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Position-Based Machine Learning Propagation Loss Model Enabling Fast Digital Twins of Wireless Networks in ns-3

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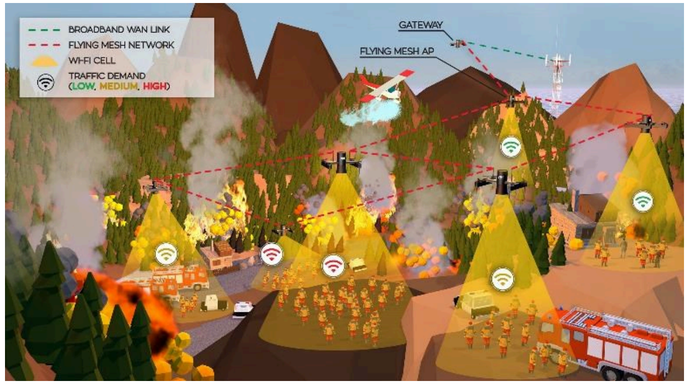
OUTLINE

INTRODUCTION

Next-Generation Wireless Networks Require Realistic Performance Evaluation

EXPERIMENTAL TESTBED

- ✓ Perfect Accuracy
- ✗ Cost & Availability
- ✗ Complexity



SIMULATION

- ✗ Medium Accuracy
- ✓ Repeatability
- ✓ Simplicity

DIGITAL TWIN

- ✓ Reproduction of experimental environment in simulation
- ✓ Simplicity, accuracy and repeatability

DIGITAL TWINS OF WIRELESS NETWORKS

ACCURATE & CUSTOM
DIGITAL MODELS

REALISTIC
SIMULATED ENVIRONMENTS

REPLICATE
ENVIRONMENT DYNAMICS

SCALE UP
EXPERIMENTAL TESTBEDS

COMPLEX
NETWORK SCENARIOS

GENERATE
DATASETS FOR ML

ML-BASED PROPAGATION LOSS (MLPL) MODEL

- Propagation loss model for ns-3
  - Deterministic path loss + stochastic fast-fading
  - Considering distance between Tx / Rx nodes
  - ML model trained with experimental network traces
  - Repeatable, reproducible and flexible scenario parameters
- Accuracy in complex scenarios can be improved
  - E.g., multi-path, obstacles
- Can not model channel asymmetry

E. N. Almeida et al., *"Machine Learning Based Propagation Loss Module for Enabling Digital Twins of Wireless Networks in ns-3,"* in Proceedings of the 2022 Workshop on ns-3, ACM, 2022, pp. 17–24.

CONTRIBUTIONS

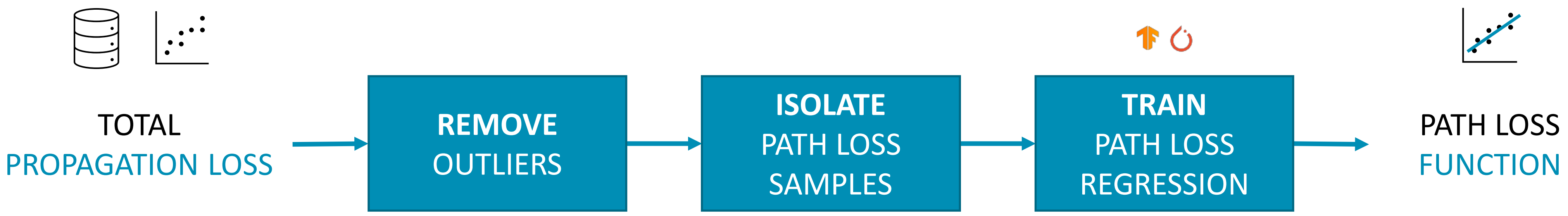
- Position-based ML Propagation Loss (P-MLPL) model for ns-3
  - Based on MLPL model
  - Considering node positions and traffic direction
  - Increased precision and channel asymmetry
  - Cache for ML queries to improve performance and mitigate overhead

- Fast digital twin of experimental wireless network
  - Environment represented by network traces
  - Repeatable, reproducible and flexible scenario parameters

P-MLPL MODEL

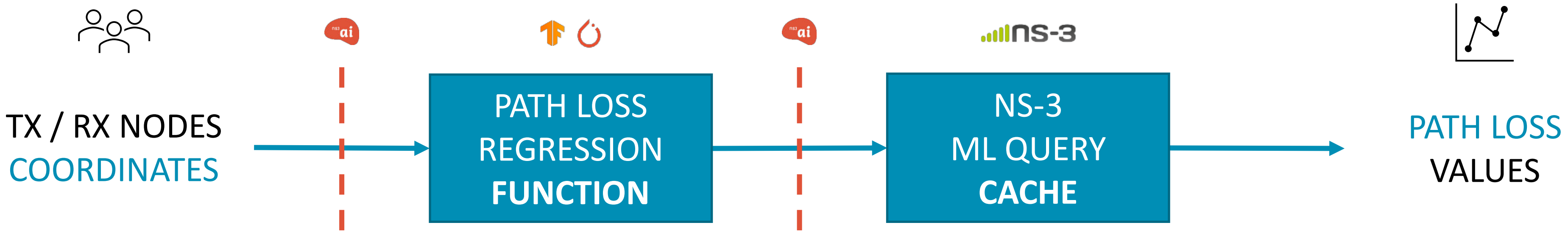
DETERMINISTIC PATH LOSS

TRAINING



DETERMINISTIC VALUE CALCULATED ACCORDING TO TX / RX NODES COORDINATES

ESTIMATION



ML INTEGRATION VIA NS3-AI   MINIMIZE ML OVERHEAD

P-MLPL MODEL

STOCHASTIC FAST-FADING

TRAINING

TOTAL PROPAGATION LOSS → **REMOVE** OUTLIERS → **ISOLATE** FAST-FADING SAMPLES → **FIT** FAST-FADING EMPIRICAL CDF → FAST-FADING EMPIRICAL CDF (X, Y) PAIRS

