Survey on AI based Network Anomaly Detection for next generation wireless communication system for performance enhancement.

Amithesh Y[1], Dhyuthi K A[2], Rathna V[3], Priyadarshini K Desai[4]

[1]*Department of Electronics and Communication Engineering, BNMIT, Bangalore, India*
[2]*Department of Electronics and Communication Engineering, BNMIT, Bangalore, India*
[3]*Department of Electronics and Communication Engineering, BNMIT, Bangalore, India*
[4] *Associate Professor, Department of Electronics and Communication Engineering, BNMIT, Bangalore, India*

Abstract - *An AI-driven channel modeling framework in MATLAB evaluates 4G, 5G, and 6G links across terrains, elevations, and obstacle densities using an interactive GUI for BER–SNR, BER–distance, and SNR–distance analyses. A neural network trained on synthetic Rayleigh fading predicts effective channel gain and path loss with environment-aware corrections, improving accuracy and adaptability over analytical baselines. An end-to-end voice transmission through the learned channel validates practical reliability and latency awareness, indicating benefits for robust, next-generation wireless design and evaluation.*

Key Words: **AI-based channel modeling; 4G/5G/6G wireless systems; millimeter-wave and sub-THz propagation; path loss prediction; Rayleigh and Rician fading; BER–SNR analysis; received signal strength (RSSI); OFDM and link adaptation; QPSK, 16-QAM, 64-QAM, 256-QAM; environment-aware estimation (terrain, elevation, obstacle density); neural networks for channel gain and path loss; MATLAB simulation GUI; voice transmission over learned channel; physics-informed learning; dataset curation and anomaly filtering for robust training.**

1. INTRODUCTION

The evolution from 4G to 5G and towards 6G has amplified demands for high data rates, ultra-low latency, and robust connectivity across diverse, dynamic environments, making accurate channel modeling central to reliable system design and evaluation. Classical analytical and statistical models (e.g., Rayleigh, Rician, log-distance path loss) provide useful baselines but often fall short in capturing nonlinear, time-varying behaviors driven by mobility, blockage, multipath richness, terrain, elevation, and obstacle density, leading to gaps in predicting key metrics such as BER, SNR, and RSSI across heterogeneous scenarios.

AI-driven approaches address these challenges by learning effective channel gain, path loss, and fading dynamics from data, enabling adaptive, environment-aware prediction and faster performance assessment across 4G, 5G, and 6G settings. Within a MATLAB-based workflow, an interactive interface supports BER–SNR, BER–distance, and SNR–distance analyses under selectable standards, modulations, and propagation conditions, while an end-to-end voice transmission pipeline validates real-time feasibility and reliability, highlighting gains in accuracy, adaptability, and scalability over traditional models for next-generation wireless design and testing.

2. LITERATURE SURVEY

[1] Millimeter Wave Channel Modeling via Generative Neural Networks: Demonstrates that GAN-based synthesis can reproduce realistic mmWave spatial–temporal multipath statistics, aiding data augmentation and beam management evaluation beyond fixed parametric models.

[2] Attention-Guided Wireless Channel Modeling for Next-Generation Networks: Uses attention to focus on dominant paths and blockage, improving generalization across environments and reducing prediction error for channel reconstruction and prediction tasks.

[3] Path Loss Modeling Based on Neural Networks for Diverse Terrains: Shows terrain-aware neural and ensemble models significantly lower RMSE versus log-distance baselines, enabling environment-conditioned planning across urban, suburban, and rural settings.

[4] Machine Learning in 6G Wireless Communications: Surveys model-driven and data-driven methods for channel estimation, link adaptation, and resource allocation, highlighting robustness, sample efficiency, and interpretability as core challenges for 6G adoption.

[5] Advances and Future Challenges on 6G Wireless Channel Measurements and Models: Identifies gaps in multi-band, mobility-aware datasets and calls for physics-informed learning to capture sparsity, blockage dynamics, and THz propagation nuances.

[6] Adaptive/Implicit Deep Learning for Channel Tasks: Indicates implicit neural representations can capture fine-grained channel variations with fewer parameters and continuous function priors, improving fast adaptation and accuracy with limited pilots.

