Prediction of Future States with 5G Network Digital Twin

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Abstract. Digital Twin (DT) technology is becoming an essential tool in various industries, including manufacturing, healthcare, and telecommunications. In the context of 5G networks, DTs enable real-time simulation and prediction of network behavior, which can significantly improve resource allocation and decision-making processes. Despite its potential, ensuring real-time accuracy in modeling and prediction remains a key challenge, requiring an interdisciplinary approach that integrates telecommunications, machine learning, and software engineering. This paper presents the development of a DT for a 5G network using Open5GS, UERANSIM, and srsRAN with machine learning modeling implemented in Python. The proposed model leverages real-time and historical network data to forecast future network states, enhancing the efficiency of network operations. The outcome of this work is a functional Digital Twin that contributes to the advancement of intelligent network management and optimization strategies in modern telecommunications. Furthermore, the developed system serves as a foundational model that can be extended for more complex simulations and scenarios in future research and applications.

Keywords: Digital Twins · 5G Technology · Future State Production · LSTM · Open5GS · srsRAN · UERANSIM · Energy Consumption.

1 Introduction

Digital Twin (DT) technology is rapidly becoming a key pillar across various domains of information technology, finding applications in manufacturing, healthcare, and increasingly in telecommunications [1]. These virtual representations of physical systems allow for detailed simulation and prediction of system behavior, leading to more efficient processes and improved decision-making.

In the context of 5G networks, DTs offer a unique opportunity to simulate and predict the behavior of complex, dynamic infrastructures. However, creating accurate and real-time models of such systems remains a major challenge [2]. The dynamic nature of 5G (characterized by heterogeneous traffic, service slicing, and strict performance requirements) demands precise modeling techniques and the

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ability to generalize across unseen topologies. Furthermore, the successful deployment of DTs in telecommunications requires an interdisciplinary approach that combines knowledge from telecommunications engineering, machine learning, and software development [3].

This work aims to contribute to the growing field of Digital Twins in networking by designing and implementing a DT of a 5G network. Using tools such as Open5GS [4], UERANSIM [5], and srsRAN [6], we construct a virtual version capable of generating real and synthetic data from simulated network interactions. This data is then used to train a machine learning capable of predicting the future state of the network several seconds ahead. Such predictive capabilities can be leveraged to optimize resource usage, detect anomalies, and support intelligent decision-making [7].

The core contribution of this paper lies in demonstrating the feasibility of constructing data-driven Digital Twin of a 5G network that not only mirrors its behavior but also anticipates future states. The ability to forecast key metrics in near real-time opens the door to more resilient and adaptive network management strategies in future mobile systems.

2 Digital Twin

2.1 Definition and Evolution

The concept of a Digital Twin (DT) refers to a virtual representation of a physical object, system, or process that is updated continuously with real-time data [19]. This digital counterpart allows for simulation, analysis, and control, providing insights into performance and potential issues before they occur in the physical world (See Fig. 1). The evolution of DTs has been driven by advancements in sensor technology, data analytics, and computational power, making it feasible to create accurate and dynamic models of complex systems.

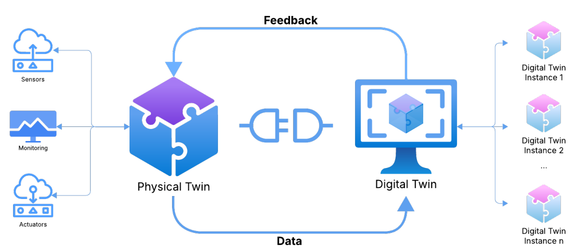

Fig. 1. Features and components of the environment for digital twins, inspired by Michael Grieves's Mirrored Spaces Model [10].

2.2 Distinctions Among Related Concepts

While the term "Digital Twin" is widely used, it is essential to distinguish it from related concepts such as digital models and digital shadows [11]:

- `Digital Model:` A static digital representation of a physical object or system, lacking real-time data integration.
- `Digital Shadow:` A digital representation that receives data from the physical entity but does not interact or influence it.
- `Digital Twin:` A dynamic model with bidirectional data flow, allowing both monitoring and control of the physical counterpart.

These distinctions are crucial for understanding the capabilities and applications of each concept in various contexts.

