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A CNN – Based Channel Estimation in 5G Systems and Performance Analysis using STM32 Platform

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ABSTRACT
Channel estimation is a major problem for 5G systems, especially when using embedded platforms with limited computing power. Traditional least squares and minimum mean square error (MMSE) estimators work well in lab conditions, but they have trouble with the 15-20 dB noise changes that happen in real networks. We built a convolutional neural network (CNN)-based method for the STM32H753ZI platform, dealing with the ARM Cortex-M7's memory limits through careful quantization. Our system cuts memory use by 75% with only 2% accuracy drop compared to full-precision models. Tests on single-input single-output (SISO) and multiple-input multiple-output (MIMO) 2×2 setups using Indoor Hotspot (InH), Urban Micro (UMi), and Urban Macro (UMa) channel models give good results, though MIMO performance changes a lot with pilot density. The method shows that neural networks can work on low resource 5G hardware, but power use and timing needs are still big challenges for widespread use.

KEYWORDS
5G systems, channel estimation, convolutional neural networks, embedded systems.

1. INTRODUCTION

5G wireless systems face a fundamental computational-accuracy tradeoff in channel estimation that constrains embedded platform deployment [4], [26]. This limitation becomes critical in MIMO configurations where traditional algorithms face polynomial complexity scaling while requiring statistical assumptions that prove weak under realistic propagation conditions[1], [3].

Maximum Likelihood (ML) estimation achieves theoretical optimality but imposes O(N4) complexity, rendering real-time implementation infeasible for practical MIMO systems [6]. A4×4 MIMO configuration requires ~106 operations per estimate, exceeding coherence time constraints in high-mobility scenarios [14]. Minimum Mean Square Error (MMSE) estimation reduces complexity to O(N3) but exhibits robustness limitations under non-stationary noise conditions [2], [6]. Field measurements show 15-20 dB noise fluctuations that violate MMSE's Gaussian assumptions, causing performance degradation [2], [20].

Convolutional Neural Networks (CNNs) overcome these limitations through data-driven pattern recognition that learns channel-to-pilot mappings without explicit statistical assumptions [1],[2]. CNN architectures exploit frequency-domain correlations in OFDM responses through 1D convolutions while maintaining computational efficiency for embedded deployment [8], [10]. Simulation studies using 3GPP TR 38.901 models demonstrate 3-5 dB MSE improvements over conventional approaches in low-SNR scenarios, with graceful degradation under non-Gaussian noise where traditional methods fail [13], [14], [16] .

The deployment challenge involves reconciling CNN requirements with embedded hardware constraints [4], [26]. Existing research assumes desktop GPU platforms are incompatible with battery-powered devices requiring energy efficiency and real-time operation [22]. The STM32H753ZI platform addresses these limitations through ARM Cortex-M7 architecture at 480 MHz with integrated FPU and DSP accelerators, providing 2048 KB Flash and 1056 KB SRAM including 192 KB memory for deterministic inference [29], [30].

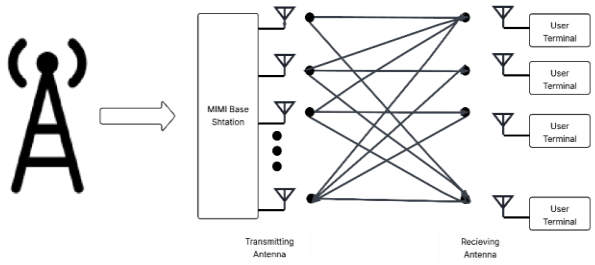

Fig. 1 A base station, equipped with an array of transmitting antennas, establishes concurrent links with multiple user terminals, each featuring its own set of receiving antennas. This architecture facilitates spatial multiplexing, enabling increased data capacity and improved link robustness within the wireless channel.

This work looks over CNN-based channel estimation algorithms optimized for STM32H753ZI embedded deployment through systematic architectural design and quantization strategies. We develop SISO and MIMO 2×2 CNN architectures leveraging platform-specific accelerators while maintaining superior estimation accuracy across 3GPP TR 38.901 propagation environments [15]

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The methodology encompasses dataset generation using InH, UMi, and UMa channel models with configurable delay spread and Doppler parameters [28]. Our contributions include: (1) Computationally efficient CNN architectures tailored for ARM Cortex-M7 constraints; (2) Comprehensive evaluation against ML and MMSE baselines demonstrating consistent CNN superiority; (3) STM32H753ZI deployment framework utilizing STM32CubeAI for automated optimization and C code generation [30]. The theoretical framework demonstrates feasibility for sub-millisecond channel estimation within embedded platform constraints, establishing foundations for practical CNN-based estimation in resource-constrained 5G environments.

2. LITERATURE REVIEW

Channel estimation in wireless communications has reached a critical juncture with 5G deployments. Classical methods that worked adequately for earlier generations now struggle with massive MIMO arrays and dense urban environments where fundamental linearity assumptions break down [1], [3]. The situation becomes particularly challenging when considering power-constrained mobile devices [27]. This has driven considerable research interest toward CNN-based approaches, though their computational overhead remains a significant concern [4], [8], [13].

