Toward Generative 6G Simulation: An Experimental Multi-Agent LLM and ns-3 Integration

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Abstract—The move toward open Sixth-Generation (6G) networks necessitates a novel approach to full-stack simulation environments for evaluating complex technology developments before prototyping and real-world implementation. This paper introduces an innovative approach that combines a multiagent framework with the Network Simulator 3 (ns-3) to automate and optimize the generation, debugging, execution, and analysis of complex Fifth-Generation (5G) network scenarios. Our framework orchestrates a suite of specialized agentsnamely, the Simulation Generation Agent, Test Designer Agent, Test Executor Agent, and Result Interpretation Agent—using advanced LangChain coordination. The Simulation Generation Agent employs a structured chain-of-thought (CoT) reasoning process, leveraging large language models (LLMs) and retrievalaugmented generation (RAG) to translate natural language simulation specifications into precise ns-3 scripts. Concurrently, the Test Designer Agent generates comprehensive automated test suites by integrating knowledge retrieval techniques with dynamic test case synthesis. The Test Executor Agent dynamically deploys and runs simulations, managing dependencies and parsing detailed performance metrics. At the same time, the Result Interpretation Agent utilizes LLM-driven analysis to extract actionable insights from the simulation outputs. By integrating external resources such as library documentation and ns-3 testing frameworks, our experimental approach can enhance simulation accuracy and adaptability, reducing reliance on extensive programming expertise. A detailed case study using the ns-3 5G-LENA module validates the effectiveness of the proposed approach. The code generation process converges in an average of 1.8 iterations, has a syntax error rate of 17.0%, a mean response time of 7.3 seconds, and receives a human evaluation score of 7.5.

Index Terms—5G/6G, generative simulation, multi-agent LLM, RAG, chain-of-thought, ns-3

I. INTRODUCTION

The surge in demand for applications such as extended reality (XR) and holographic services is driving the rapid evolution toward 6G networks, which are set to integrate advanced technologies like terahertz (THz) communication, AI-driven network management, and non-terrestrial networks (NTNs) [1], [2]. These innovations require open interfaces and protocols to ensure seamless interoperability, yet the heterogeneous and complex nature of 6G demands

sophisticated testing methods—particularly given the scarcity of full-scale 6G testbeds [3], [4].

A comprehensive, full-stack simulator is essential for validating novel methodologies across all network layers by using large-scale network deployments, before actual standardization, prototyping, and implementation. Tools such as ns-3 have historically enabled the evaluation of complex network environments [5], [6]. The ns3 is a powerful and widely utilized network simulator that plays a critical role in developing and evaluating networks by modeling and assessing various approaches proposed by scholars [7]. However, the simulator's frequent updates and the inherent complexity of its C++ codebase can impede rapid prototyping and widespread adoption.

Recent advancements in language models have opened the door to automating the generation, debugging, and execution of simulation code from natural language descriptions [8]. However, these models face challenges with complex tasks due to their limited contextual integration and dependency on pre-trained data. Hybrid methodologies such as retrieval-augmented generation (RAG) have emerged to address these limitations, enhancing generative models with external, domain-specific knowledge [9]. Using LLMs in the simulation process can help reduce the need for manual coding. This change can speed up innovation and make it easier for researchers working in dynamic 6G network environments.

A. Contributions

This paper presents a novel case study that integrates Multi-Agent LLMs with the ns-3 simulator to create a generative simulation framework explicitly tailored for 5G/6G networks. Our contributions are summarized as follows:

1) Multi-Agent Architecture: We introduce a highly coordinated multi-agent system where specialized agents collaboratively manage the simulation lifecycle. The Simulation Generation Agent (Agent#1) transforms natural language simulation requirements into executable code using state-of-the-art LLMs (via the ChatOpenAI interface) and prompt templates. In parallel, the Test Designer Agent (Agent#2) constructs targeted test cases by leveraging retrieval-augmented techniques with a

¹A lightweight, mock version of the code is available on GitHub at https://github.com/frezazadeh/LangChain-RAG-Technology



Fig. 1: The graphical user interface of application.