[7] Anomaly Detection in Wireless Sensor Networks: A Survey: Maps ML approaches that detect traffic/PHY anomalies affecting measurement integrity, informing preprocessing and dataset curation for robust AI-based channel modeling.

[8] Anomaly Detection in Beacon-Enabled IEEE 802.15.4 Wireless Sensor Networks: Details beacon timing behaviors and interference patterns that can bias RSSI/BER labels, motivating anomaly-aware filtering in channel datasets.

[9] Wireless Anomaly Detection Based on IEEE 802.11 Behavior Analysis: Provides features and traffic signatures for dense deployments, contextualizing non-channel sources of variability that should be accounted for in feature engineering.

[10] An Anomaly Detection Model for Ultra Low Powered IEEE 802.15.4e/TSCH Traffic: Shows timing and synchronization perturbations that distort PHY measurements, underscoring the need for de-noising and outlier rejection before training.

[11] Model-Driven Deep Learning and Robustness in 6G Wireless Networks: Argues for physics-regularized networks that encode propagation priors to improve out-of-distribution generalization for channel estimation/prediction.

[12] Survey on Wireless Sensor Network Anomaly Detection Using ML Approaches: Compares supervised, unsupervised, and hybrid detectors applicable to cleaning channel datasets and improving downstream predictor stability.

[13] Millimeter Wave Channel Modeling via Generative Neural Networks (Globecom Workshops): Validates GANs for mmWave channel synthesis, reproducing sparsity and angular spread statistics for scalable simulation and training.

[14] Attention-Guided Wireless Channel Modeling and Generating (Applied Sciences): Confirms attention improves path/cluster saliency, reducing NMSE and enhancing reconstruction of delay–Doppler structure across scenarios.

[15] Path Loss Modeling Based on Neural Networks and Ensemble Method for Future Wireless Networks (Heliyon): Finds ensemble learners more robust under distribution shift than single models, sustaining accuracy across terrains.

[16] Machine Learning in 6G Wireless Communications (IEICE): Highlights RIS, massive MIMO, and hybrid model–data paradigms for sample-efficient channel tasks with improved interpretability.

[17] PIMRC 2021 Workshop on 6G Channel Measurements and Models: Emphasizes standardized campaigns and unified benchmarking protocols across bands and mobility regimes to evaluate AI channel models fairly.

[18] Adaptive Implicit-Based Deep Learning Channel Estimation for 6G Communications: Reports improved estimation accuracy with fewer pilots and faster convergence, aligning with latency/overhead constraints in 6G links.

[19] Wireless Sensor Networks Anomaly Detection Using Machine Learning: Presents de-noising and change-point techniques that can stabilize training for AI channel predictors in interference-prone settings.

[20] Anomaly Detection in Beacon-Enabled IEEE 802.15.4 Wireless Sensor Networks (Springer LNCS): Provides early methodological foundations for integrating anomaly awareness into dataset labeling and filtering.

[21] Wireless Anomaly Detection Based on IEEE 802.11 Behavior Analysis (ResearchGate): Adds practical indicators of network-level behaviors that influence measured PHY metrics, supporting context-aware training pipelines.

[22] An Anomaly Detection Model for Ultra Low Powered Wireless Sensor Networks (Journal of Communications and Mobile): Reinforces the importance of low-power timing artifacts in shaping measurement noise, guiding preprocessing choices.

3. CONCLUSION

AI-driven channel modeling demonstrably enhances fidelity, adaptability, and scalability for next-generation wireless systems by learning nonlinear, time-varying propagation effects that classical analytical models struggle to capture across heterogeneous environments and frequency bands. A MATLAB-based workflow with an interactive interface supports rigorous evaluation via BER–SNR, BER–distance, and SNR–distance analyses under selectable standards and modulations, while an end-to-end voice transmission path affirms practical reliability and latency awareness in realistic conditions.

Neural estimators trained on Rayleigh fading with terrain, elevation, and obstacle-aware corrections improve effective channel gain and path loss prediction, enabling more accurate link assessment and resource decisions in 4G, 5G, and 6G contexts. The overall findings indicate clear gains over conventional baselines in accuracy and robustness, offering a viable foundation for robust design and testing of future networks; remaining challenges include broader, standardized datasets, physics-regularized learning for out-

of-distribution generalization, and interpretable models for safety-critical deployments.

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