3 Related work

In their study, Enders and Hoßbach [1] examined the adoption of Digital Twin technology across a range of industries. They identified key sectors where DTs are most prevalent, including manufacturing [12], aerospace [13], energy [14], and automotive [15], among others. Their analysis highlighted that the primary applications of Digital Twins in these sectors are in control, simulation, and monitoring. Over time, the scope of DT applications has broadened to encompass tasks such as design, validation, error prevention, training, optimization, and predictive analysis.

3.1 Real-world implementations

Practical implementations of Digital Twins further underscore their value. For example, Huawei has deployed Digital Twin solutions to monitor production lines in real time [16]. Likewise, urban centers like Bristol [17] and Singapore [18] have integrated DTs into their smart city infrastructures to enable proactive failure detection, resource optimization, and reduced downtime. In the telecommunications domain, DTs are increasingly applied in the simulation of Radio Access Networks (RAN), the monitoring of core network operations, and overall resource management. Siemens utilizes Digital Twins to manage and optimize network components [19]. In another notable case, ZTE and China Mobile [20] successfully enhanced 5G connectivity for a high-speed rail network in southern China by employing a precise 3D model of the infrastructure along the railway. This approach resulted in network performance improvements, with coverage reaching 98.5% and download speeds exceeding 300 Mbps.

Despite these promising applications, several challenges remain, particularly in terms of deployment complexity, scalability, and simulationaccuracy. Overcoming these issues is essential for advancing Digital Twin technologies and unlocking their full potential in future network and industrial solutions.

4 Proposed solution design

The objective of this project is to develop a Digital Twin (DT) of a 5G network capable of real-time emulation of the actual network's behavior. This emulation is based on historical and current observations, as well as predictions of future states. The system aims to provide valuable tools for optimizing and analyzing 5G network performance. Its implementation involves a combination of open-source software solutions and advanced data processing methods, culminating in the creation of an effective machine learning model.

The DT will simulate key aspects of the 5G network through three primary components: Open5GS for core network implementation, srsRAN for simulating the Radio Access Network (RAN), and UERANSIM for emulating user equipment (UE) and testing various scenarios. Integrating these tools will enable modeling of data flow within the network and analysis of metrics such as latency, throughput, and connection stability. These metrics will serve as inputs for machine learning, facilitating the prediction of future network states and changes.

Each DT component serves a specific role. Open5GS ensures fundamental functions for managing the control plane and user data. Its flexible architecture allows seamless integration with other tools and supports the latest 5G standards. srsRAN simulates radio access, enabling testing of various network configurations to assess their impact on overall performance. UERANSIM focuses on emulating the behavior of devices connected to the network, generating realistic traffic scenarios, including video calls and massive IoT device connectivity. This combination of tools allows for comprehensive analysis and testing, which is crucial for developing a reliable predictive model. The architecture and specific interconnections of each component are illustrated in Fig. 2 below.

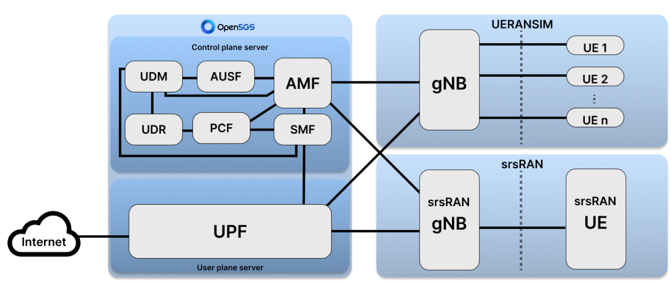

Fig. 2. Architecture of individual components of Open5GS [4], srsRAN [6] and UERANSIM [5] and their interconnection.

The DT architecture is designed for seamless collaboration among components. The Radio Access Network, simulated by srsRAN, collects and sends data to the core network implemented via Open5GS. This core processes the data and forwards it to other components. UERANSIM generates realistic communication scenarios between devices and the simulated network, such as testing situations where the network is overloaded or experiences temporary connection drops. Collected data is then used to train the predictive model, which analyzes these scenarios and helps fine-tune parameters to better respond to future situations.

For data processing, Python will be utilized, offering a rich ecosystem of libraries for data collection, scraping, cleaning, and preprocessing. Tools such as Beautiful Soup and Scrapy facilitate efficient data extraction and parsing from various sources. The process begins with data acquisition from simulations, followed by cleaning to remove invalid or incomplete values. Subsequently, the data is normalized to ensure suitability for analysis and modeling. The model will be designed to predict critical network parameters, such as latency and throughput, several seconds into the future. Such predictions can contribute to network operation optimization, improved service quality, and energy savings.