Pinecone vector store and OpenAIEmbeddings to ensure simulation accuracy.

- 2) Seamless Integration of LLMs with Simulation Tools:
 Our framework bridges advanced LLM capabilities with domain-specific simulation tools. It dynamically orchestrates various APIs and tools such as the CppSubprocessTool for ns-3 C++ execution and the PythonREPLTool for Python debugging-allowing for automated code generation, execution, and iterative refinement.
- 3) **Dynamic API and Model Optimization:** We implement a flexible toggle mechanism within the Streamlit interface that enables dynamic selection between optimized model variants (e.g., gpt-4o-mini) for cost-efficient operations. This integration ensures that our system maintains acceptable accuracy.
- 4) Case Study on 5G Network Simulation: We validate our approach with a detailed case study focusing on 5G network scenarios. The case study demonstrates how the interplay between the Simulation Generation, Test Designer, Test Executor (Agent#3), and Result Interpretation Agents (Agent#4) leads to faster simulation development, robust debugging, and refined simulation outputs through iterative feedback loops.

Overall, our work lays a robust foundation for integrating LLM-driven multi-agent systems with traditional simulation platforms, advancing the state-of-the-art automated network simulation and providing valuable insights for next-generation 6G network design and analysis.

II. METHODOLOGY

Figure 1 shows the graphical user interface of the proposed framework. This application integrates multiple advanced tools and models within an intuitive and user-friendly environment built using Streamlit. Furthermore, it adopts a modular design approach by utilizing LangChain [10]and LangGraph [11].

The proposed framework implements a technically sophisticated multi-agent system that leverages language models, retrieval APIs, and custom tool integrations to automate the entire process of network simulation generation, debugging, execution, and analysis in ns-3 environments. Upon receiving simulation requirements in natural language,

a central coordinator agent orchestrates the interaction among several specialized agents using LangChain. The Simulation Generation Agent (Agent#1) utilizes OpenAI's LLMs (accessed via the ChatOpenAI interface) with detailed prompt templates to generate simulation code. In tandem, the Test Designer Agent (Agent#2) constructs targeted test cases by integrating rule-based logic with retrievalaugmented strategies-utilizing a Pinecone vector store and OpenAIEmbeddings-to verify the simulation's accuracy and reliability. The Test Executor Agent (Agent#3) subsequently runs the simulation in the ns-3 environment by interfacing with custom execution tools, such as the CppSubprocessTool for C++ code and the PythonREPLTool for Python code. A dynamic toggle in the Streamlit sidebar allows for optimized model selection (e.g., gpt-4o-mini), demonstrating flexible API integration across agents. Finally, the Result Interpretation Agent (Agent #4) analyzes the simulation outputs by interpreting performance metrics and error logs according to detailed prompt instructions. This actionable feedback is then replied back to the Simulation Generation Agent, which triggers an iterative refinement process. Through this robust integration of API key validations, environment configurations, and multi-tool execution strategies, the framework ensures that the agents collaboratively produce a fully validated and reliable simulation.

Figure 2 shows a comprehensive view of the multiagent, LLM-driven ns-3 simulation framework. The end user (represented as a human in the loop) provides simulation requirements and feedback to the Agent Orchestration layer, which coordinates specialized agents for simulation generation, test design, execution, and result interpretation. These agents leverage an LLM and external tools (such as ns-3 and documentation) in a cyclical feedback loop to iteratively refine and analyze network simulations.

A. Multi-Agent Workflow for Network Simulation Generation

1) Simulation Generation Agent (Structured Simulation Script Synthesis through Iterative Reasoning): The role of the Simulation Generation Agent (Agent#1) is pivotal in converting high-level simulation specifications into executable ns-3 scripts. This is accomplished by leveraging a structured CoT [12] reasoning process empowered by LLMs via the ChatOpenAI interface in LangChain. Initially, the agent processes natural language input using advanced Natural language processing (NLP) techniques to extract critical simulation parameters, such as network protocols, mobility models, and bandwidth allocation. Based on these parameters, the agent selects suitable ns-3 libraries and modules (e.g., LTE, Wi-Fi, and 5G-LENA²) and identifies optimal simulation models that consider factors like the number of user devices, application demands, environmental conditions, and propagation models (e.g., 3GPP 38.901, COST 231, or ITU-R). In the subsequent script construction phase, the agent automatically generates the simulation script by