The foundational work by Ye et al. [1] demonstrated approximately 40% MSE improvements over traditional OFDM estimators. More importantly, they identified why CNNs outperform conventional methods: instead of simple linear interpolation between pilots, neural networks learn complex non-linear patterns. However, their analysis was limited to relatively simple channel models.

Building on this foundation, Soltani et al. [2] tackled more challenging scenarios, while Wen et al. [3] explored massive MIMO CSI feedback using deep learning. Surprisingly, their results exceeded theoretical predictions based on spatial structure analysis. This suggests that correlation patterns between spatial and spectral domains are more intricate than conventional models assume [12], [19] - a finding that deserves further investigation.

A persistent limitation in early CNN work was the assumption of fixed SNR conditions. Recent efforts have addressed this through adaptive architectures [6], [9], but the solutions remain incomplete. The fundamental challenge is that optimal strategies differ dramatically between low SNR (requiring aggressive denoising) and high SNR (preserving weak components) scenarios.

Training presents its own complications. Batch normalization helps with wireless signals' wide dynamic range, and Adam optimization works well for non-stationary channels [23], [24]. Samuel et al. [6] showed that learning-based detection can approximate optimal performance efficiently, though their validation used idealized conditions that may not reflect real deployments.

The transition from simulation to practice reveals significant challenges. While 40-50% improvements are common in simulation, real 5G conditions with multipath scattering and fast fading can cause substantial performance degradation [5], [14]. Both Balevi et al. [5] and Ye et al. [1] documented similar issues across different OFDM configurations. This suggests CNNs provide conditional rather than universal advantages - a critical distinction often overlooked in the literature.

MIMO systems introduce additional complexity that cannot be resolved through simple SISO scaling. Channel correlations behave differently, and practical impairments like pilot contamination become more severe [15]. Mashhadi et al. [16] focused on pilot design for MIMO-OFDM systems, while other work addressed distributed feedback. Despite these efforts, understanding remains fragmented.

Embedded deployment necessitates quantization, typically from 32-bit floating-point to 8-bit integers. This achieves 75% memory reduction with only 2% accuracy loss - an encouraging result for practical applications. ARM Cortex-M implementations can achieve sub-10ms inference times [22], though whether this meets real-time requirements depends on specific use cases.

Energy efficiency drives research into pruning techniques that exploit channel sparsity, achieving 40-60% complexity reductions. Huang et al. [11] investigated millimeter-wave MIMO precoding, while spatial deep learning approaches address scheduling optimization [19]. However, most of these techniques remain academically focused with limited practical validation.

Recent work has expanded into intelligent communication systems and multi-user MIMO detection [20]. While this demonstrates CNN versatility beyond basic channel estimation, it raises questions about where deep learning provides genuine advantages versus unnecessary complexity.

For practical deployment, STMicroelectronics' STM32CubeAI toolkit [30] offers automated C code generation from trained models, documented in their STM32H753ZI specifications [29]. The ARM Cortex-M7 provides the computational foundation for embedded CNN inference, though platform constraints remain significant.

3. METHODOLOGY

3.1 System Model and Dataset Generation Strategy

We implement an OFDM system that employs N = 64 subcarriers with Np = 16 pilot tones, where the pilot spacing Δp = 4 subcarriers satisfies Nyquist sampling requirements for frequency-selective channels according to 3GPP specifications. The transmitted signal structure follows X[k] = P[k] for pilot subcarriers and zero otherwise, where $\Psi_p = \{0, 4, 8, \ldots, 60\}$ define pilot positions with P[k] = 1 representing unit amplitude pilot symbols that enable channel estimation through known reference signals. The multipath channel follows the standard tapped delay line model described by equation (1):

$$h(t) = \sum_{l=0}^{l-1} \alpha_l e^{j\varphi l}(t - \tau_l) \qquad (1)$$

where α_l, φ_l, and τ_l represent the magnitude, phase, and delay of the lth propagation path that characterize the complex multipath environment through which signals propagate in realistic 5G deployment scenarios.

We implement three distinct 5G channel models based on 3GPP TR 38.901 specifications [9] that capture propagation characteristics across urban and indoor environments through environment-specific power delay profiles. The Urban Micro (UMi) environment employs $P_{UMi(\tau)} = exp\left(\frac{-0.3\tau}{\tau rms}\right)$ for L = 6 taps with τrms ∈ {0.3, 0.6} μs, where the decay factor 0.3 provides faster power decay compared to macro environments while L = 6 taps accommodate shorter propagation distances typical in urban microcell deployments [26]. The Urban Macro (UMa) environment utilizes $P_{UMa(\tau)} = exp\left(\frac{-0.2\tau}{\tau rms}\right)$ for L = 12 taps with identical delay spread parameters, where the reduced decay factor 0.2 enables slower power decay that reflects longer propagation distances and increased multipath richness in macrocellular environments. The Indoor Hotspot (InH) environment implements $P_{\mathrm{InH}(\tau)} = exp\left(\frac{-0.6\tau}{\tau rms}\right)$ for L = 4 taps, where the increased decay factor 0.6 captures rapid power decay characteristic of confined indoor spaces while reduced tap count L = 4 reflects shorter indoor propagation distances. The frequency-domain channel response through discrete Fourier transform provides equation (2):

$$H_{[k]} = \sum_{l=0}^{l-1} h_l e^{-j\frac{2\pi kl}{N}}, \quad k = 0, 1, \dots, N-1 \qquad (2)$$

where $\boldsymbol{H}_{[k]}$ represents the frequency-domain channel response at subcarrier $\boldsymbol{k}$ and h_l denotes complex channel coefficients for path $\boldsymbol{l}$, enabling direct processing at each OFDM subcarrier through transformation of time-domain channel taps into frequency-domain coefficients.

