WHITE PAPER

Enabling AI-Driven Innovation in 5G-Advanced and 6G Air Interfaces

The role of next-generation simulation platforms

KEYSIGHT

Executive Summary

As wireless communication advances toward 5G-Advanced and the emerging vision of 6G, the air interface faces growing complexity. Artificial Intelligence and Machine Learning (AI/ML) are no longer optional enhancements; they are becoming foundational technologies for optimizing performance, managing dynamic environments, and enabling intelligent, adaptive networks.

However, integrating AI/ML into wireless systems introduces new challenges. Traditional 3GPP-compliant simulation tools, while effective for conventional modeling, often lack the flexibility, computational efficiency, and native AI/ML integration needed to support modern research and development workflows.

To address this gap, a new class of simulation platforms is emerging. These next-generation frameworks combine high-fidelity wireless modeling with built-in AI/ML capabilities, enabling researchers and developers to iterate faster, validate more rigorously, and contribute more effectively to the evolution of wireless standards.

Such platforms accelerate 3GPP-compliant simulations at both the physical (PHY) and MAC layers while supporting seamless integration of AI/ML models. They offer comprehensive modeling of channels, topologies, and performance metrics, empowering users to explore and optimize AI-enhanced designs with unprecedented speed and precision.

Therefore, these advanced simulation environments are not just tools, rather they are catalysts for the next wave of wireless innovation.

Why Simulation is Indispensable in Wireless Communication?

In the rapidly evolving landscape of wireless communication, simulation has become a foundational tool for innovation. As networks grow more complex and diverse, the ability to model, test, and refine new technologies in a controlled environment is not just beneficial - it is essential.

Real-world testing, while valuable, is often constrained by cost, time, and logistical complexity. Analytical models, though useful for early-stage exploration, rely on simplifying assumptions that may not hold in practical deployments. Field trials, meanwhile, are expensive, difficult to scale, and subject to unpredictable variables such as user mobility and environmental interference.

Simulation bridges this gap by offering a flexible, repeatable, and scalable environment for experimentation. It enables researchers to prototype new algorithms, evaluate performance under diverse conditions, and explore edge cases that would be difficult or impossible to replicate in the field. From urban macro cells to dense indoor deployments, simulation provides the breadth and depth needed to understand system behavior across a wide range of scenarios.

Moreover, simulation plays a critical role in the standardization process. It allows stakeholders to evaluate proposed features, identify interoperability issues, and build consensus based on reproducible results. Organizations such as 3GPP rely heavily on simulation to validate new technologies before they are adopted into global standards.

In essence, simulation is not merely a substitute for real-world testing. It is a key enabler of innovation, efficiency, and collaboration in the wireless industry.

Foundations of Wireless System Simulation

Simulating a wireless communication system involves more than modeling signal transmission and reception. It requires a comprehensive understanding of how signals propagate, how networks behave, and how performance is evaluated. This section outlines the foundational components that make simulation both powerful and indispensable in wireless research and development.

System modeling: Building the network blueprint

At the core of any simulation lies the system model - a digital representation of the wireless network. This includes transmitters and receivers (e.g., base stations and user equipment), each defined by parameters such as modulation and coding, multi-antenna configurations, power levels, interference modeling and signal processing capabilities. The network topology - whether a structured hexagonal grid or a more irregular urban layout - also plays a crucial role.

Effective system modeling must account for interference, including co-channel and adjacent-channel effects, as well as noise and user mobility. Realistic traffic and mobility models simulate behaviors ranging from video streaming to pedestrian movement. Together, these elements form the basis for evaluating network performance and resource allocation strategies.

Channel modeling: Capturing the real world

While system modeling defines the network structure, channel modeling captures the unpredictable nature of wireless propagation. Factors such as path loss, shadowing, and fading significantly influence signal quality. Accurate modeling of these effects - whether through Rayleigh fading in dense urban environments or Rician fading in line-of-sight conditions—is essential for realistic simulation.

Standardized models, such as those defined in 3GPP’s TR 38.901, ensure consistency and comparability across studies. As research moves toward 6G, more advanced techniques like ray tracing and AI-enhanced models are being explored to better represent sub-THz bands and highly dynamic environments.