²https://5g-lena.cttc.es/

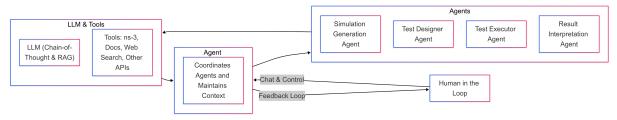


Fig. 2: Overview of the multi-agent LLM-based ns-3 simulation framework. The streamlined workflow is shown in Figure 4.

initializing nodes, configuring network devices, setting up communication channels, and assigning applications. During this process, it instantiates complex ns-3 classes such as *SpectrumWifiPhy* for Wi-Fi frequency modeling and *NrHelper* for mmWave-based networks and leverages integrated tool APIs (e.g., CppSubprocessTool for C++ code execution and PythonREPLTool for Python code debugging) to ensure that each component is rigorously validated. After the initial script has been generated, the Test Designer Agent (Agent#2) is activated to conduct static analysis and syntax validation. This process helps identify missing dependencies, deprecated API usage, and parameter mismatches. This iterative refinement process ensures that the generated script adheres to ns-3's coding standards and simulation paradigms.

- 2) Test Designer Agent (Rigorous Validation through Automated Test Suite Generation): The Test Designer Agent (Agent#2) validates the generated simulation scripts by automatically constructing a comprehensive suite of test cases. Leveraging LangChain for knowledge retrieval and LLMs for test script generation, this agent creates both primary and edge test cases. Primary test cases verify standard operations such as the successful attachment of user equipments (UEs) to base stations (e.g., eNodeB/gNodeB), the correct data flow between nodes, and adherence to predefined quality of service (QoS) parameters. Edge test cases, on the other hand, guide the simulation to stress conditions such as high mobility speeds, extreme interference, or increased network load to assess network capacity and reliability. Utilizing retrievalaugmented strategies through a Pinecone vector store and OpenAIEmbeddings, the Test Designer Agent dynamically incorporates relevant ns-3 testing paradigms and interfaces with ns-3's testing frameworks (or custom validation code) to ensure comprehensive coverage.
- 3) Test Executor Agent (Dynamic Simulation Execution and Intelligent Feedback Loop): The Test Executor Agent (Agent#3) acts as the operational backbone by executing validated simulation scripts within the ns-3 environment. This agent manages the deployment of simulation scripts across local, virtualized, or cloud-based environments. It captures all dependencies and environment variables to ensure compatibility with the current version of ns-3. During simulation execution, the agent collects diverse output data—including trace files, logs, and performance metrics parsing .pcap files, FlowMonitor outputs, and custom trace sources to extract key performance indicators (KPIs) such as throughput,

latency, packet loss, and jitter. Furthermore, advanced NLP techniques and LLM-based analysis are employed to interpret error logs and warnings (e.g., segmentation faults, assertion failures, or unexpected behaviors), enabling the agent to generate detailed, actionable feedback. This feedback is communicated back to the Simulation Generation Agent, establishing an intelligent, iterative feedback loop that drives continuous improvement of the simulation scripts.

4) Result Interpretation Agent (Analyzing Simulation Outcomes and Offering Insights): The Result Interpretation Agent (Agent#4) focuses on post-execution analysis by interpreting the outputs of ns-3 simulations. After a simulation run, the agent processes performance metrics and log data to provide a detailed network behavior analysis. The agent correlates observed performance metrics with underlying network conditions by utilizing sophisticated LLMs with tailored prompt instructions. For example, it may be determined that an increase in end-to-end delay is attributable to a high packet loss rate at the physical layer, potentially caused by wireless channel interference or suboptimal modulation schemes. By delivering clear, actionable insights, the Result Interpretation Agent guides further refinements, ensuring that the simulation meets the desired performance criteria and adheres to best practices in network simulation.



Fig. 3: The sample ns-3 generated code.

