k$ is the primary performance metric throughout this work. All SE values are computed under power constraint $\sum_{k} p_k = P_{total}$ with uniform power allocation $p_k = P_{total}/K$.

IV. Proposed Methodology: FuzzyBeam-Net

4.1 Architecture Overview

FuzzyBeam-Net processes the pilot-estimated channel matrix $\hat{H} \in \mathbb{C}^{M\times K}$ and auxiliary measurements (RSSI vector $r \in \mathbb{R}^K$, AoA estimate vector $\hat{\theta} \in \mathbb{R}^K$, CSI confidence $c \in \mathbb{R}^K$) through four sequential processing stages before generating the final precoding weight matrix $W_{FBN} \in \mathbb{C}^{M\times K}$.

The complete inference pipeline is: $\{\hat{H}, r, c, \hat{\theta}\}$ → FLL → [AANBM ‖ AG-SOCM] → TCDC → Platt Calibration → Fusion → W_{FBN} → SE.

4.2 Fuzzy Logic Layer (FLL)

The FLL maps each of the three auxiliary measurements to a graded membership triple (μ_L, μ_M, μ_H) via trapezoidal membership functions, producing soft uncertainty signals that propagate to AANBM and AG-SOCM.

4.2.1 RSSI Membership Functions

RSSI values r_k in dBm are normalised to [0, 1] and mapped to three linguistic classes:

$$\mu_L^r(r_k) = \max(0, \min(1, (0.4 - r_k) / 0.2)) \quad (6)$$

$$\mu_M^r(r_k) = \max(0, \min((r_k - 0.2)/0.2, (0.8 - r_k)/0.2)) \quad (7)$$

$$\mu_H^r(r_k) = \max(0, \min(1, (r_k - 0.6) / 0.2)) \quad (8)$$

4.2.2 CSI Confidence Membership Functions

The CSI confidence score c_k from Equation (4) is similarly fuzzified:

$$\mu_L^c(c_k) = \max(0, \min(1, (0.35 - c_k) / 0.15)) \quad (9)$$

$$\mu_H^c(c_k) = \max(0, \min(1, (c_k - 0.65) / 0.15)) \quad (10)$$

with $\mu_M^c = 1 - \mu_L^c - \mu_H^c$ (partition of unity). The combined fuzzy feature vector for user k is $\varphi_k = [\mu_L^r, \mu_M^r, \mu_H^r, \mu_L^c, \mu_H^c] \in \mathbb{R}^5$.

4.2.3 Defuzzification

The aggregated fuzzy confidence for user k is recovered via centroid defuzzification:

$$FuzzyConf_k = (0.2\mu_L^c + 0.5\mu_M^c + 0.9\mu_H^c) / (\mu_L^c + \mu_M^c + \mu_H^c) \quad (11)$$

A user with $c_k = 0.8$ maps to approximately $FuzzyConf_k = 0.82$, reflecting high but not absolute confidence, compared to the hard threshold $c_k \geq 0.7$ → "reliable" used in classical systems.

4.3 Adaptive Attentive Neural Beamforming Module (AANBM)

AANBM replaces the linear ZF/MMSE precoding step with a self-attention mechanism followed by a three-layer MLP. Input to AANBM is the concatenation of the real-imaginary split channel representation $\tilde{H}_k = [Re(\hat{H}_k); Im(\hat{H}_k)] \in \mathbb{R}^{2M}$ and the fuzzy feature vector φ_k, forming the augmented user representation:

$$x_k = [\tilde{H}_k ; \alpha_f \cdot FuzzyConf_k \cdot \varphi_k] \in \mathbb{R}^{2M+5} \quad (12)$$

where $\alpha_f \in [0, 1]$ is a trainable fuzzy blending coefficient initialised at 0.60 (selected by grid search on validation set). The K user representations are stacked into $X \in \mathbb{R}^{K\times(2M+5)}$.

4.3.1 Self-Attention Mechanism

Multi-head self-attention is applied across users to capture inter-user spatial correlation:

$$Q = X W_Q,\ K_{mat} = X W_K,\ V = X W_V \quad (13)$$

$$A^{att} = \mathrm{softmax}(QK_{mat}^T / \sqrt{d_k})\, V \quad (14)$$

where $W_Q, W_K, W_V \in \mathbb{R}^{(2M+5)\times d_k}$ are learnable projection matrices, d_k is the key dimension, and the softmax is applied row-wise. The attention output $A^{att} \in \mathbb{R}^{K\times d_k}$ captures correlation structure across users that linear precoding cannot exploit.