Performance metrics: Measuring what matters

The value of a simulation lies in the insights it provides. Key performance indicators include throughput, latency, spectral and energy efficiency, reliability, and fairness. These metrics help researchers evaluate trade-offs, optimize system designs, and ensure that networks meet the diverse requirements of modern applications - from Ultra-Reliable Low-Latency Communication (URLLC) to enhanced mobile broadband (eMBB).

Validation and verification: Trusting the results

Simulation results must be both accurate and credible. Verification ensures that the simulation is implemented correctly and free of logical errors. Validation confirms that the model accurately reflects real-world behavior, often through comparison with analytical models, standardized benchmarks, or empirical measurements. Cross-validation with other simulation tools can further enhance confidence in the results.

Without rigorous validation and verification, simulation outcomes lack the reliability needed to inform design decisions or contribute to standardization efforts.

Link-Level and System-Level Simulation in 3GPP

To fully understand and optimize wireless systems, researchers rely on two complementary simulation approaches: Link-Level Simulation (LLS) and System-Level Simulation (SLS). Each provides unique insights into different layers of the communication stack and plays a critical role in the development and standardization of wireless technologies.

Link-level simulation: Zooming in on the PHY layer

Link-level simulation focuses on a single communication link - typically between one transmitter and one receiver—under controlled conditions. It models the physical (PHY) layer in fine detail, including aspects such as modulation and coding schemes, MIMO techniques, channel estimation, and receiver algorithms while considering the overhead of the physical channels.

Outputs from LLS, such as Block Error Rate (BLER) versus signal-to-interference + noise ratio (SNR) curves, provide essential insights into link quality and spectral efficiency. These simulations are crucial for designing robust PHY-layer algorithms and understanding the fundamental performance limits of wireless links. They also generate link budgets that inform higher-level simulations.