An essential aspect of this implementation is the integration of Open5GS and the physical twin's 5G core with Prometheus API for monitoring and data collection. Both can be configured to route logs to Prometheus, enabling real-time monitoring and analysis of network performance metrics (See Fig. 3). This integration facilitates the continuous collection of relevant data, which is vital for training and refining the machine learning model.

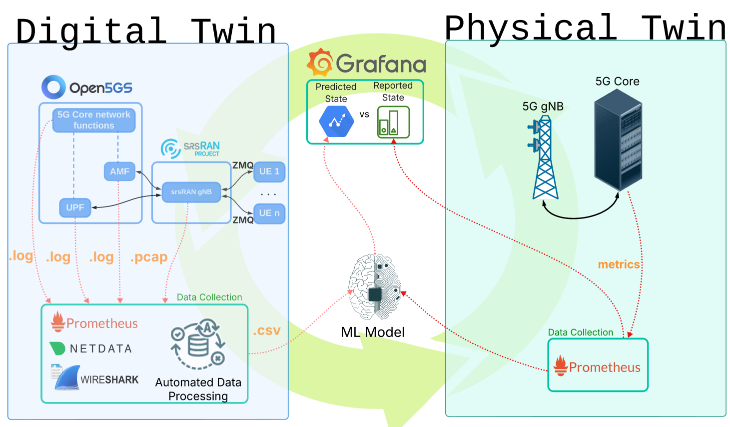

Fig. 3. The solution design illustrates the data flow between different parts of the project. Data collection involves PCAP files captured by software (e.g., Wireshark) and logs recorded from different parts of the 5G network. These data are preprocessed and used to train the ML model and subsequent predictions of future states.

This solution, however, faces several challenges. The accuracy of predictions depends on the quality and volume of available data. Simulations can be computationally intensive and limited by hardware performance. Moreover, implementing and testing the predictive model requires considerable time. These factors will be carefully considered throughout the project's lifecycle, from implementation to deployment.

5 Results

5.1 Current state

At present, the project is actively under development. We are in the process of collecting and processing data, with key system components running inside Docker containers. The core elements, Open5GS for implementing the 5G core network, srsRAN for simulating the Radio Access Network (RAN), and UERANSIM for emulating user equipment (UE), are integrated with monitoring tools such as Prometheus, Grafana, and Netdata. In our current setup, these components work together seamlessly to generate logs that are scraped and processed in real time.

We are testing various scenarios to evaluate how the model performs under different network conditions. For instance, in one scenario, the system simulates sequential UE connections (e.g., UE1 connects, a 5-second pause occurs, then UE2 connects, followed by another pause before UE3 connects). During these tests, logs from the network are captured and transformed into rows of a dataset, which are further correlated with performance metrics obtained from Prometheus and Netdata. The ultimate aim of this stage is to create a "digital shadow" that accurately mirrors the physical twin based solely on the processed logs.

6 Future of the project

6.1 Next steps

Following the successful demonstration of the digital shadow, our roadmap will focus on further refining the data pipeline and enhancing the predictive model. The next steps include:

- `Data Collection:` Broaden and standardize the acquisition of logs and metrics from Open5GS, srsRAN, and the 5G core of the physical twin.
- `Data Preparation:` Scrape, clean, and preprocess the raw logs to eliminate noise and ensure data quality.
- `Dataset Creation:` Structure the processed data into a comprehensive dataset that accurately reflects various network scenarios.
- `Model Training:` Train a predictive machine learning model to forecast key network parameters, such as latency and throughput, based on historical and real-time data.

6.2 LSTM Model

For the predictive component, we are adopting an LSTM-based (Long Short-Term Memory) model due to its proven capability in handling time-series data and capturing temporal dependencies. The following Python code snippet outlines the initial architecture of our model - See Fig. 4.

This model comprises two LSTM layers (with 100 and 50 units respectively), where the first layer returns sequences to feed into the subsequent LSTM layer.