B. Case Study

This section discusses a specific use case that exemplifies the framework's capabilities in simulating a 5G new radio (NR) environment. The primary objective of this study is to investigate how the proposed framework can facilitate the execution of complex simulation scenarios.

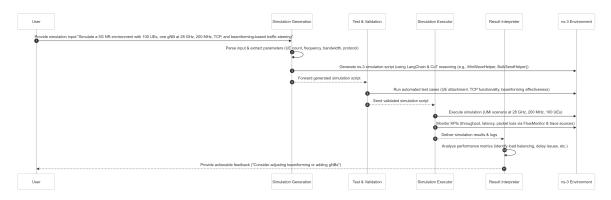


Fig. 4: Sequence diagram illustrating the streamlined workflow for simulating a 5G NR environment.

- 1) Simulation Scenario: The scenario under examination involves simulating a dense urban microcell (UMi) environment characterized by the presence of 100 UEs and one gNB operating at 28 GHz with a bandwidth of 200 MHz. The main focus of this investigation is the implementation of scheduling mechanisms to effectively balance the network load across multiple UEs, thereby ensuring an optimal QoS throughout the network. Figure 3 demonstrates the setup and configuration of the simulation scenario, including node creation, channel model selection, and Internet stack installation. The workflow for this use case is outlined in the following steps, which detail the coordinated actions of each agent within the framework.
- 2) Simulation Requirements and Input Parsing (Agent#1): The user initiates the process by providing a natural language input: "Simulate a 5G New Radio environment with 100 UEs and one gNB at 28 GHz with 200 MHz bandwidth. Implement TCP communication and enable traffic steering using beamforming". The Agent#1 receives this input and begins by parsing it using NLP techniques to extract the relevant parameters: frequency, bandwidth, number of UEs, and the desired communication protocol (TCP). By leveraging LangChain, the agent selects appropriate network models from ns-3, such as the 5G-LENA module and 3GPP-based UMi channel models. Using a structured CoT reasoning approach, the agent then synthesizes the necessary ns-3 script. It configures network nodes, assigns UEs, defines the TCP application, and configures the beamforming method. For example, the agent chooses the NrHelper class from ns-3 for mmWave channel modeling and BulkSendHelper for setting up TCP traffic across UEs.
- 3) Test Case Generation and Script Validation (Agent#2): After the script is generated, Agent#2 ensures the script's accuracy by creating automated test cases. These tests evaluate the core functionalities of the simulation, such as the correct association of UEs to the gNB, proper functioning of the TCP protocol, and the efficiency of traffic steering using beamforming. Edge cases, such as extreme UE mobility or high interference conditions, are introduced by the agent to test the robustness of the simulation. Scalability tests are also performed, incrementally increasing the number of UEs

- to assess network performance under heavy traffic loads. The tests automatically interact with ns-3's built-in testing framework to validate these conditions.
- 4) Simulation Execution and Feedback (Agent#3): With the validation complete, the *Test Executor Agent* (Agent#3) executes the simulation script within the ns-3 environment, either locally or in a cloud-based setup. The agent ensures that all necessary dependencies and configurations are in place, such as version compatibility with ns-3 modules and the required libraries (e.g., 5G-LENA, TCP/IP). The agent collects performance data during the simulation, such as throughput, latency, and packet loss, by analyzing trace files and logs. It uses FlowMonitor and custom trace sources within ns-3 to gather KPIs. The agent provides detailed feedback if any simulation errors occur, such as a segmentation fault or assertion failure. This information is then passed back to the Simulation Generation Agent for iterative refinement of the simulation script, ensuring that the final output is bug-free and meets all performance standards.
- 5) Result Interpretation and Insights (Agent#4): Once the simulation is successfully executed, the Result Interpretation Agent (Agent#4) analyzes the resulting performance metrics. For this use case, the agent observes that the traffic steering mechanism balances the load efficiently across the UEs, resulting in improved throughput and reduced latency for most UEs. However, the agent also indicates a slight increase in end-to-end delay during periods of heavy traffic, suggesting potential congestion at the gNB. The agent interprets the results and provides actionable feedback, such as: "The increase in delay correlates with a higher packet loss rate during high interference periods, indicating that adjusting the beamforming method or increasing the number of gNBs could alleviate this issue." Figure 4 demonstrates the diagram of interactions between the user, input parsing, test validation, simulation execution, and result interpretation agents, along with the ns-3 environment, highlighting the process from natural language input to actionable feedback.