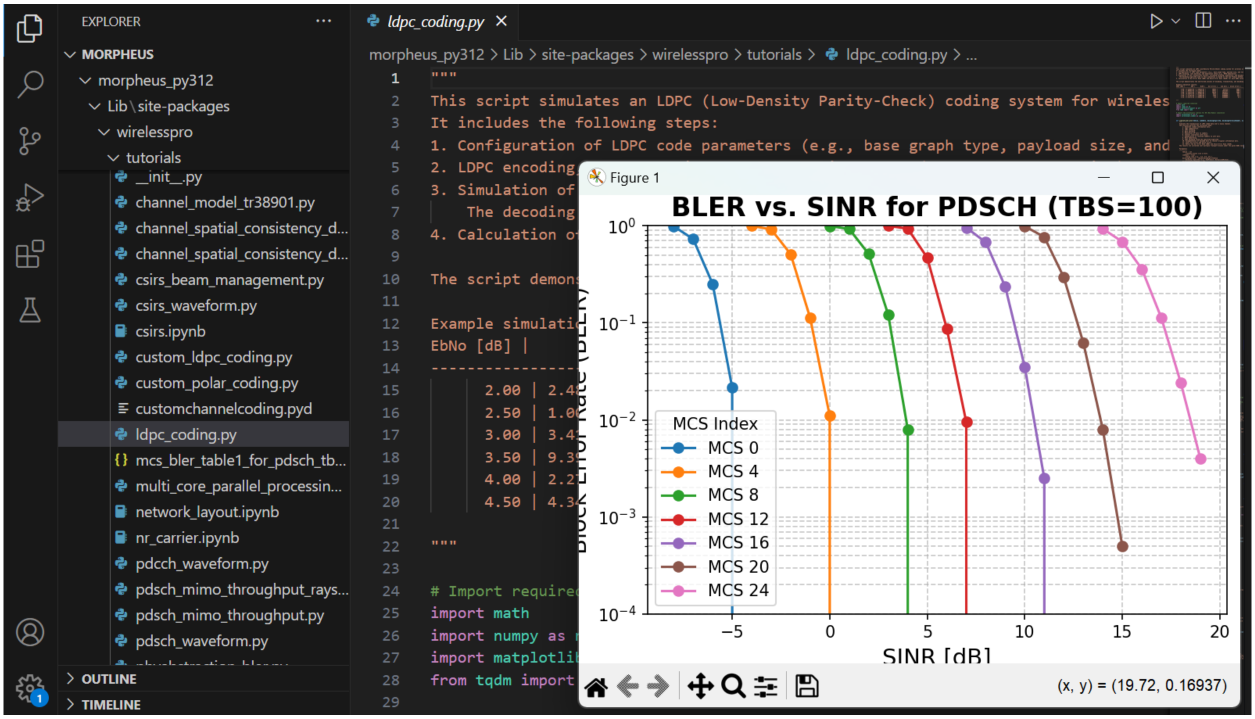

Figure 1. Visualization of a WirelessPro link-level simulation environment in VS Code, illustrating the Python-based simulation script alongside a BLER vs. SINR performance graph for PDSCH under varying MCS configurations. This figure highlights the detailed PHY-layer modeling capabilities used to evaluate link robustness and spectral efficiency across different modulation and coding schemes.

System-level simulation: Capturing network dynamics

System-level simulation takes a broader perspective, modeling multiple users with various mobility classes when placed randomly in the coverage area, base stations, and cells across a geographic area. While it abstracts the PHY-layer details—often using LLS results as lookup tables—it focuses on higher-layer behaviors, particularly those governed by the Medium Access Control (MAC) layer.

A key component of SLS is the MAC scheduler, which determines how resources such as time, frequency, and power are allocated among users. Different scheduling algorithms—such as Round Robin, Proportional Fair, or Quality-of-Service (QoS)-aware strategies—can significantly impact system throughput, latency, and fairness. SLS also incorporates mobility, interference coordination, and traffic modeling, making it indispensable for evaluating real-world network performance.