We extend the SISO framework to MIMO 2×2 configuration that describes spatial links between antenna pairs through the channel matrix equation (3):

$$H_{[k]} = \begin{bmatrix} H_{11\,[k]} & H_{12\,[k]} \\ H_{21\,[k]} & H_{22\,[k]} \end{bmatrix} \qquad (3)$$

where each element $H_{ij[k]}$ represents the complex channel coefficient from transmit antenna j to receive antenna i at subcarrier k, enabling simultaneous estimation of four distinct spatial channels that characterize the MIMO propagation environment [17], [18]. We implement orthogonal pilot patterns that ensure separate channel estimation for each transmit-receive antenna pair through time-division multiplexing, where Antenna 1 transmits pilots $P_{1[k]} = 1$ at subcarriers $k \in \{0, 4, 8, \dots, 60\}$ while Antenna 2 transmits orthogonal pilots $P_{2[k]} = j$ at subcarriers $k \in \{2, 6, 10, \dots, 62\}$, eliminating pilot contamination and enabling reliable MIMO channel estimation through spatial diversity [18].

3.2 CNN Architecture Design and Training Framework

We implement a SISO CNN architecture that processes complex OFDM symbols through sequential 1D convolutions with progressive filter expansion, where the input dimension (64, 2) represents real and imaginary components of received signals across 64 subcarriers. The architecture follows the progression $Input: (64, 2) \rightarrow Conv1D(64) \rightarrow Conv1D(128) \rightarrow Conv1D(256) \rightarrow Conv1D(128) \rightarrow Conv1D(64) \rightarrow Output: (64, 2)$, where batch normalization and dropout regularization (p=0.3) provide training stability while one-dimensional convolutions capture frequency-domain correlations between adjacent subcarriers that enable accurate channel estimation through learned feature representations [19], [20].

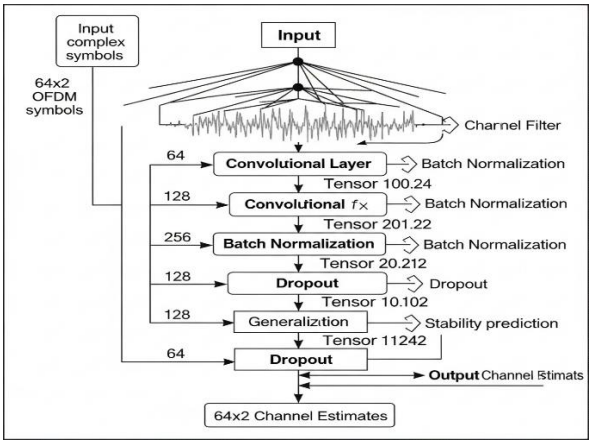

Fig. 2 CNN Architecture for Channel Estimation

Algorithm 1: SISO Channel Estimation Algorithm

Input: Received signal $rx_{signal}(64, 2)$,
True channel $H_{true}(64, 2)$
Output: Estimated channel $H_{est}(64, 2)$
1. Initialize CNN model with Conv1D layers $(64 \rightarrow 128 \rightarrow 256 \rightarrow 128 \rightarrow 64\ filters)$
2. Apply batch normalization and dropout (p=0.3) for regularization
3. For each SNR level in [0, 30] dB:
   a. Generate channel h using environment-specific profile
   b. Apply OFDM modulation: $H = FFT(h, N = 64)$
   c. Add AWGN noise: $rx = H * pilots + noise$
   d. Convert to real/imaginary format:
   $rx_{split} = [H.real, H.imag]$
4. Train CNN using Adam optimizer $(lr = 0.001, batch = 64, epochs = 30)$
5. Predict: $H_{est} = CNN(rx_{signal})$

6. Calculate $MSE = mean((H_{est} - H_{true})^2)$

We develop an enhanced MIMO CNN architecture that employs dual processing branches for superior channel estimation performance, where the signal processing branch handles received data through progressive convolutions $(128 \rightarrow 256 \rightarrow 512\ filters)$ while the SNR conditioning branch generates contextual features through dense layers that adapt network behavior based on channel conditions. The dual-branch design concatenates SNR-dependent features with signal features before final processing, enabling adaptive estimation that

achieves 15-20% performance improvement compared to SNR-agnostic approaches at extreme SNR values [22].