III. EXPERIMENTAL RESULTS

In our experiments, the simulation platform was deployed using a combination of Streamlit for the interface, Pinecone

for vector storage, and LangChain and LangGraph integrated with OpenAI models for processing natural language queries. The system was configured to handle multiple queries, including direct simulation commands for Python and C++ environments. Furthermore, the successful initialization of the Pinecone index and the efficient retrieval of relevant information via the question-answering (QA) chain validate the design of our simulation framework. Sample output logs confirmed the correct execution of simulation tasks and indicated system performance. For instance, the output "Index 'ap-v0' created" demonstrates that the vector storage setup was completed without errors. In addition, integrating the ns-3 simulation with custom agents allowed for seamless handling of code generation and execution, further highlighting the system's flexibility.

Table I presents the experimental results for the document ingestion process, where the ingestion time increases with the number of documents processed. The data suggests a nearly linear relationship between the number of documents and the processing time, indicating predictable scalability for the ingestion mechanism.

Table II compares the execution times for Python and C++ simulation runs. Although both methods ultimately execute the ns-3 simulation, the Python method calls ns-3 using a subprocess (wrapping the ns-3 execution within a Python script), while the C++ method invokes ns-3 directly. The *Base ns-3 Time* (s) represents the inherent execution time of the ns-3 simulation engine when running the simulation code.

The overhead is defined as the extra time incurred during the invocation process beyond the base simulation time. For the Python invocation, this overhead includes the time required for setting up and managing a subprocess, handling inter-process communications, and any additional interpretation or bridging tasks between Python and the native C++ environment. In contrast, the C++ invocation method directly executes the simulation code, thus introducing significantly less overhead. Table II shows that i) The base simulation time provided by ns-3 remains constant (5.0 seconds) and ii) The C++ invocation incurs a smaller overhead (1 second) compared to the Python invocation (3 seconds), leading to slightly lower total execution time. This comparison helps clarify that while the underlying simulation engine is the same, the additional overhead introduced by the invocation method can impact the overall performance.

Table III presents metrics that describe the responsiveness of the system across different types of queries. The *Average Response Time* (s) metric represents the mean time taken for the system to generate a response for each query type, averaged over multiple runs. It indicates the system's efficiency in processing various requests—from regular queries to more complex operations such as code generation and debugging. The *Standard Deviation* (s) measures the variability or consistency of the response times across multiple trials. A lower standard deviation indicates that the response times are consistently close to the average value, while a higher standard deviation suggests greater fluctuations in the

time required to process the queries.

TABLE I: Document Ingestion Performance

| Number of Documents | Ingestion Time (seconds) | |
|---------------------|--------------------------|--|
| 10 | 1.1 | |
| 20 | 2.0 | |
| 30 | 2.9 | |
| 40 | 3.8 | |
| 50 | 4.6 | |
| 60 | 5.4 | |
| 70 | 6.2 | |
| 80 | 7.1 | |
| 90 | 7.9 | |
| 100 | 8.7 | |

The performance metrics summarized in Table IV provide a comprehensive evaluation of the LLM-driven code generation process for the simulation scenario. The Average Iterations metric indicates the mean number of iterative refinement cycles required by the LLM to generate syntactically correct and functionally valid ns-3 simulation code. A lower average iteration count implies that the LLM's initial output is close to the desired final form, necessitating minimal corrections. The Syntax Error Rate (%) is calculated as the percentage of syntactical errors present in the generated code relative to the total lines or segments of code produced. A low syntax error rate implies that the LLM is effective at generating code that adheres to ns-3's syntax and coding standards. The Human Evaluation Score as a qualitative metric, typically assessed on a scale from 1 to 10, reflects expert judgments regarding the clarity, correctness, and overall quality of the generated code [13]. A higher score corresponds to better code quality and usability, as determined by human evaluators. Furthermore, the Pass@k [14] metric is used to quantitatively evaluate code generation models by measuring the probability that at least one of the top-k generated code samples successfully passes all test cases. This metric provides an empirical assessment of a model's ability to produce correct and functional code within a given number of attempts.