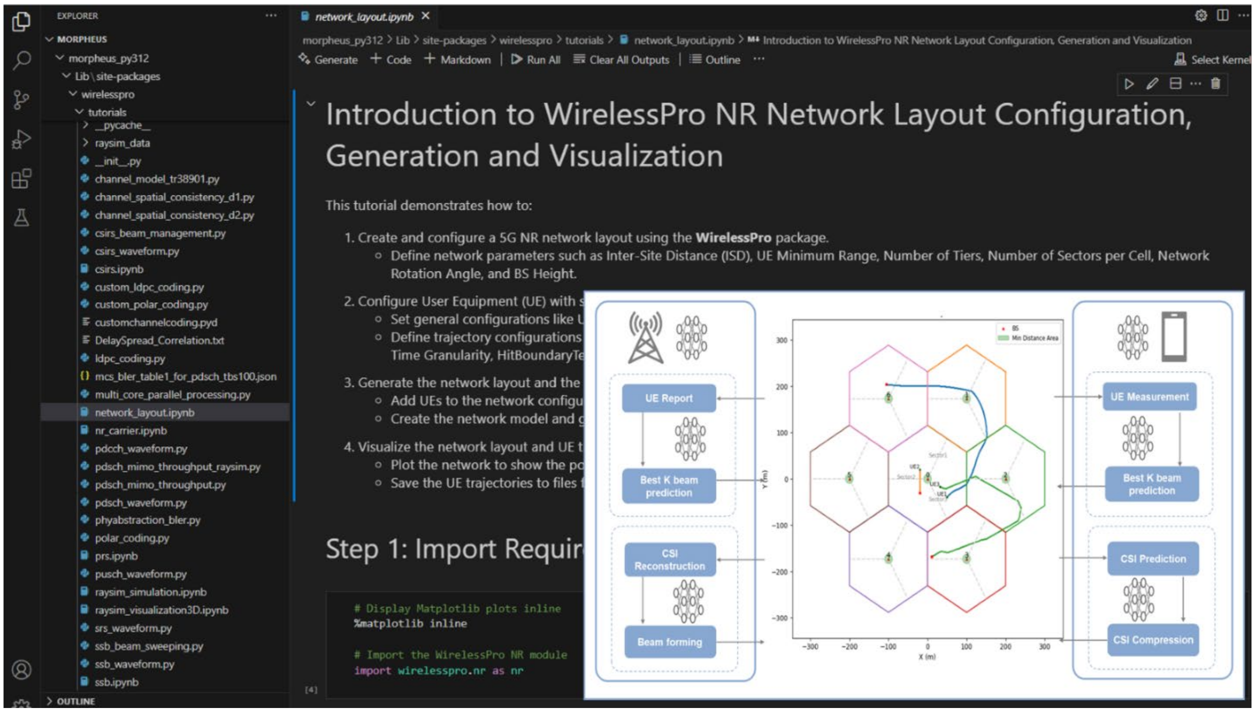

Figure 2. Example of a WirelessPro system-level simulation script in Python, demonstrating a 7-cell network layout with three User Equipment (UEs) following distinct mobility trajectories. The visualization captures the spatial distribution of base stations and dynamic user movement, illustrating the platform's capability to model realistic network topologies and mobility patterns essential for evaluating MAC-layer performance and scheduling strategies.

The interplay between LLS and SLS

LLS and SLS are not isolated tools, they are complementary. LLS informs SLS through link-to-system mapping, where detailed PHY-layer results are used to estimate achievable data rates based on signal-to-interference-plus-noise ratio (SINR). Conversely, insights from SLS—such as user distribution or interference patterns—can guide refinements in LLS configurations.

This iterative process enables a holistic approach to system optimization, ensuring that both link-level performance and system-level dynamics are accurately captured and aligned with real-world conditions.

AI/ML: The Future of the Air Interface

As wireless systems evolve toward 5G-Advanced and 6G, the traditional model-driven approach to air interface design is reaching its limits. The increasing complexity, scale, and dynamics of next-generation networks demand a new paradigm—one that integrates Artificial Intelligence and Machine Learning (AI/ML) as foundational components of wireless system architecture.

Why AI/ML?

Modern wireless networks are characterized by massive MIMO, dynamic spectrum sharing, and highly diverse traffic profiles. These systems generate vast parameter spaces and nonlinear interactions that challenge conventional optimization techniques. AI/ML excels in such environments, learning patterns from data, adapting in real time, and making decisions that are difficult to encode manually.

AI/ML also enhances adaptability. Wireless channels are inherently unpredictable, but machine learning models can anticipate changes, estimate interference, and optimize resource allocation dynamically. In scenarios where traditional mathematical models fall short—such as non-Gaussian noise or complex urban multipath—AI/ML offers robust alternatives.

Beyond performance, AI/ML enables automation. From self-organizing networks to intelligent scheduling, it reduces operational complexity and supports the development of more resilient and efficient systems.

3GPP's AI/ML milestone: TR 38.843

The integration of AI/ML into wireless standards is already underway. 3GPP's Technical Report 38.843 outlines several key use cases, including:

- Enhanced CSI Feedback: AI-driven compression and prediction techniques reduce overhead while improving accuracy. The example neural network architecture is shown in Figure 3.
- Beam Management: Intelligent beam selection and tracking enhance access and mobility.
- Positioning: AI fuses sensor and radio data to improve location accuracy.
- Interference Management: Predictive models enable proactive mitigation strategies.
- Load Balancing: AI optimizes resource distribution across cells and users.

These cases are shaping the roadmap for future 3GPP releases and highlight the growing importance of AI/ML in wireless system design.

Neural receivers: A transformative approach

One of the most promising applications of AI/ML is the neural receiver. Unlike traditional receivers that rely on conventional signal processing blocks, neural receivers use deep learning models trained to perform tasks such as channel estimation, detection, and decoding in a unified framework.

The potential benefits include improved robustness to hardware imperfections, adaptability to diverse channel conditions, and performance gains in challenging environments. However, challenges remain, including computational demands, training data requirements, and the interpretability of neural network decisions.