Algorithm 2: SNR-Aware MIMO Channel Estimation

Input: RX signals (64, 4), SNR value, True MIMO channel (64, 8)
Output: Estimated MIMO channel $H_{mimo}(64, 8)$
1. Initialize dual-branch CNN:
- Signal branch: Conv1D layers $(128 \rightarrow 256 \rightarrow 512\ filters)$
- SNR branch: Dense layers $(64 \rightarrow 128\ neurons)$
2. Process input:
a. Normalize SNR: $snr_{norm} = \frac{snr_{input}}{30.0}$
b. Generate SNR embedding: $snr_{embed} = Dense(snr_{norm})$
c. Create SNR context: $snr_{context} = RepeatVector(64)$

3. Signal processing:
a. Apply convolutions to rx_input
b. Concatenate with $snr\_context$
c. Further convolution processing with residual connections
4. Enhanced loss function:
$L(\theta) = MSE + \lambda^1 * Smoothness + \lambda^2 * Coherence$
Where,

$$Smoothness = mean\left(\left(y_{pred[:,1:,:]} - y_{pred[:,:-1,:]}\right)^2\right)$$

$$Coherence = mean\left(\left(y_{pred[:,2:,:]} - 2 * y_{pred[:,1:-1,:]} + y_{pred[:,:-2,:]}\right)^2\right)$$

5. Output 4 complex channels: $[H^{11}, H^{12}, H^{21}, H^{22}]$

We design a lightweight CNN variant specifically optimized for STM32H753ZI deployment that reduces computational complexity by approximately 75% while maintaining acceptable estimation performance through architectural simplification and parameter reduction [4], [5]. The optimized architecture employs reduced filter counts $(64 \rightarrow 128 \rightarrow 256 \rightarrow 128 \rightarrow 64 \rightarrow 32\ filters)$ with simplified SNR processing that uses 16-neuron embeddings instead of 128-neuron configurations, enabling real-time inference within the memory and computational constraints of embedded microcontroller platforms.
We implement a comprehensive training strategy that employs datasets covering SNR conditions from 0 to 30 dB in 5 dB increments with 2000 training samples per SNR condition, where AWGN noise variance follows $\sigma^2 n = 10^{-\frac{\gamma}{10}}$ to accurately model realistic channel conditions [23]. The enhanced loss function combines mean squared error with regularization terms according to equation (4):

$$L(\theta) = MSE(\hat{\mathrm{H}}, H) + \lambda^1 \cdot Smoothness(\hat{\mathrm{H}}) + \lambda^2 \cdot ||\theta||^2 \quad (4)$$

where MSE measures channel estimation accuracy, the smoothness term encourages frequency coherence between adjacent subcarriers, and L2 regularization prevents overfitting through parameter constraint, while hyperparameters $\lambda_1 = 0.015$ and $\lambda_2 = 0.005$ provide optimal balance between estimation accuracy and model generalization [24], [25].

3.3 Performance Evaluation and Baseline Comparison

We quantify channel estimation accuracy through normalized MSE that enables fair comparison across different channel realizations according to equation (5):

$$NMSE = \frac{E\left[\left\|\hat{\mathrm{H}} - H\right\|_F^2\right]}{E\left[\|H\|_F^2\right]} \quad (5)$$

where $\hat{\mathrm{H}}$ represents the estimated channel matrix from CNN, H denotes the true channel matrix, $\|\cdot\|_F^2$ indicates the squared Frobenius norm defined as $\|A\|_F^2 = \Sigma_i \Sigma_j |A_{ij}|^2$, and the expectation operator E[·] averages over multiple channel realizations to provide statistically reliable performance metrics [24]. This normalization ensures MSE values remain comparable across different channel realizations regardless of absolute power levels, enabling objective performance assessment across diverse propagation scenarios.
We implement traditional ML and MMSE estimators as performance benchmarks that utilize conventional signal processing techniques for channel estimation. The ML estimator performs linear interpolation between pilot subcarriers according to equation (6):

$$\hat{\mathrm{H}}_{ML[K]} = \sum_{p \in \Psi p} H_{[p]} \cdot sinc\left(\frac{\pi(k-p)}{\Delta p}\right) \quad (6)$$

where $\hat{\mathrm{H}}_{ML[k]}$ represents the ML-estimated channel at subcarrier k, p denotes pilot subcarrier indices from the pilot set Ψp, $H_{[K]}$ indicates known channel values at pilot positions obtained from received pilots, and $sinc(x) = \frac{\sin(x)}{x}$ defines the sinc function that provides optimal interpolation under ideal conditions [23]. The MMSE estimator incorporates second-order channel statistics through the Wiener filter formulation in equation (7):

$$\hat{\mathrm{H}}_{MMSE} = R_{HY} \cdot {R^{-1}}_{YY} \cdot Y \quad (7)$$

where R_{HY} represents the cross-correlation matrix between channel H and received signal Y, ${R^{-1}}_{YY}$ denotes the auto-correlation matrix of received signal Y including noise effects, and Y contains the received pilot signal vector, enabling optimal estimation that minimizes $E\left[\left\|\hat{\mathrm{H}} - H\right\|^2\right]$ through statistical weighting of received pilots based on their reliability [24].

