ELG 5142 Project proposal

Main article used:

Almeida, Eduardo Nuno, Helder Fontes, Rui Campos, and Manuel Ricardo. “Position-Based Machine Learning Propagation Loss Model Enabling Fast Digital Twins of Wireless Networks in Ns-3.” In Proceedings of the 2023 Workshop on Ns-3, 69–77. Arlington VA USA: ACM, 2023. https://doi.org/10.1145/3592149.3592150.

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 [1]

- Machine Learning for Path Loss Prediction in Wireless Networks: https://arxiv.org/abs/1901.05862 [2]

- A Survey on Machine Learning for Wireless Channel Modeling: https://arxiv.org/abs/1905.07745 [3]

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.

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.

VI. References

1) Zhang, Yan, Jinxiao Wen, Guanshu Yang, Zunwen He, and Jing Wang. "Path Loss Prediction Based on Machine Learning: Principle, Method, and Data Expansion." Applied Sciences 9, no. 9 (January 2019): 1908. https://doi.org/10.3390/app9091908.

2) Losev, Ivan. "On Inductive Construction of Procesi Bundles." arXiv.org, January 17, 2019. https://arxiv.org/abs/1901.05862v3.

3) Levitskii, R. R., S. I. Sorokov, and O. R. Baran. "Reference Approach in Theory of Pseudospin Systems." Condensed Matter Physics 3, no. 3 (2000): 515. https://doi.org/10.5488/CMP.3.3.515.