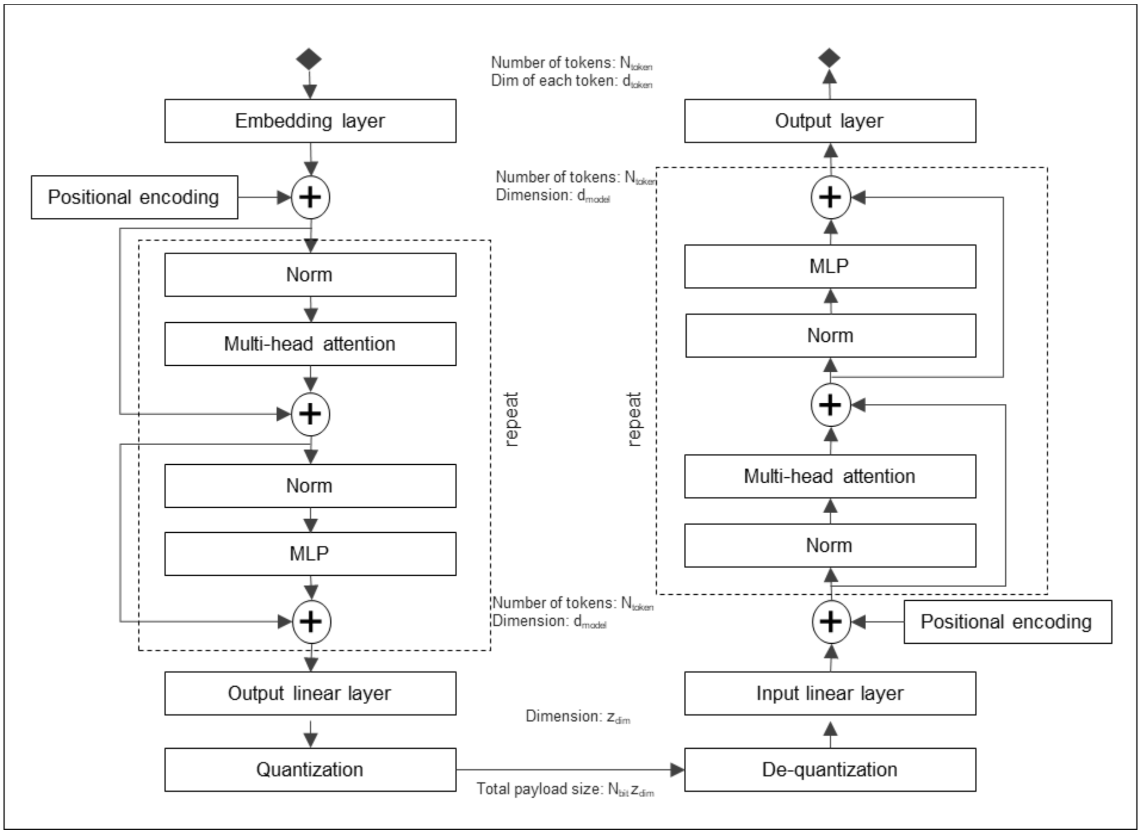

Figure 3. Simplified block diagram of a Transformer neural network architecture applied to the CSI feedback use case. The encoder compresses high-dimensional Channel State Information (CSI) into a compact representation, while the decoder reconstructs the original CSI from this compressed form. This approach enables efficient CSI compression and recovery, minimizing information loss and reducing feedback overhead in next-generation wireless systems.

Beyond the standard: Emerging AI/ML use cases

The potential of AI/ML extends well beyond current standardization efforts. Emerging applications include:

- Intelligent Scheduling: Learning-based schedulers that adapt to traffic patterns and QoS requirements as well as channel conditions experienced by the UEs.
- Predictive Mobility Management: Anticipating user movement to optimize handovers and resource allocation.
- Energy Efficiency Optimization: Reducing power consumption through intelligent control strategies.
- Network Slicing and Orchestration: Dynamically managing virtualized network resources.
- Physical Layer Security: Enhancing security through anomaly detection and adaptive encryption.
- Digital Twins: Creating real-time, AI-enhanced replicas of network environments for proactive planning and optimization.

In summary, AI/ML is not just a tool - it is a transformative force that redefines how wireless networks are designed, operated, and evolved.

Bridging the Gap: Integrating AI/ML with Traditional Simulation

While the potential of AI/ML in wireless communication is widely recognized, integrating these technologies into traditional simulation environments presents significant challenges. Achieving seamless interoperability between data-driven intelligence and model-based simulation requires rethinking how simulations are designed, executed, and validated.