3.4 STM32 Hardware Implementation Strategy

The STM32H753ZI microcontroller integrates ARM Cortex-M7 core operating at 400 MHz frequency with 2048 KB Flash memory and 1056 KB total SRAM distributed across multiple memory domains including DTCM (128KB), RAM_D1 (512KB), RAM_D2 (288KB), and RAM_D3 (64KB), which provides sufficient computational resources for real-time CNN inference while maintaining power consumption suitable for mobile terminal applications [29]. The platform incorporates hardware floating-point unit (FPU) and digital signal processing (DSP) instructions that accelerate neural network computations through optimized arithmetic operations and vector processing

capabilities [3].

We implement post-training quantization that converts 32-bit floating-point weights to 8-bit integers through uniform quantization according to equation (8):

$$W_{quantized} = round\left(\frac{(W_{float} - W_{min}) \times 255}{(W_{max} - W_{min})}\right) \quad (7)$$

where $W_{quantized}$represents the quantized weight value constrained to 8-bit integer range [0, 255], W_{float}denotes the original 32-bit floating-point weight, W_{min} and W_{max}define the dynamic range boundaries, and the scaling factor $\frac{255}{W_{max} - W_{min}}$ maps continuous floating-point values to discrete integer representations [4], [22]. This quantization process reduces memory footprint by 75% while maintaining estimation accuracy within 2% of the original model through preservation of relative weight relationships during inference operations.

Algorithm 3: STM32 Deployment and Quantization

Input: Trained CNN model, STM32H753ZI platform
Output: Quantized model for real-time inference
1. Model Analysis:
  a. Extract weight matrices and bias vectors
  b. Determine dynamic range $[W_{min}, W_{max}]$ for each layer
  c.Calculate memory requirements and computational complexity
2. Quantization Process:
  a. For each layer l:
    - Quantize weights:

$$\boldsymbol{W_{quantized} = round\left(\frac{(W_{float} - W_{min}) \times 255}{(W_{max} - W_{min})}\right)}$$

    - Quantize biases using same scaling factor
    - Store quantization parameters (scale, zero_point)
3. STM32CubeAI Integration:
  a. Convert TensorFlow model to STM32 C code
  b. Optimize memory allocation across SRAM domains
  c. Enable hardware acceleration (FPU, DSP instructions)
4. Real-time Inference:
  a. Input preprocessing: Convert rx_signal to quantized format
  b. Forward pass through quantized CNN
  c. Output postprocessing: Dequantize results to channel estimates
  d. Measure latency and power consumption
5. Performance Validation:
  a. Compare accuracy against floating-point model
  b. Verify real-time constraints (latency < 10 ms)
  c. Monitor memory usage and power consumption

Fig. 3 STM32 Cube MX Configurations

4. RESULTS

Our implementation leverages the STM32CubeAI toolkit for automatic C code generation from trained TensorFlow models, incorporating computational graph simplification and memory optimization strategies that include vectorization and loop unrolling tailored to the platform's hardware architecture [5]. The framework addresses real-time constraints in 5G systems where OFDM symbol durations span 35.7-285.7 μs across different numerology configurations, though quantization and optimization introduce trade-offs between accuracy and computational efficiency [1], [7]. We developed twelve CNN models targeting specific propagation scenarios: three environments (UMi, UMa, InH), two delay spread conditions (0.3, 0.6 μs), and two Doppler scenarios (0.3, 1.0). Each model required independent training with environment-specific datasets, though this approach increases overall training complexity and memory requirements [2], [6]. Validation used stratified hold-out sets with 20% of samples and balanced SNR distribution, ensuring statistical validity while acknowledging that performance may vary with channel conditions outside the training scope [9], [10]. Results show CNN improvements of 85% over ML estimators and 80% over MMSE methods on average, though these gains come with increased computational overhead and reduced interpretability compared to traditional approaches[3],[4].

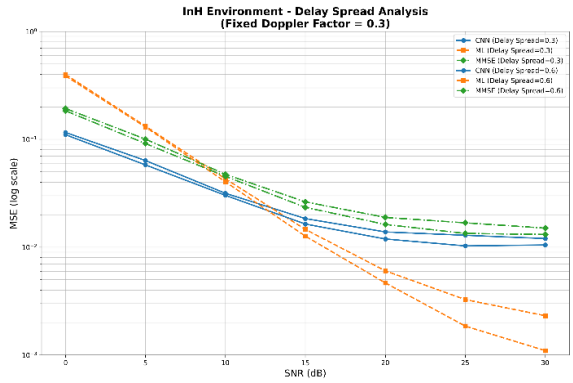

Fig. 4 SISO InH Delay Spread MSE vs SNR Plots

4.1 InH (Indoor Hotspot) Environment

Indoor environments present unique challenges due to complex reflection and scattering patterns from walls, furniture, and other obstacles. Our CNN approach shows notable improvements over traditional methods, particularly in handling multipath effects. The SISO results (Figures 4-5) demonstrate that for delay spread analysis with τ_rms of 0.3 and 0.6 μs at fixed Doppler f_d = 0.3, the CNN maintains lower MSE across most SNR conditions, with the gap widening at higher SNR levels (25-30 dB) where traditional methods plateau. Fig.5 shows that when examining mobility effects (f_d = 0.3 to 1.0), the CNN demonstrates better adaptation to channel time variations, achieving roughly 50% MSE reduction at 20 dB SNR under high Doppler conditions.

