ELG 5142 Project proposal

Group ID: 13

Main article used:

"Position-Based Machine Learning Propagation Loss Model Enabling Fast Digital Twins of Wireless Networks in Ns-3." https://dl.acm.org/doi/10.1145/3592149.3592150.[1]

I. Introduction

The paper "Position-Based Machine Learning Propagation Loss Model Enabling Fast Digital Twins of Wireless Networks in ns-3" introduces the concept of digital twins as a hybrid approach that combines the advantages of network simulators and experimental testbeds. Digital twins consist of digital models that replicate the behavior of physical systems and dynamic conditions of experimental environments. They can be used to validate networking solutions and evaluate their performance in simulated environments that realistically replicate the dynamic conditions of physical environments. The paper focuses on the wireless channel model, which is a key component of wireless network digital twins. It proposes the Position-based ML Propagation Loss (P-MLPL) model for ns-3, which improves the precision of the ML-based Propagation Loss (MLPL) model by considering the absolute positions of nodes and the traffic direction. The P-MLPL model allows for the development of fast and more precise digital twins of wireless networks in ns-3, enabling the validation of novel solutions and the evaluation of their performance in realistic conditions. The paper also discusses an optimization technique that adds an internal cache to the P-MLPL model to improve computational performance. The model is validated and evaluated through experiments and simulations, and the paper concludes with a summary of the results and suggestions for future work.

II. Literature Review

The paper "Position-Based Machine Learning Propagation Loss Model Enabling Fast Digital Twins of Wireless Networks in ns-3" by Eduardo Nuno Almeida, Helder Fontes, Rui Campos, and Manuel Ricardo proposes a new machine learning-based propagation loss model for the ns-3 network simulator. The model, called P-MLPL, is trained on a dataset of network traces collected in an experimental testbed. The model takes as input the absolute positions of the transmitter and receiver nodes, as well as the traffic direction, and outputs the estimated propagation loss.

The authors compare the performance of P-MLPL to two other propagation loss models in ns-3: the Friis model and the Hata model. The results show that P-MLPL can predict the propagation loss with a median error of 2.5 dB, which is significantly lower than the error of the Friis and Hata models. Moreover, ns-3 simulations with P-MLPL estimated the throughput with an error up to 2.5 Mbit/s, when compared to the real values measured in the testbed.

The paper is well-written and the results are convincing. The authors have made a significant contribution to the development of machine learning-based propagation loss models for wireless networks.

Here are some additional related papers:

- Path Loss Prediction Based on Machine Learning: Principle, Method, and Data Expansion: https://www.mdpi.com/2076-3417/9/9/1908 [2]
- A Note on a Simple Transmission Formula: https://ieeexplore.ieee.org/document/1697062 [3]
- An improved IEEE 802.16 WiMAX module for the ns-3 simulator: https://dl.acm.org/doi/10.4108/ICST.SIMUTOOLS2010.8653 [4]

III. Objectives of the Project

The primary objectives of this project are:

- The proposal of a new machine learning-based propagation loss model for ns-3.
- The validation of the model on a dataset of network traces collected in an experimental testbed.
- The comparison of the performance of the model to two other propagation loss models in ns-3.

IV. Proposed Methodology (from the paper)

The proposed approach in this paper is to utilize the Position-based Machine Learning Propagation Loss (P-MLPL) model for the creation of digital twins of wireless networks in ns-3. This methodology involves several steps: data collection from experimental testbeds, preprocessing of the dataset, training of ML models for path loss and fast-fading, implementation of the P-MLPL model in ns-3, validation of the model's precision through a test suite, and performance optimization. By combining simulators and experimental testbeds, the P-MLPL model provides a way to accurately evaluate next-generation wireless networks in realistic conditions.
The outcomes will be evaluated by comparing the P-MLPL model's predicted propagation loss values with the actual values in the test set. Prediction errors will be calculated as the differences between the predicted and actual propagation loss values. CDFs will be used to visualize the distribution of both real and absolute prediction errors, providing insights into the model's accuracy and potential biases. By examining these CDFs, we can assess the model's precision and its ability to capture variations in real-world propagation loss. Additionally, comparisons will be made with baseline models (Friis and Log-Distance) with the inclusion of a Normal fast-fading distribution to ensure fair assessments of the P-MLPL model's performance against existing methods. P-MLPL model is expected to result in more accurate path loss prediction & consequently accurate propagation loss than baseline models.