Data: Fuel for AI

AI/ML models, particularly those based on deep learning, require large volumes of diverse, high-quality data. Traditional wireless simulators were not originally designed with this need in mind. Generating labeled datasets across a wide range of scenarios - such as varying channel conditions, interference levels, and traffic patterns - is a non-trivial task. Ensuring that this data accurately reflects real-world conditions adds another layer of complexity.

Computational load: A critical bottleneck

Training AI models is computationally intensive, often requiring specialized hardware such as GPUs or TPUs and extended runtimes. Even inference - applying trained models during simulation - can introduce significant overhead. In large-scale or near-real-time simulations, this computational burden can become a limiting factor, affecting both speed and scalability.

Framework incompatibility: Bridging two worlds

Wireless simulation environments are typically built using languages and tools such as C++, MATLAB, or Python, while AI/ML models are developed in frameworks like TensorFlow or PyTorch. Bridging these ecosystems involves integrating separate APIs, managing data format conversions, and maintaining synchronization between simulation and learning components. These integrations can be unstable and difficult to maintain, slowing down development and experimentation.

Reproducibility and interpretability

AI/ML introduces stochastic elements—such as random weight initialization and non-deterministic training paths—that can make reproducibility a challenge. Additionally, the “black box” nature of many AI models complicates interpretability, making it harder to understand why a model behaves a certain way. This lack of transparency can hinder debugging, validation, and acceptance in standardization processes.

Architectural considerations

To support AI/ML integration effectively, simulation platforms must adopt modular, extensible architecture. Components such as PHY and MAC layers, channel models, and AI modules should be independently configurable and replaceable. The platform must also reconcile differences in time and frequency granularity between traditional simulations and AI models, and scale from single-link evaluations to full-system simulations all while maintaining compliance with 3GPP standards.

Enabling Innovation: A Framework for AI-Native 3GPP Simulation

To meet the growing demands of AI-enabled wireless innovation, a new class of simulation platforms is emerging designed specifically to support the research and development of 5G-Advanced and 6G air interfaces. These platforms go beyond traditional simulation tools by integrating high-performance modeling with native AI/ML capabilities, offering a unified environment for rapid prototyping, evaluation, and optimization.

