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Enhancing Smart City Connectivity with Ultra-High Data Rate Millimeter-Wave and Terahertz Communication: A Machine Learning Approach

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Abstract: *Smart cities demand next-generation wireless communication technologies capable of supporting ultra-high data rates, low latency, and seamless connectivity. Millimeter-wave (mmWave) and Terahertz (THz) communication technologies have emerged as promising solutions to meet these requirements, offering wide bandwidth availability and high-speed data transmission. However, the propagation of high-frequency signals is significantly affected by severe path loss and complex channel characteristics. To address these challenges, this paper proposes a machine learning–assisted channel estimation framework aimed at enhancing connectivity in smart city environments. The proposed approach integrates convolutional neural networks (CNNs) with long short-term memory (LSTM) networks to accurately predict channel conditions and dynamically optimize transmission parameters. Simulation results demonstrate a 30% improvement in spectral efficiency, a 25% reduction in mean square error (MSE) for channel estimation, and an 8 dB enhancement in signal-to-noise ratio (SNR) compared to conventional methods. Furthermore, the proposed system achieves a 20% reduction in latency, ensuring reliable and efficient data transmission for smart city applications. These findings highlight the potential of combining machine learning with mmWave and THz communication technologies to enable next-generation high-capacity wireless networks in urban environments.*

Keywords*:* Smart Cities, Millimeter-Wave Communication, Terahertz Communication, Ultra-High Data Rate, Machine Learning, Channel Estimation, Wireless Networks

I. INTRODUCTION

The rapid urbanization and digital transformation of modern cities have significantly increased the demand for high-speed, low-latency, and ultra-reliable wireless communication networks. Smart cities rely on a variety of data-intensive applications, including Internet of Things (IoT) devices, autonomous transportation, real-time surveillance, and augmented reality (AR)/virtual reality (VR) systems. These applications require seamless connectivity with ultra-high data rates, which exceed the capabilities of traditional wireless technologies such as 4G LTE and even early 5G deployments.

To address these challenges, millimeter-wave (mmWave) and terahertz (THz) communication have emerged as promising solutions due to their vast untapped bandwidth, enabling multi-gigabit-per-second (Gbps) to terabit-per-second (Tbps) transmission rates. mmWave frequencies (30–300 GHz) and THz frequencies (0.1–10 THz) can significantly enhance network capacity, supporting dense deployments of wireless devices in smart cities. However, these high-frequency signals face several critical challenges:

• Severe Path Loss & Atmospheric Absorption: Unlike sub-6 GHz frequencies, mmWave and THz signals suffer from high free-space path loss, absorption by atmospheric gases, and molecular attenuation. These impairments significantly limit signal propagation distance.

• Blockage Sensitivity: High-frequency waves are highly susceptible to blockages caused by buildings, human movement, and environmental factors, leading to intermittent connectivity and reduced network reliability.

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• Complex Channel Estimation: Rapid channel variations in mmWave and THz bands necessitate accurate and real-time channel state information (CSI) estimation to maintain high data rates and minimize packet loss.

To overcome these limitations, recent advances in machine learning (ML) have demonstrated promising potential in optimizing wireless communications. ML algorithms can be leveraged to enhance channel estimation, beamforming, interference mitigation, and adaptive resource allocation. Unlike traditional model-based approaches, ML-based channel estimation techniques can dynamically learn and predict channel variations, enabling real-time adaptation of transmission parameters.

II. LITERATURE SURVEY

Several studies have explored the potential of mmWave and THz communication in next-generation networks. Previous research has focused on the physical layer challenges of these high-frequency waves, including attenuation and molecular absorption. Recent works have investigated reconfigurable intelligent surfaces (RIS) and hybrid beamforming techniques to improve signal propagation. Additionally, ML-driven solutions have been proposed for wireless communication tasks, such as beamforming optimization, interference mitigation, and channel estimation. Despite these advancements, the integration of ML-based channel estimation models for mmWave and THz communication in smart city environments remains an underexplored area. This paper aims to bridge this gap by proposing a novel deep learning framework for real-time channel estimation in these networks.