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4.3.2 MLP Beamforming Predictor

The attention output is passed through a three-layer MLP to predict the real and imaginary components of the precoding weight vector for each user:

$$z_k^{(1)} = \mathrm{ReLU}(W_1 A^{att}_k + b_1) \quad (15)$$

$$z_k^{(2)} = \mathrm{ReLU}(W_2 z_k^{(1)} + b_2) \quad (16)$$

$$[\mathrm{Re}(w_k); \mathrm{Im}(w_k)] = W_3 z_k^{(2)} + b_3 \quad (17)$$

The complex precoding vector is then recovered as $w_k = \mathrm{Re}(w_k) + j\cdot\mathrm{Im}(w_k)$. All weight matrices W_1, W_2, W_3 and biases b_1, b_2, b_3 are learned end-to-end by maximising expected spectral efficiency on the training set.

4.4 Attention-Gated Self-Organising Cluster Mapper (AG-SOCM)

AG-SOCM partitions K users into S spatial clusters based on the similarity of their fuzzy-augmented channel representations, providing a cluster-membership signal that AANBM uses as an additional input. The clustering step is analogous to the IKSOM component in HybridMIMO-Net [1] but replaces uniform weight updates with confidence-gated updates.

4.4.1 BMU Selection

The Best-Matching Unit (BMU) for user k is the cluster centroid w_s closest in EISEN cosine distance:

$$\mathrm{BMU}(k) = \mathrm{argmin}_s\, D_{EISEN}(x_k, w_s) \quad (18)$$

$$D_{EISEN}(x, w) = 1 - (x^T w) / (\|x\| \cdot \|w\|) \quad (19)$$

4.4.2 Confidence-Gated Weight Update

The BMU confidence for user k is computed via a Gaussian kernel over EISEN distance:

$$\omega(k, \mathrm{BMU}) = \exp(-D_{EISEN}(x_k, w_{BMU})^2 / \tau^2) \quad (20)$$

The confidence gate $g(\omega_k) \in (0, 1]$ is modelled by a trainable sigmoid:

$$g(\omega_k) = \sigma(W_g \cdot \omega_k + b_g) \quad (21)$$

The centroid update then becomes:

$$w_s(t+1) = w_s(t) + g(\omega_k) \cdot \gamma(t) \cdot h(s, \mathrm{BMU}, t) \cdot [x_k - w_s(t)] \quad (22)$$

where $\gamma(t)$ is the scheduled learning rate and $h(s, \mathrm{BMU}, t)$ is the neighbourhood function. When D_{EISEN} is large (unreliable assignment), $g(\omega_k) \approx 0$ and the centroid is not moved, preventing the cluster geometry from being distorted by low-confidence pilot observations.

4.4.3 Convergence Theorem

Theorem 1. For AG-SOCM with L2-regularised centroid updates (penalty λ on $\|w_s\|^2$), the objective $\mathscr{L} = \Sigma_k \|x_k - w_{BMU(k)}\|^2 + \lambda\Sigma_s \|w_s\|^2$ converges to a local minimum. Proof: (Sketch) The regularised centroid update $w_s^* = \Sigma_{k: BMU(k)=s}\, x_k / (|C_s| + \lambda)$ is the unique minimiser of $\mathscr{L}$ for fixed assignments, as $\mathscr{L}$ is strictly convex in w_s with curvature $(|C_s| + \lambda) > 0$. The assignment step cannot increase $\mathscr{L}$. The gate $g(\omega_k)$ reduces the effective step size monotonically, accelerating convergence without violating the descent property. By the Monotone Convergence Theorem, convergence follows. □

4.5 Temporal Channel Drift Corrector (TCDC)

To account for Doppler-induced temporal evolution of the channel, TCDC applies exponential decay weighting to historical channel estimates over a sliding window of N_h snapshots:

$$\hat{H}^{eff}_k(t) = \Sigma_{n=0}^{N_h-1} \delta_n \cdot \hat{H}_k(t-n) / \Sigma_{n=0}^{N_h-1} \delta_n \quad (23)$$

$$\delta_n = \exp(-n / \tau_{ch}), \quad \tau_{ch} = 1 / (2\pi f_D T_s) \quad (24)$$

where f_D is the estimated maximum Doppler frequency and T_s is the OFDM symbol period. The effective channel $\hat{H}^{eff}_k(t)$ serves as input to AANBM and AG-SOCM, replacing the raw instantaneous estimate and suppressing stale measurements that no longer reflect the current channel state.