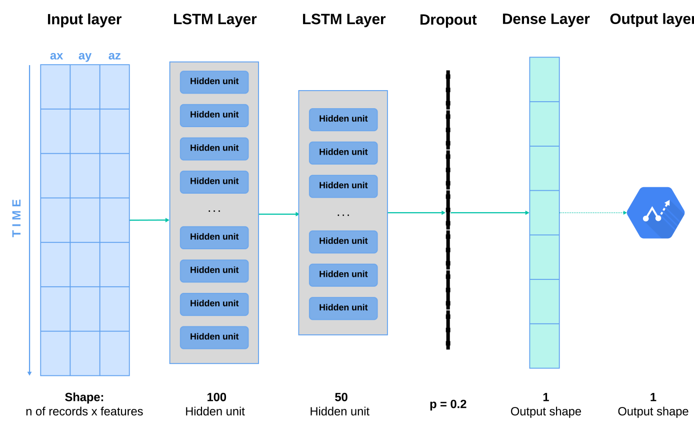

Fig. 4. Initial architecture of model using LSTM layers.

A dropout layer (with a dropout rate of 0.2) to help prevent overfitting. A dense output layer that produces a single value, suitable for regression tasks. The model is compiled with the Adam optimizer and mean squared error as the loss function. In the upcoming phases, we plan to refine this model architecture by exploring different hyperparameters and potentially integrating additional layers or alternative neural network architectures. The goal is to enhance the model's ability to predict future network states accurately and support dynamic network management.

7 Discussion

Our work demonstrates that a Digital Twin for a 5G network can effectively simulate core network behavior in real time by leveraging open-source components. In our implementation, Open5GS, srsRAN, and associated monitoring tools (Prometheus, Grafana, and Netdata) are orchestrated within Docker containers, with ZeroMQ (ZMQ) facilitating communication between the components. This configuration is well-suited for our purposes of replicating network behavior based on logs from the physical twin.

A significant outcome of this project is that the current configuration, using ZMQ with srsRAN, adequately supports the simulation of a 5G core network under emulated conditions. Since our setup relies solely on simulated radio connections rather than actual radio wave propagation, we have deliberately limited our scope to higher-layer network functionalities. This choice avoids the need for specialized RF hardware, though it also means that the system does not capture the complexities of real-world radio frequency behavior. An unexpected observation was that the connection time for a UE in the srsRAN environment is noticeably longer than that seen in earlier simulations with UERANSIM. This discrepancy affects our data collection process, as longer connection times result in fewer data points over a given period. While srsRAN provides a detailed simulation of the network's interface, the extended connection delays reduce the volume of logs available for model training, which may impact the overall predictive accuracy. This difference in connection times underscores the trade-offs inherent in our current approach. For projects focused on core network functionalities and predictive performance, where the emphasis is on processing log data, the use of ZMQ with srsRAN is both efficient and sufficient. However, if future work necessitates detailed analysis of the physical layer or over-the-air (OTA) experiments, alternative configurations involving actual RF hardware would be required.

Another limitation is that the reconfigurability of our system is confined to a small segment of the overall 5G network, restricting its potential to dynamically adapt based on predicted future states. In addition, the variance in connection times between srsRAN and previous simulations highlights the need for further calibration of our data collection methods. For future research, we recommend expanding the range of metrics and variables used to enrich the dataset to improve the predictive capabilities of the machine learning model, extending the Digital Twin to encompass larger portions of the network for more comprehensive simulation and analysis, and investigating alternative model architectures while fine-tuning hyperparameters to address discrepancies in data collection and enhance prediction accuracy. These steps will help evolve our Digital Twin from its current proof-of-concept stage into a robust, scalable tool for dynamic 5G network management.

8 Conclusion

This paper presented the design and early implementation of a Digital Twin for a 5G network, built using open-source components including Open5GS, srsRAN, and UERANSIM. Integrated with Prometheus, Grafana, and Netdata, the system enables real-time data collection and monitoring. The current stage demonstrates a functioning digital shadow that mirrors selected behaviors of the physical network, using logs and metrics to feed a predictive model based on LSTM. This digital shadow serves as a fundamental building block for the creation of a full Digital Twin, enabling structured data collection and analysis necessary for its development. While the system currently allows modification of only a limited portion of the network, early results show promising potential for future expansion. Continued work will focus on enriching the dataset, improving the model, and scaling the Digital Twin to broader network contexts for more intelligent and adaptive management.

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