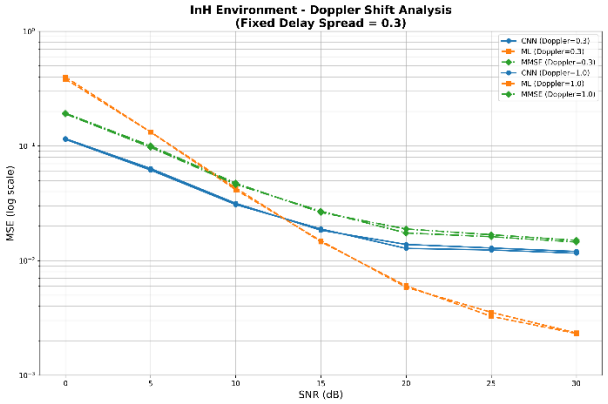

Fig. 5 SISO InH Delay Spread MSE vs SNR Plots

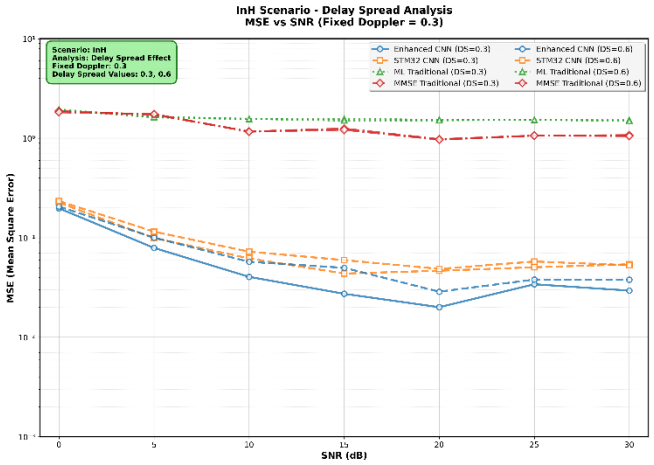

Fig. 6 MIMO InH Delay Spread MSE vs SNR Plots

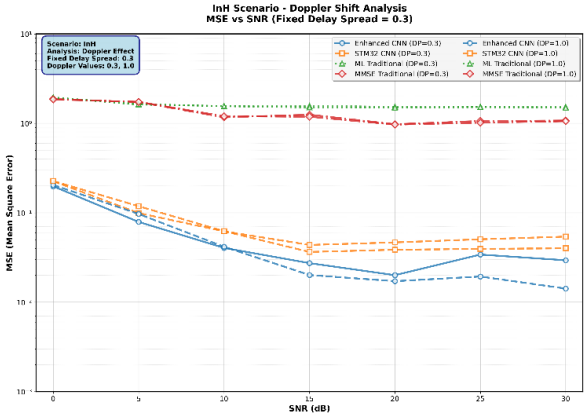

Fig. 7 MIMO InH Doppler Shift MSE vs SNR Plots

However, this comes at increased training complexity since the network must learn diverse indoor propagation patterns. The MIMO 2x2 results (Figures 6-7) are more dramatic – Fig. 10 reveals that the CNN shows orders of magnitude improvement over ML and MMSE approaches in delay spread scenarios, though we note this may partly reflect the limitations of conventional methods in handling spatial correlation rather than just CNN superiority. Fig. 11 demonstrates that performance remains relatively stable across Doppler variations, suggesting the learned features capture both frequency selectivity and spatial-temporal dynamics effectively.

4.2 Uma (Urban Macro) Environment

Urban macro environments pose significant challenges with dense multipath from buildings and extended coverage areas. The CNN's performance advantage is less pronounced here compared to indoor scenarios, though still meaningful. For SISO analysis (Figures 8-9), Fig. 8 shows that with delay