4.6 Multi-Stream Calibration and Fusion

AANBM and AG-SOCM produce beamforming weight proposals w^{CF}_k (CF stream from AANBM) and w^{CL}_k (cluster stream from AG-SOCM) respectively. DCD-KNN produces a content-driven beam estimate w^{CB}_k via semantically-indexed codebook lookup. Each stream score is calibrated via Platt scaling before fusion:

$$P_k^{(s)}(w_k) = \sigma(A_s \cdot s_k + B_s), \quad s \in \{CF, CL, CB\} \quad (25)$$

$$w_k^{FBN} = \mathrm{Normalise}(0.45 \cdot P_k^{CF} \cdot w_k^{CF} + 0.28 \cdot P_k^{CB} \cdot w_k^{CB} + 0.27 \cdot P_k^{CL} \cdot w_k^{CL}) \quad (26)$$

where calibration parameters A_s and B_s are fitted on a held-out validation split. The fused weight vector is L2-normalised before precoder application.

Fusion weights {0.45, 0.28, 0.27} were selected by grid search over the unit simplex at resolution 0.05.

V. Experimental Setup

5.1 Datasets

Three publicly available channel simulation datasets are used, covering diverse propagation environments and enabling generalisability assessment:

- *DeepMIMO O1 (Outdoor):* Ray-tracing based channel generation for a dense urban environment with buildings, vehicles, and pedestrians at 3.5 GHz carrier frequency [22]. Grid spacing 0.5 m; 18,980 user locations used (15,180 train / 1,900 validation / 1,900 test). M = 64, 32, 16 antennas; K = 8 UEs; 10 active paths per user.
- *DeepMIMO I3 (Indoor):* Ray-tracing scenario for a large indoor hall at 60 GHz mmWave frequency [22]. 12,080 user locations (9,664 / 1,208 / 1,208 split). M = 64; K = 8; 5 active paths per user. Provides a higher-frequency, more complex multipath environment.
- *QuaDRiGa 3GPP 38.901 UMa:* Geometry-based stochastic channel model for urban macro deployment at 3.5 GHz [23]. 20,000 Monte Carlo channel realisations (16,000 / 2,000 / 2,000 split). M ∈ {16, 32, 64}; K = 8; user velocities from 0 to 60 km/h to exercise the TCDC component.

5.2 Baseline Methods

Six baselines are compared across all three datasets:

- *ZF Precoding:* Classical zero-forcing precoder with ideal CSI [5].
- *MMSE Precoding:* Regularised minimum mean square error precoder with pilot-estimated CSI [6].
- *FD-Net [21]:* Feed-forward deep network for beamforming weight prediction, trained end-to-end with perfect CSI inputs.
- *Transformer-Beam [13]:* Multi-head attention transformer for joint beam selection, applied to the K-user channel matrix.
- *CR-LSTM [15]:* Convolutional-recurrent LSTM for channel prediction and temporal beamforming.
- *HybridMIMO-Net [1]:* Direct predecessor — SVD + CDK-KNN + IKSOM-CF + K-Means++ pipeline without fuzzy logic or temporal correction.

5.3 Implementation Details

FuzzyBeam-Net is implemented in PyTorch 2.0.1 with CUDA 11.8 on an NVIDIA RTX 4090 (24 GB VRAM). Training uses the AdamW optimiser with learning rate 1e-4, cosine annealing schedule, linear warmup (500 steps), weight decay 0.01, and gradient clipping at 1.0. Batch size = 64; maximum 200 epochs with early stopping (patience = 10 on validation SE). $\alpha_f = 0.60$, τ_{ch} = window $N_h = 8$ snapshots, $\lambda = 0.01$ (centroid regularisation). The MLP hidden dimensions are [512, 256, 2M]. AG-SOCM is initialised with K-Means++ and S = K clusters. All random operations use seed = 42. Training loss is negative expected spectral efficiency, approximated by the differentiable soft lower bound from [24].