V. Simulation Setup

The simulation setup for the P-MLPL model in ns-3 involved integrating the model as an ns-3 module using the ns-3-ai module for communication with external ML frameworks. The model was trained using a dataset of propagation loss samples collected in an experimental testbed. The precision of the model was evaluated using a test suite that compared the model's propagation loss estimates with experimental values. Overall, the setup allowed for the creation of fast and precise digital twins of wireless networks in ns-3, enabling the evaluation of network performance in realistic conditions.

<u>Modules & Models:</u>

1- Path Loss ML Model:

The Path Loss ML Model employs supervised learning algorithms to estimate the deterministic path loss between wireless devices. To integrate this model into ns-3 simulations, the ns3-ai module is utilized, allowing seamless interaction with external ML frameworks like TensorFlow. The communication between the simulation and the ML model occurs through shared memory. To enhance computational efficiency and reduce overhead, the P-MLPL model incorporates an internal cache. This cache stores previously queried path loss values, avoiding repeated expensive queries to the ML model via shared memory. Instead, the cached values are reused whenever needed, saving computational resources.

2- ns3-ai Module:

The ns3-ai module allows seamless integration of external ML models (e.g., TensorFlow) into ns-3 simulations. It facilitates shared memory communication for efficient data exchange and path loss caching, streamlining computational operations.

3- Fast-Fading Model:

The Fast-Fading Model simulates random signal fluctuations in the wireless channel. It generates pseudo-random samples using a stochastic process and an empirical Cumulative Distribution Function (CDF) fitted to dataset samples. To ensure simulation reproducibility, the fast-fading model setup is within ns-3 module & configured to share the same random seed used in the overall simulation. This guarantees that the pseudo-random samples for fast fading remain consistent across simulations, providing reliable and repeatable results.

4- Random Number Generator (RNG) Module in ns-3:

The RNG module in ns-3 generates pseudo-random numbers for the Fast-Fading Model, it produces random samples with consistency by sharing the same seed across simulations.

5- Test Suite Module:

The test suite validates data exchange and propagation loss calculations in the P-MLPL ns-3 module. It checks the accuracy of calculated loss values against experimental data from an example dataset. The suite includes tests to ensure the proper functioning and correctness of the module. Used to verify the data exchange between the P-MLPL model and the external ML framework through shared memory. Additionally, it validates the accuracy of propagation loss values calculated by the P-MLPL model, comparing them with experimental values from the dataset from testbeds.

VI. References

[1] E. N. Almeida, H. Fontes, R. Campos, and M. Ricardo, "Position-based machine learning Propagation Loss Model Enabling Fast Digital Twins of wireless networks in NS-3," *Proceedings of the 2023 Workshop on ns-3*, 2023. doi:10.1145/3592149.3592150

[2] Y. Zhang, J. Wen, G. Yang, Z. He, and J. Wang, "Path loss prediction based on machine learning: Principle, method, and data expansion," *Applied Sciences*, vol. 9, no. 9, p. 1908, May 2019. doi:10.3390/app9091908

[3] H. T. Friis, "A note on a simple transmission formula," *Proceedings of the IRE*, vol. 34, no. 5, pp. 254–256, 1946. doi:10.1109/jrproc.1946.234568

[4] M. A. Ismail, G. Piro, L. A. Grieco, and T. Turletti, "An improved IEEE 802.16 WiMAX module for the NS-3 simulator," *Proceedings of the 3rd International ICST Conference on Simulation Tools and Techniques*, Mar. 2010. doi:10.4108/icst.simutools2010.8653