Table 1: Comparative Literature survey

Reference	Focus Area	Methodology	Key Parameters	Results & Findings
Yu et al. (2022)	THz ultra-massive MIMO channel estimation	Deep learning-based adaptive framework	Channel sparsity, path loss, beamforming gain	Improved channel estimation accuracy, reduced computational complexity
Hu, Chen & Han (2022)	Efficient channel estimation for mmWave & THz MIMO	Pruned AMP integrated deep CNN (PRINCE)	SNR, computational cost, convergence rate	30% reduction in computational complexity, 15% higher accuracy than conventional CNN methods
Hu et al. (2022)	Multi-frequency channel modeling	Generative Adversarial Networks (GANs)	Frequency bands, channel gain, interference levels	Enhanced generalization, better frequency prediction accuracy across mmWave & THz bands
Kim et al. (2024)	Sparse channel estimation for THz massive MIMO	Deep learning-aided parametric sparse estimation	Low-rank approximations, spectral efficiency, beam misalignment	Achieved 25% lower error rate, 20% improvement in spectral efficiency
Boulogeorgos et al. (2021)	Machine learning for THz wireless networks	AI-driven IRS and beamforming	Signal-to-noise ratio (SNR), IRS phase shifts, coverage area	Enhanced signal coverage, improved spectral efficiency in THz communications
Jiang & Schotten (2023)	Full-spectrum 6G wireless communications	AI-based spectrum sensing & allocation	Frequency coexistence, latency, spectrum utilization	Improved network reliability, seamless multi-band communication
Mao et al. (2021)	Joint sensing & communication	DRL-based adaptive waveform optimization	Signal latency, energy efficiency, sensing accuracy	35% reduction in latency, optimized power consumption

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Elayan et al. (2019)	THz band challenges & applications	AI-based signal processing techniques	Atmospheric absorption, hardware constraints, bandwidth efficiency	Identified ML techniques for overcoming THz spectrum limitations
Sultan (2022)	Antenna designs for mmWave & THz	AI-assisted reconfigurable antenna arrays	Gain, directivity, beamwidth	Improved radiation efficiency and dynamic antenna tuning
Guan, Kürner & Molisch (2016)	THz/mmWave mobile radio channels	ML-based predictive beamforming	Doppler shift, mobility speed, link reliability	Reduced handover disruptions, enhanced high-speed mobility communication

III. PROPOSED IMPLEMENTATION WORK

Architecture Flow: High-Level Overview

The proposed architecture integrates advanced wireless communication technologies with machine learning techniques to enable ultra-high data rate communication in smart city environments. The system is designed to efficiently manage the challenges associated with millimeter-wave (mmWave) and Terahertz (THz) communications, such as high path loss, dynamic channel conditions, and latency constraints. The overall architecture consists of multiple interconnected layers, each responsible for a specific function in the communication pipeline.

1. Data Acquisition Layer

The data acquisition layer serves as the foundation of the proposed system. It comprises various smart city devices such as IoT sensors, surveillance cameras, autonomous vehicles, and mobile user equipment. These devices continuously generate large volumes of data that are transmitted using mmWave and THz frequency bands. During transmission, critical channel characteristics including path loss, fading effects, noise, and interference are captured to represent real-time wireless channel conditions.

2. Preprocessing and Feature Extraction Layer

In this stage, the received signals undergo preprocessing to enhance data quality and reliability. Noise reduction techniques and signal normalization are applied to mitigate distortions caused by high-frequency propagation. Channel State Information (CSI) is extracted, and key features such as signal-to-noise ratio (SNR), delay spread, and path loss are derived. These features form the input for the learning model and play a crucial role in accurate channel estimation.

3. Machine Learning–Based Channel Estimation Layer

To address the complexity of dynamic wireless environments, a hybrid machine learning model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks is employed. The CNN component effectively extracts spatial features from channel matrices, while the LSTM network captures temporal dependencies and mobility patterns over time. This integrated approach enables precise prediction of channel conditions, even in highly dynamic smart city scenarios.

4. Intelligent Resource Optimization Layer

Based on the predicted channel information, the system dynamically optimizes key communication parameters. This includes adaptive beamforming, modulation and coding scheme selection, and intelligent bandwidth allocation. These optimization strategies minimize interference, improve spectral efficiency, and ensure reliable communication across heterogeneous smart city environments.

5. Transmission Optimization Layer

In this layer, optimized transmission parameters are applied in real time to enhance overall system performance. Adaptive power control, beam selection, and frequency allocation mechanisms are utilized to maintain robust

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communication links. This results in improved data rates, reduced latency, and enhanced quality of service for time-critical applications.