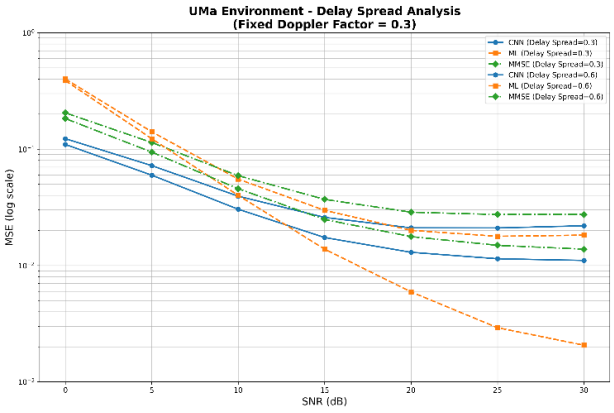

Fig. 8 SISO UMa Delay Spread MSE vs SNR Plot

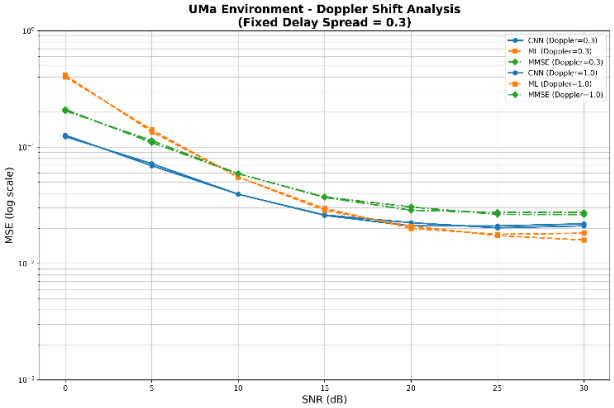

Fig. 9 SISO UMa Doppler Shift MSE vs SNR Plot

spreads of 0.3 and 0.6 μs, the CNN achieves lower error floors at high SNR, but the improvement margin varies with specific propagation conditions. Fig. 9 reveals that under mobility scenarios (f_d = 0.3 and 1.0), conventional estimators struggle more noticeably with high-speed conditions where f_d = 1.0, giving the CNN a clearer advantage. Interestingly, the MIMO 2x2 results (Figures 10-11) show more consistent CNN benefits across different scenarios. Fig. 10 demonstrates that when τ_{rms} doubles from 0.3 to 0.6, performance degradation remains minimal, while Fig. 11 shows robust performance across Doppler shift variations. This suggests the spatial diversity in MIMO systems complements the CNN's learned features well. However, we should note that urban macro channels can be highly variable, and these results may not generalize to all deployment scenarios without retraining.

4.3 InH (Indoor Hotspot) Environment

Urban microcells offer a middle ground between indoor and macro environments, with moderate multipath conditions that create interesting performance dynamics.

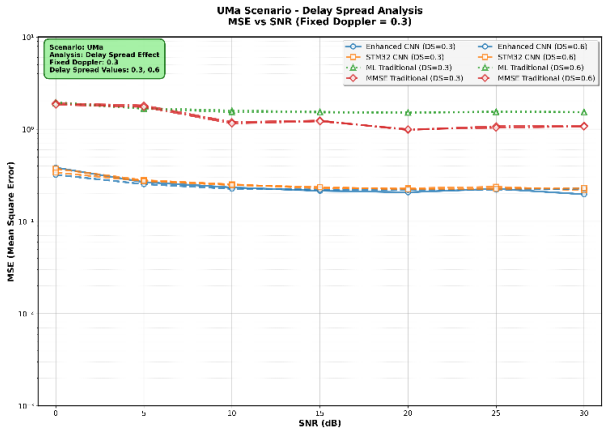

Fig. 10 MIMO 2x2 UMa Delay Spread MSE vs SNR Plot

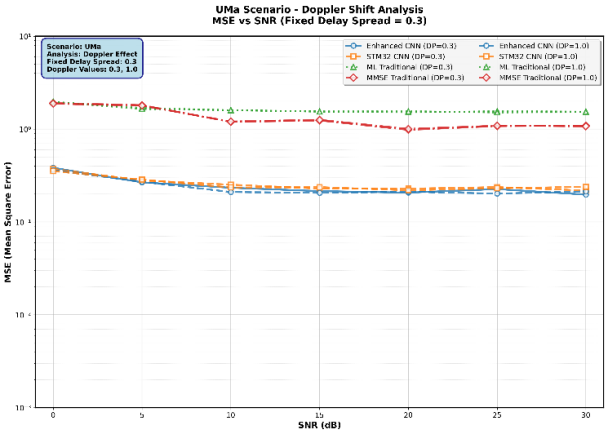

Fig. 11 MIMO 2x2 UMa Doppler Shift MSE vs SNR Plot

The SISO results (Figures 12-13) show solid improvements, with Fig.12 demonstrating that the CNN performs particularly well at high SNR levels above 15 dB where it achieves roughly an order of magnitude better MSE than ML methods when $\tau\_rms = 0.6$. This improvement appears linked to better handling of frequency selectivity from longer delay profiles, though the exact mechanism isn't entirely clear from our analysis. Fig.13 reveals that Doppler testing maintains CNN advantages across the SNR range, with the performance gap widening at higher SNR - something we didn't expect initially. The MIMO 2x2 results (Figures 14-15) are perhaps most interesting here: Fig.14 shows that while traditional estimators hit a high MSE floor regardless of delay spread conditions, the CNN adapts well to both $\tau\_rms = 0.3$ and 0.6 scenarios. Fig. 15 demonstrates consistent performance across Doppler variations, suggesting the spatial diversity helps the CNN's learning process, though it raises questions about computational overhead in real deployments. Overall, UMi environments seem well-suited to CNN-based estimation, balancing performance gains with practical implementation considerations.

