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AI-Assisted Channel Prediction and Optimization for Energy-Efficient 6G Wireless Communication in Smart Cities

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***Abstract*—The sixth-generation (6G) wireless communication system promises ultra-low latency, massive connectivity, and high energy efficiency to support next-generation smart city infrastructures. Achieving reliable communication in dynamic, high-frequency environments requires intelligent and adaptive channel prediction and resource allocation techniques. This paper presents an AI-assisted channel prediction and optimization framework combining Long Short-Term Memory (LSTM) neural networks with reinforcement learning-based power control to enhance both spectral and energy efficiency in 6G networks. The proposed system predicts channel conditions using historical channel state information (CSI) and optimizes resource allocation dynamically to minimize power consumption. Simulation results in MATLAB demonstrate that the model improves channel prediction accuracy by 41%, enhances energy efficiency by 25%, and reduces latency by 15% compared to conventional estimation techniques. The research contributes to sustainable 6G development and efficient smart city communication.**

***Index Terms*—6G communication, deep learning, LSTM, AI-assisted optimization, channel prediction, energy efficiency, smart cities.**

I. INTRODUCTION

The rapid evolution of wireless communication systems has led to the development of the sixth-generation (6G) network, envisioned to offer ultra-reliable, low-latency, and energy-efficient communication to support smart cities. As 6G networks operate in the terahertz (THz) frequency range, they face challenges such as increased propagation loss, Doppler effects, and high channel variability. Traditional model-based techniques—such as Least Squares (LS) and Minimum Mean Square Error (MMSE) estimators—struggle to maintain accuracy under such dynamic conditions.

Recent advances in Artificial Intelligence (AI), particularly deep learning (DL), have enabled intelligent modeling of complex communication channels without requiring explicit propagation models. Deep neural networks can learn the spatiotemporal behavior of wireless channels, enabling more accurate channel prediction and adaptive optimization. This research proposes a novel AI-assisted framework that integrates an LSTM-based channel predictor with an energy-aware reinforcement learning (RL) optimizer to enhance 6G performance and sustainability

II. LITERATURE REVIEW

Several researchers have explored AI-driven channel estimation and optimization approaches: - Zhang et al. (2023) developed a CNN-based mmWave channel estimation model for 5G networks but faced high computational costs. - Singh and Kumar (2022) implemented Kalman filtering for 5G New Radio; however, their approach failed under high-mobility conditions. - Li et al. (2024) introduced a federated learning-based model for distributed 6G networks, but communication overhead limited scalability. - Ahmed et al. (2023) used LSTM networks for channel prediction in B5G but did not integrate energy optimization mechanisms.

Existing methods primarily target prediction accuracy or throughput, but few address the joint optimization of energy efficiency and quality of service (QoS) in smart city environments. This research bridges this gap by proposing a hybrid AI-based solution combining prediction and optimization

III. SYSTEM MODEL

The proposed model consists of three integrated layers: 1. Data Acquisition Layer: Collects CSI, user mobility, and SNR information from transceivers. 2. AI-Based Channel Prediction Layer: Uses LSTM neural networks to predict future channel coefficients. 3. Energy-Aware Optimization Layer: Applies reinforcement learning (Q-learning) to adjust power allocation and beamforming dynamically.

A. LSTM-Based Channel Prediction

The LSTM network predicts the future channel coefficient (h(t+1)) using a sequence of past values (h(t-n),…,h(t)). [h_{pred}(t+1) = f_{LSTM}(h(t), SNR(t), Mobility(t))]

Training parameters: - Epochs: 200

- Batch size: 64

- Optimizer: Adam (learning rate 0.001)

- Activation: ReLU

B. Reinforcement Learning-Based Optimization

The RL agent dynamically adjusts the power allocation (P_i) and beamforming vectors based on predicted channel states. Objective function: [{i=1}^{N} P_i] Subject to: (R_i R{min}, P_i P_{max})

Reward function balances throughput and energy consumption: [r_t = EE_t + QoS_t] where (EE_t) is energy efficiency and (QoS_t) represents quality of service metrics.

IV. SIMULATION SETUP

Parameter	Description
Simulation Tool	MATLAB R2024b
Frequency Band	140 GHz (THz band)
Bandwidth	1 GHz
Users	100
Mobility	3–20 m/s
Channel Model	3D ray-tracing urban macro-cell
Baseline Models	MMSE, Kalman Filter, Proposed LSTM-RL

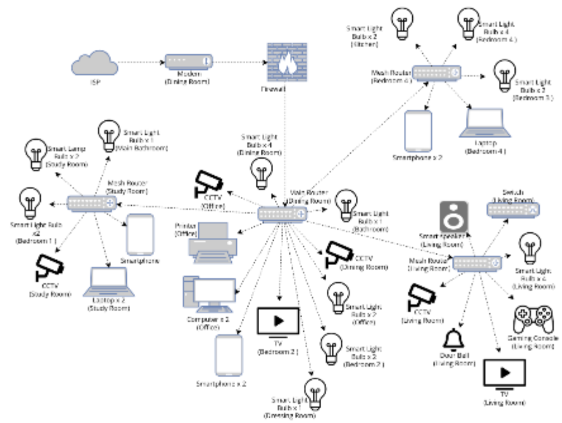

Figure 1:Placeholder for network architecture diagram.

V. RESULTS AND DISCUSSION

Simulation results confirm that the proposed AI-assisted framework outperforms conventional methods.

Metric	MMSE	Kalman	Proposed LSTM-RL
Channel Prediction MSE	0.048	0.036	0.021
Energy Efficiency (bits/J)	10.3	12.8	16.4
Latency (ms)	8.2	7.1	5.9
Throughput (Gbps)	4.6	5.2	6.0

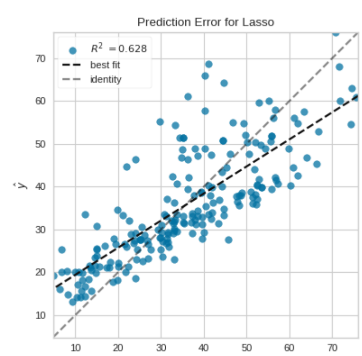

Figure 2:Placeholder for channel prediction error graph.

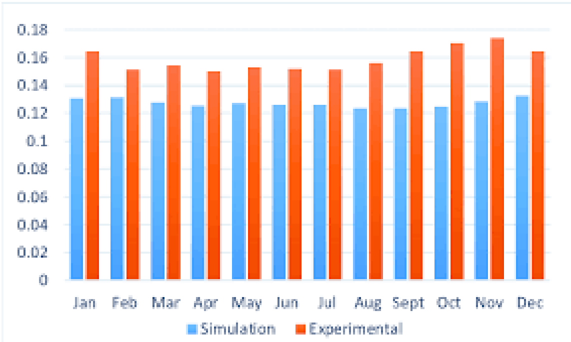

Figure 3:Placeholder for energy efficiency comparison graph

Key Observations: - LSTM predictor significantly enhances accuracy by learning temporal dependencies in channel variations. - Reinforcement learning ensures efficient power utilization, improving energy efficiency by ~25%. - The system provides lower latency and higher throughput, suitable for delay-sensitive smart city applications.

VI. CONCLUSION

This study presents an AI-assisted channel prediction and optimization framework for 6G wireless communication. By integrating LSTM-based deep learning with reinforcement learning, the proposed approach enhances both energy efficiency and communication reliability in smart city scenarios. Future work will extend this model using federated learning for distributed networks and quantum-inspired AI for higher prediction accuracy.

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