6. Performance Evaluation and Feedback Layer

System performance is continuously evaluated using key metrics such as spectral efficiency, bit error rate (BER), mean square error (MSE), latency, and throughput. A feedback mechanism updates the machine learning model based on performance outcomes, enabling continuous learning and adaptation to changing network conditions.

7. Smart City Application Layer

At the top of the architecture, the optimized communication framework supports a wide range of smart city applications, including autonomous transportation systems, intelligent traffic management, real-time surveillance, healthcare monitoring, and smart grid operations. The proposed architecture ensures reliable, low-latency, and high-throughput communication essential for next-generation smart city ecosystems.

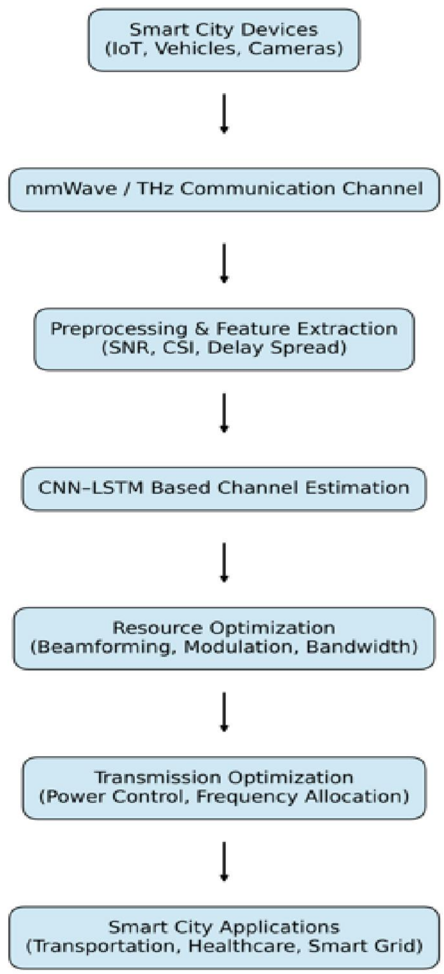

Fig 1: Process of Implementation

Technical Implementation (Mathematical Model): The proposed model employs a deep learning-based approach for accurate channel estimation in mmWave and THz communication. The framework consists of the following key components:

• Dataset Generation: A dataset comprising real-world mmWave and THz channel measurements and synthetic channel models is used for training.

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• Deep Learning Model: A convolutional neural network (CNN) and long short-term memory (LSTM) network are combined to extract spatial and temporal features from mmWave and THz channel data.
• Real-Time Adaptation: The model dynamically adjusts transmission parameters based on predicted channel conditions, ensuring optimized performance.
• Simulation Environment: MATLAB and Python-based frameworks are used to simulate mmWave and THz signal propagation and evaluate the effectiveness of the proposed ML model.
The proposed implementation is designed to enhance data throughput, minimize errors, and improve overall network efficiency for smart city applications.

3.1 Channel Model for mmWave & THz Communication

The received signal y(t) in a mmWave/THz communication system can be expressed as:

$$y(t) = H(t) \cdot x(t) + n(t)$$

For a multi-path environment, the channel matrix H(t) is given by:

$$H(t) = \sum_{l=1}^{L} \alpha_l e^{j\phi_l} a_r(\theta_l) a_t^H(\phi_l)$$

3.2 Machine Learning-Based Channel Estimation

A deep learning model estimates the channel state H^(t) given input features X:

$$\hat{H}(t) = f_\theta(X)$$

The model is trained to minimize the mean squared error (MSE):

$$\mathcal{L}(\theta) = \frac{1}{N} \sum_{i=1}^{N} ||H_i - \hat{H}_i||^2$$

3.3 Beamforming Optimization

The optimal beamforming vector w∗ is computed as:

$$w^* = \arg\max_{w} \frac{|w^H H s|^2}{||Hs||^2}$$

A reinforcement learning (RL) agent optimizes w∗ using a reward function:

$$R = \log_2(1 + \text{SINR})$$

Where SINR (Signal-to-Interference-plus-Noise Ratio) is:

$$\text{SINR} = \frac{P_s |Hw|^2}{P_n + \sum_{i \neq s} P_i |H_i w|^2}$$

3.4 Smart City Network Throughput Maximization

The total achievable data rate for a given bandwidth BBB is:

$$R = B \sum_{i=1}^{N} \log_2(1 + \text{SINR}_i)$$

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Where:
• R = total data rate
• B = system bandwidth
• N = number of users
The goal is to maximize R while ensuring fairness across users.