5.4 Evaluation Metrics

Primary metric: Aggregate downlink spectral efficiency (bps/Hz) = $\Sigma_k SE_k$, averaged over all test channel realisations. Secondary metrics: Beam alignment error (°), convergence epochs, average precoder design time (ms/sample). Statistical significance: Paired Wilcoxon signed-rank test and paired t-test (5 independent runs, α = 0.05).

VI. Results And Discussion

6.1 Spectral Efficiency Comparison

Table 1 presents the aggregate spectral efficiency (bps/Hz) of FuzzyBeam-Net and all six baselines on the three benchmark datasets at SNR = 20 dB, M = 64 antennas, K = 8 users.

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Table 1: Aggregate Spectral Efficiency (bps/Hz) at SNR = 20 dB, M = 64 antennas, K = 8 users. * p < 0.05 vs. all baselines (paired t-test).

Method	DeepMIMO O1	DeepMIMO I3	QuaDRiGa UMa	Average
ZF Precoding	32.1	28.4	29.7	30.1
MMSE Precoding	35.4	31.2	32.8	33.1
FD-Net [21]	41.2	37.8	39.1	39.4
Transformer-Beam [13]	42.7	39.1	40.6	40.8
CR-LSTM [15]	41.9	38.6	40.2	40.2
HybridMIMO-Net [1]	43.6	40.3	41.8	41.9
FuzzyBeam-Net (Ours)	47.8*	44.1*	45.6*	45.8*

FuzzyBeam-Net achieves 47.8, 44.1, and 45.6 bps/Hz on DeepMIMO O1, I3, and QuaDRiGa UMa respectively, surpassing the direct predecessor HybridMIMO-Net [1] by 4.2, 3.8, and 3.8 bps/Hz (approximately 9.5% relative improvement). All six pairwise comparisons are statistically significant at $p < 0.05$ in paired t-tests across 5 independent runs.

The improvement over ZF (15.7 bps/Hz, 49%) and MMSE (12.4 bps/Hz, 35%) reflects the substantial advantage of learned non-linear precoding over classical linear algebra under imperfect CSI.

6.2 Effect of Antenna Count

Table 2 shows the spectral efficiency variation with $M \in \{16, 32, 64\}$ on DeepMIMO O1 at SNR = 20 dB.

Table 2: Spectral Efficiency (bps/Hz) vs. Antenna Count (M) on DeepMIMO O1, SNR = 20 dB. * p < 0.05.

Method	M=16	M=32	M=64
ZF Precoding	16.8	24.2	32.1
MMSE Precoding	18.4	26.9	35.4
Transformer-Beam [13]	22.1	32.8	42.7
HybridMIMO-Net [1]	23.2	33.7	43.6
FuzzyBeam-Net (Ours)	25.8*	36.9*	47.8*

FuzzyBeam-Net consistently ranks first across all antenna configurations. The relative gain over HybridMIMO-Net [1] increases from 11.2% at M=16 (2.6 bps/Hz) to 9.6% at M=64 (4.2 bps/Hz). The slightly smaller relative gain at M=64 is expected: with more antennas, classical methods improve faster due to channel hardening, narrowing the gap.

FuzzyBeam-Net nonetheless maintains absolute superiority across the entire range.

6.3 SNR Sensitivity Analysis

Table 3 reports spectral efficiency across the SNR range from 0 to 30 dB on DeepMIMO O1 with M = 64.

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Table 3: Spectral Efficiency (bps/Hz) across SNR Range, DeepMIMO O1, M = 64, K = 8. * p < 0.05.

Method	SNR = 0 dB	SNR = 5 dB	SNR = 10 dB	SNR = 20 dB	SNR = 30 dB
ZF Precoding	9.2	14.3	21.8	32.1	38.4
MMSE Precoding	12.1	17.8	25.4	35.4	41.6
HybridMIMO-Net [1]	18.7	24.6	31.9	43.6	49.2
FuzzyBeam-Net (Ours)	21.4*	27.8*	35.2*	47.8*	52.9*

FuzzyBeam-Net delivers consistent advantages across the full SNR range. The gain over HybridMIMO-Net [1] is largest at SNR = 0 dB (2.7 bps/Hz, 14.4%), where imperfect CSI has the most severe impact and the FLL uncertainty-awareness is most critical. At high SNR (30 dB), where CSI quality improves and the uncertainty benefit diminishes, the gap narrows to 3.7 bps/Hz (7.5%) but remains statistically significant.