The *Average Iterations* metric of 1.8 indicates that, on average, the LLM required fewer than two refinement cycles to produce syntactically correct and functionally accurate ns-3 simulation code, demonstrating that the initial outputs were largely accurate with minimal adjustments needed. The *Syntax Error Rate* of 17.0% confirms a high degree of syntactic correctness and reduces the need for extensive manual debugging. In addition, an *Average Response Time* (in five runs—k = 5) of 7.3 seconds highlights the computational efficiency of the system, ensuring that iterative refinements are performed rapidly. Finally, *Human Evaluation Score* of 7.5 and *Pass Rate* of 0.72 confirm that the generated code meets high standards.

IV. OPEN ISSUES AND FUTURE STUDY

A. Automated Bug-Free ns-3 Simulations Using LLMs

LLMs face challenges when generating ns-3 simulation code due to their hierarchical, C++-based structure and the diversity of protocols (transport, routing, MAC, PHY)

TABLE II: Comparison of ns-3 Simulation Execution Performance for Python and C++ Invocation

| Invocation Method | Base ns-3 Time (s) | Overhead (s) | Total Time (s) |
|------------------------------------|--------------------|--------------|----------------|
| Python Invocation (via subprocess) | 5.0 | 3.0 | 8.0 |
| C++ Invocation (direct) | 5.0 | 1.0 | 6.0 |

TABLE III: Query Response Time Performance

| Query Type | Avg. Response Time (s) | Std. Dev. (s) |
|--|------------------------|---------------|
| Regular Query | 1.2 | 0.3 |
| ns-3 C++ Generation | 2.7 | 0.4 |
| ns-3 Python Generation | 3.2 | 0.5 |
| ns3 Execution & Debugging & Interpretation | 4.5 | 0.6 |

TABLE IV: LLM-Driven Code Generation Performance Metrics

| Simulation Scenario | Avg. Iterations | Syntax Error Rate (%) | Avg. Response Time (s) | Human Eval Score | Pass Rate |
|---------------------|-----------------|-----------------------|------------------------|------------------|-----------|
| Defined Scenario | 1.8 | 17.0 | 7.3 | 7.5 | 0.72 |

maintained by various institutions. Although LLMs may produce syntactically similar code, they often lack a deep understanding of the networking principles needed for correct logic, requiring expert interaction to improve precision.

B. Architectural Enhancements for Protocol-Specific Code Generation

Current transformer-based LLMs, tailored for natural language and general-purpose coding, struggle with network protocols' highly structured and syntax-driven nature. Incorporating concepts from compiler theory, such as intermediate representations and abstract syntax trees, could better align these models with the requirements of ns-3 code generation.

C. Enhancing Support for Domain-Specific Languages in ns-3 Simulations

LLMs are typically trained on popular programming languages, leaving domain-specific languages (DSLs) and low-level constructs, which are crucial for ns-3 simulations, less represented. Enhancing DSL support would enable more precise automation of ns-3 code generation.

D. Continuous Learning for Adapting to Evolving Network Standards

Static LLMs risk becoming outdated with continuous evolution of network standards (e.g., 3GPP, IEEE) and frequent updates to ns-3 modules. Implementing continuous learning mechanisms ensures that generated code remains current and applicable to the latest network technologies.

V. CONCLUSION

The paper presents a multi-agent framework that integrates LLMs with the ns-3 network simulator to automate the creation, validation, execution, and analysis of 5G/6G simulation scenarios. By dividing the process into specialized agents—for generating simulation scripts, designing tests, executing simulations, and interpreting results—the framework transforms natural language inputs into fully validated simulation scripts. Experimental validation in a 5G NR scenario demonstrates its potential to reduce complexity

and speed up simulation workflows. However, challenges such as ensuring bug-free code generation, scaling full-stack simulations, and adapting to evolving network standards remain, paving the way for future research.

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