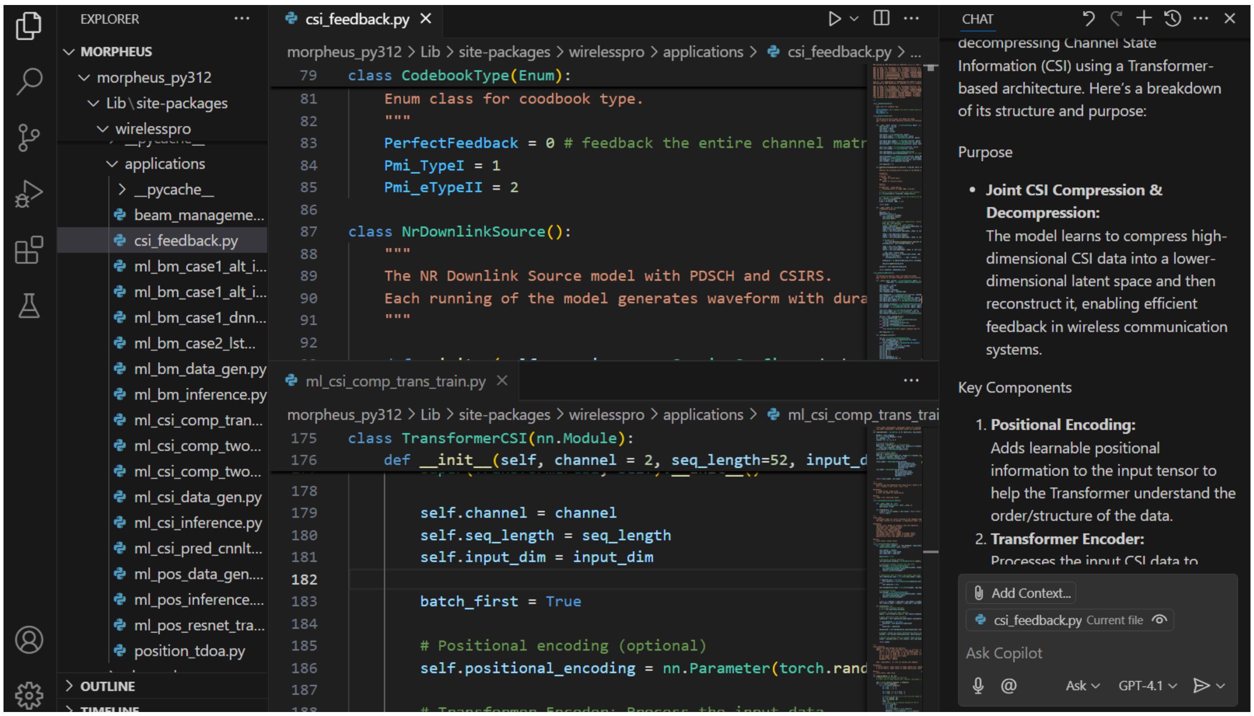

Figure 4. Integrated development environment showcasing a unified simulation framework for AI-enabled wireless research. The top panel displays a 3GPP-compliant CSI feedback simulation script, while the bottom panel features the Transformer model used for AI-based channel feedback processing. This setup exemplifies the seamless co-development of wireless signal processing and AI/ML models within a single environment. Also highlighted is a virtual code assistant, which accelerates simulation development by offering intelligent coding suggestions and real-time guidance.

A unified architecture for AI-enabled wireless simulation

Modern simulation frameworks are built on modular and scalable architectures that support a wide range of use cases from single-link analysis to full-scale, multi-cell deployments. Each component - PHY, MAC, channel models, and AI/ML modules - is encapsulated for easy configuration and replacement, enabling researchers to experiment with new ideas without overhauling the entire system.

Performance is a core design principle. These platforms leverage optimized computational engines, parallel processing, and efficient memory management to deliver high simulation speeds while maintaining fidelity. Whether training a neural receiver or evaluating a novel MAC scheduling algorithm, the simulation environment is designed to ensure that experimentation is not constrained by computational bottlenecks.

Key Capabilities of Next-Generation Simulation Platforms

- 3GPP compliance: Support for standardized models and procedures ensures alignment with industry benchmarks and facilitates contributions to ongoing standardization efforts.
- AI/ML integration: Native support for machine learning frameworks allows seamless incorporation of learning-based components into the simulation loop.
- Modularity and extensibility: Researchers can easily plug in custom models, algorithms, or datasets, accelerating innovation and reducing development overhead.
- Scalability: From detailed link-level studies to large-scale system-level evaluations, the platform adapts to the scope and complexity of the research.
- Reproducibility and transparency: Built-in tools for logging, visualization, and validation help ensure that results are interpretable and reproducible.

These capabilities make next-generation simulation platforms indispensable tools for exploring the future of wireless communication. By bridging the gap between traditional modeling and AI-driven design, they empower researchers to push the boundaries of what’s possible in 5G-Advanced and 6G networks.

Conclusion

The future of wireless communication is intelligent, adaptive, and deeply intertwined with AI/ML technologies. As the industry advances toward 5G-Advanced and 6G, the complexity of the air interface and the demands of emerging applications require a fundamental shift in how wireless systems are designed, tested, and optimized.

Traditional simulation platforms, while foundational, are no longer sufficient on their own. The integration of AI/ML into wireless networks introduces new challenges in data generation, computational efficiency, interoperability, and validation. Addressing these challenges calls for a new generation of simulation tools - ones that are as agile, intelligent, and scalable as the networks they aim to model.

Next-generation simulation frameworks are rising to meet this need. By combining rigorous 3GPP compliance with native AI/ML, modular design, and high-performance architecture, these platforms provide the foundation for accelerating research, development, and standardization in the wireless domain.

As the wireless industry stands on the threshold of 6G, these advanced simulation environments offer a clear path forward - empowering researchers, engineers, and innovators to explore, validate, and shape the intelligent air interfaces of tomorrow.

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