6.4 Ablation Study

Table 4 presents the ablation analysis on DeepMIMO O1 (M = 64, SNR = 20 dB, 5-fold CV), progressively removing each FuzzyBeam-Net component and measuring the resulting spectral efficiency degradation.

Table 4: Ablation Study on DeepMIMO O1 (M = 64, SNR = 20 dB). ΔSE relative to full FuzzyBeam-Net. * All ΔSE significant at p < 0.05.

Configuration	Components Removed	SE (bps/Hz)	ΔSE vs. Full	p-value
Full FuzzyBeam-Net	None	47.8	—	—
No FLL	Fuzzy Logic Layer	45.4	-2.4	0.008
No AANBM Attention	Self-attention (linear MLP only)	46.0	-1.8	0.016
No AG-SOCM	IKSOM from [1] replacing AG-SOCM	44.7	-3.1	0.003
No TCDC	Static channel snapshot	46.9	-0.9	0.031
No Platt Calibration	Uncalibrated score fusion	46.2	-1.6	0.019
HybridMIMO-Net [1]	FLL + AANBM-attn + AG-SOCM + TCDC	43.6	-4.2	0.001

The ablation reveals a counter-intuitive ranking of component contributions. A priori, the AANBM attention mechanism (replacing linear precoding with learned non-linear attention) was expected to be the largest contributor. Post-hoc analysis shows that AG-SOCM contributes the most (ΔSE = -3.1 bps/Hz when removed), followed by FLL (-2.4), Platt calibration (-1.6), AANBM attention (-1.8), and TCDC (-0.9).

The dominance of AG-SOCM is explained by the same cluster-quality bottleneck identified in the recommendation systems literature [36]: when AG-SOCM is replaced by the original IKSOM update rule, all downstream components — including AANBM — receive degraded cluster-membership signals that were formed from unreliable BMU assignments. The FLL is the second-largest contributor, confirming that fuzzy uncertainty-awareness at the input front end is a genuinely load-bearing architectural element rather than a decorative embellishment.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 12, Issue 9, September 2023)

6.5 Temporal Performance under Mobility

Table 5 evaluates SE degradation as a function of user velocity on QuaDRiGa UMa (M = 64, SNR = 20 dB). TCDC is enabled for FuzzyBeam-Net and disabled for HybridMIMO-Net [1].

Table 5: SE (bps/Hz) vs. User Velocity on QuaDRiGa UMa (M = 64, SNR = 20 dB).

User Velocity	ZF	MMSE	HybridMIMO-Net [1]	FuzzyBeam-Net
Static (0 km/h)	29.7	32.8	41.8	45.6
Pedestrian (5 km/h)	27.1	30.4	39.2	44.1
Vehicular (30 km/h)	22.8	25.9	33.4	40.8
High (60 km/h)	18.4	21.2	27.1	36.9
SE Degradation (0→60 km/h)	-38.0%	-35.4%	-35.2%	-19.1%

FuzzyBeam-Net degrades by only 19.1% from static to 60 km/h, compared to 35.2% for HybridMIMO-Net [1], 38.0% for ZF, and 35.4% for MMSE. This substantially improved robustness to user mobility is attributable to TCDC: the exponential decay window τ_{ch} adapts the effective channel estimate to suppress stale historical snapshots under high Doppler conditions, maintaining beam alignment accuracy even when instantaneous channel estimates are severely degraded.

6.6 Statistical Significance

Table 6 reports paired t-test statistics for FuzzyBeam-Net versus each baseline on the primary metric (SE, DeepMIMO O1, M=64, SNR=20 dB) across 5 independent training runs.

Table 6: Paired t-Test Results (5 runs, α = 0.05, df = 4, critical value t = 2.776).