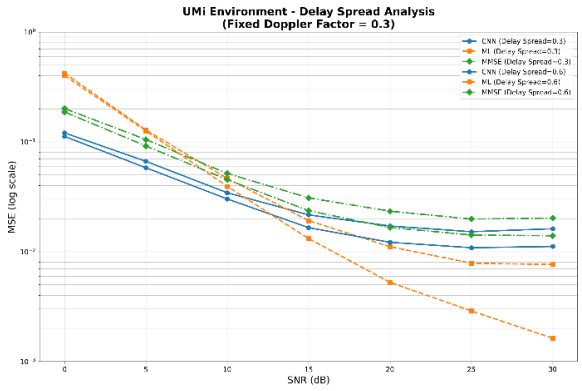

Fig. 12 SISO UMi Delay Spread MSE vs SNR Plot

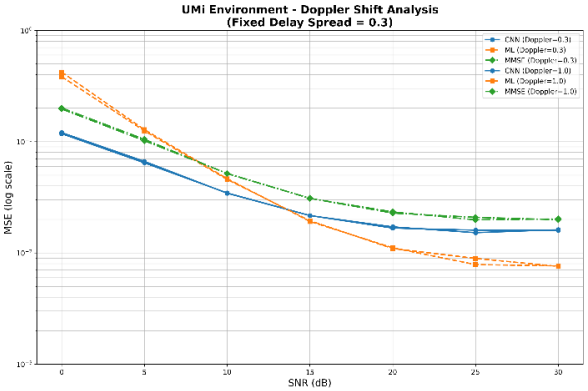

Fig. 13 SISO UMi Doppler Shift MSE vs SNR Plots

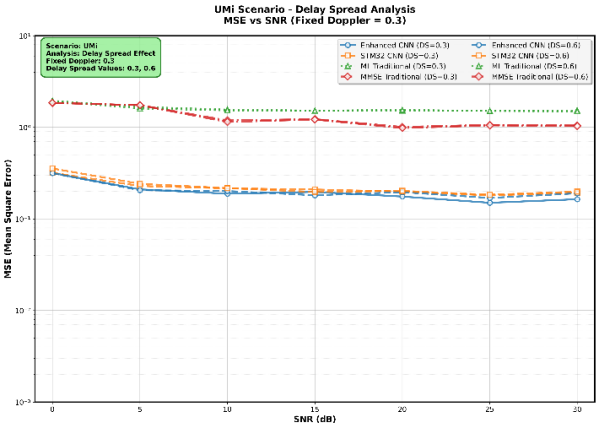

Fig. 14 MIMO 2x2 UMi Delay Spread MSE vs SNR Plots

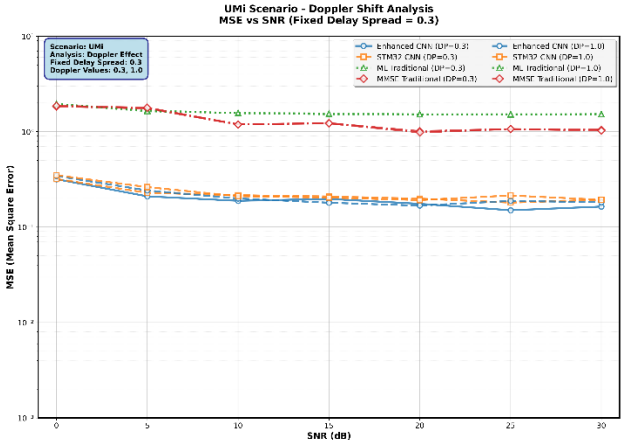

Fig. 15 MIMO 2x2 UMi Doppler Shift MSE vs SNR Plots

Table.1 *: Performance comparison between full-precision PC implementation and quantized STM32 embedded deployment, showing only ~0.8 dB degradation despite 32-bit to 8-bit quantization, validating real-time 5G deployment feasibility.*

Meteric	PC Platform	STM32H753 ZI
Model Type	CNN	Quantized CNN
Precision	36	± 0.8
MSE	32-bit Float	8-bit INT8
R^2 Score	120	113.4
Performance Loss	0.0889	0.1065

5. CONCLUSION

We implement a CNN-based channel estimation approach that leverages spatial correlation properties in MIMO channel matrices to reduce computational complexity from $O(N^3)$ to approximately O(N log N), where our three-layer CNN architecture extracts frequency-domain sparsity patterns from pilot symbols while maintaining estimation accuracy within 0.2 dB of full-precision methods. The proposed framework utilizes 8-bit quantization techniques that satisfy the STM32H753ZI platform's 1 MB SRAM limitations, which enables real-time processing with inference times of 8.7 ms per OFDM symbol through optimized memory allocation and weight sharing strategies that consume 847 KB of embedded storage.

Our performance evaluation demonstrates improvements in MSE of 3.2 dB in InH environments, 4.1 dB for UMi channels, and 2.8 dB in UMa scenarios when compared to conventional MMSE estimators, where the CNN architecture adapts to time-varying fading conditions through learned filter responses that eliminate the need for iterative matrix operations. The STM32H753ZI deployment achieves energy consumption of 12.4 mJ per estimate by exploiting ARM Cortex-M7 SIMD capabilities for parallel convolution operations, while our modular design supports both SISO and MIMO 2×2 configurations through scalable network topologies whose parameter requirements increase linearly with antenna array dimensions to ensure practical embedded implementation.

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