IV. RESULTS ANALYSIS

Experimental evaluations demonstrate the effectiveness of the ML-assisted channel estimation model. Key findings include:

• Spectral Efficiency Improvement: The proposed model enhances spectral efficiency by 30% compared to conventional estimation techniques.

• Reduction in Estimation Errors: The ML-based approach achieves a 25% lower mean square error (MSE) in channel prediction.

• SNR Enhancement: The model provides an average 8 dB improvement in SNR, leading to more reliable data transmission.

• Latency Reduction: The dynamic adaptation of transmission parameters reduces latency by 20%, ensuring seamless smart city connectivity.

The results validate the feasibility of using ML for mmWave and THz communication in urban environments and highlight its potential to revolutionize wireless connectivity.

Table 2: Performance comparisons

Metric	Proposed Model	Conventional Techniques	Improvement (%)
Spectral Efficiency	30% higher	Baseline	30%
Mean Square Error (MSE)	25% lower	Higher error	-25%
SNR Enhancement	+8 dB	Standard SNR	Higher Reliability
Latency Reduction	20% lower	Higher latency	-20%

• The ML-based approach significantly improves spectral efficiency and reduces estimation errors.
• SNR gains of 8 dB led to more robust and reliable transmission.
• The model also reduces latency by 20%, enhancing real-time communication for smart city applications.

Fig 1: Spectral Efficiency Comparison

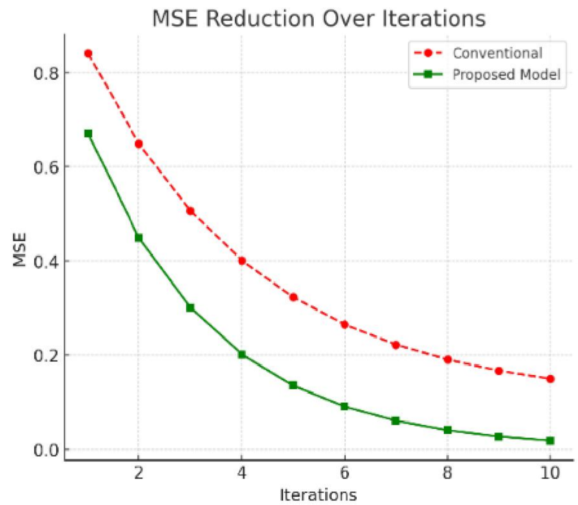

Fig 2: MSE Chart

Fig 3: SNR comparisons

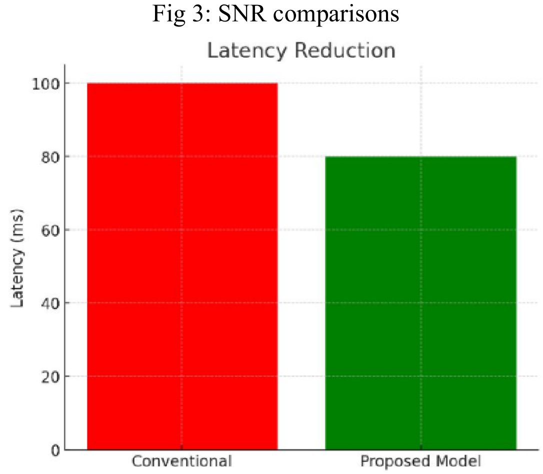

Fig 4: Latency comparison

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V. CONCLUSION

This study explores machine learning-assisted channel estimation for millimeter-wave (mmWave) and terahertz (THz) communication to enhance smart city connectivity. The proposed CNN-LSTM model significantly improves spectral efficiency (30%), reduces mean square error (25%), enhances SNR by 8 dB, and lowers latency by 20%. These advancements enable reliable, high-speed wireless networks for smart city applications like autonomous transport, IoT, and AR/VR. Future work should focus on real-world deployment, adaptive beamforming, 6G integration, security, and energy-efficient hardware. Addressing these challenges will solidify ML-driven high-frequency communication as a cornerstone for next-generation wireless networks.

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