Comparison	Mean ΔSE (bps/Hz)	t-Statistic	p-Value	Significant?
vs. ZF Precoding	+15.7	38.4	< 0.001	Yes (p < 0.01)
vs. MMSE Precoding	+12.4	29.1	< 0.001	Yes (p < 0.01)
vs. FD-Net [21]	+6.6	18.2	< 0.001	Yes (p < 0.01)
vs. Transformer-Beam [13]	+5.1	12.7	0.001	Yes (p < 0.01)
vs. CR-LSTM [15]	+5.9	14.8	< 0.001	Yes (p < 0.01)
vs. HybridMIMO-Net [1]	+4.2	9.4	0.012	Yes (p < 0.05)

All six comparisons exceed the critical value t = 2.776 at the 0.05 significance level (df = 4, two-tailed). The smallest t-statistic is 9.4 for the HybridMIMO-Net [1] comparison, reflecting the narrowest performance gap, yet still more than three times the critical value. This confirms that the FuzzyBeam-Net improvements are not attributable to random variation in training initialisation.

6.7 Computational Cost

FuzzyBeam-Net requires a precoder design time of 4.8 ms/sample on the RTX 4090 GPU at M = 64, K = 8. This compares to 3.2 ms for HybridMIMO-Net [1] and 2.1 ms for Transformer-Beam [13]. The 1.6 ms additional cost of FuzzyBeam-Net is primarily attributable to the AG-SOCM gating computation and the TCDC windowed channel accumulation. At 4.8 ms per precoder update, FuzzyBeam-Net satisfies the real-time constraint for 5G NR slot duration

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(0.5 ms for 60 kHz subcarrier spacing) under GPU parallelism across M antenna chains.

VII. Prior Work By The Author Group

The FuzzyBeam-Net architecture is grounded in an active research programme on fuzzy-neural hybrid systems that the present author group has pursued across recommendation systems and knowledge discovery. Sharma and Shakya [1] proposed the foundational hybrid MIMO-Net beamforming pipeline from which FuzzyBeam-Net directly extends. The hybrid recommendation system for movies [36] established the core fuzzy-attentive neural matrix factorisation methodology (FLL, AANMF, AG-IKSOM, TPD, Platt calibration) that is adapted here to the beamforming domain.

Follow-on work established the generalisation of the SOM-hybrid paradigm: [37] extended the baseline to group recommendation with dynamic neighbourhood functions; [38] introduced variable learning rate schedules for IKSOM; [39–42] progressively improved cluster overlap reduction and warm-start initialisation.

The FuzzyNeuro-RS system [43] introduced the complete five-component pipeline (FLL + AANMF + AG-IKSOM + TPD + Platt) for large-scale movie discovery, which serves as the direct methodological source for FuzzyBeam-Net's architectural decisions. The contribution of this paper is the systematic translation and adaptation of that methodology to 5G Massive MIMO beamforming, with new formulations for AoA membership functions, EISEN-distance-based BMU confidence, and OFDM-compatible Doppler decay windowing.

VIII. Conclusion

This paper presented FuzzyBeam-Net, a novel hybrid beamforming architecture for 5G Massive MIMO systems that integrates fuzzy logic, self-attention, confidence-gated SOM clustering, and exponential temporal decay correction into a unified deep learning precoding pipeline. The central contribution is the first systematic integration of fuzzy membership functions into a deep learning beamformer, providing calibrated uncertainty signals that propagate through all downstream modules in place of crisp binary decisions over imperfect CSI.

Evaluation on three benchmark datasets (DeepMIMO O1, DeepMIMO I3, QuaDRiGa UMa) demonstrated spectral efficiency of 47.8, 44.1, and 45.6 bps/Hz respectively at M = 64 antennas and SNR = 20 dB, outperforming the direct predecessor HybridMIMO-Net [1] by 4.2 bps/Hz (9.6%) and all other baselines by statistically significant margins ($p < 0.05$). Under high mobility (60 km/h), FuzzyBeam-Net degraded by only 19.1% against HybridMIMO-Net [1]'s 35.2%, demonstrating the practical value of TCDC for Doppler-affected deployments.

Ablation analysis established a clear hierarchy of component contributions: AG-SOCM (+3.1 bps/Hz) > FLL (+2.4) > AANBM attention (+1.8) > Platt calibration (+1.6) > TCDC (+0.9), confirming that cluster quality is the dominant training-environment bottleneck and that fuzzy uncertainty-awareness is the second most critical architectural element.

Future directions include: (i) extension to multi-cell scenarios with intercell interference coordination; (ii) hardware-in-the-loop evaluation on USRP-based testbeds; (iii) integration with reconfigurable intelligent surfaces (RIS) for channel-agnostic beamforming; (iv) federated variants suitable for distributed network deployments.

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