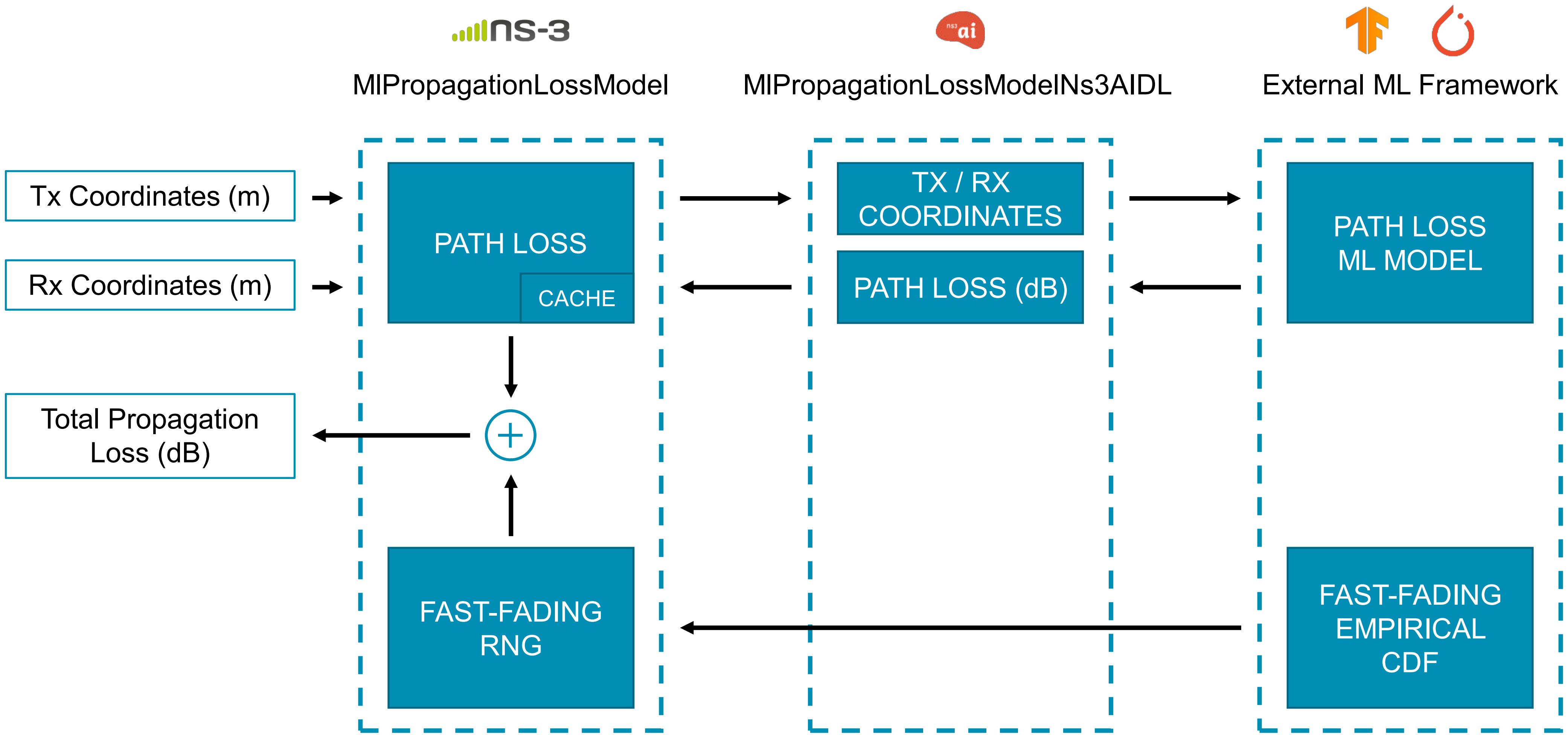
PSEUDO-RANDOM SAMPLES BASED ON EMPIRICAL CDF

ESTIMATION

FAST-FADING EMPIRICAL CDF (X, Y) PAIRS → NS-3 EMPIRICAL CDF **RNG** → FAST-FADING SAMPLES

REPEATABLE & REPRODUCIBLE SIMULATIONS CONTROLLED BY NS-3 SEED

P-MLPL MODEL ARCHITECTURE



P-MLPL MODULE STRUCTURE

TRAIN_ML_PROPAGATION_LOSS_MODEL.PY

- Train ML model with dataset
  - Train ML model using external ML framework
  - Save ML model in files

RUN_ML_PROPAGATION_LOSS_MODEL.PY

- Run trained ML model
  - Start external ML framework and load ML model
  - Start ns3-ai module
  - Wait for ns-3 simulation to start

- Using ns3-ai module
  - Allows using existing ML frameworks
  - Avoids complex integration of ML models directly in ns-3

H. Yin et al., "NS3-AI: Fostering artificial intelligence algorithms for networking research," in *Proceedings of the 2020 Workshop on ns-3*, 2020, pp. 57–64.

P-MLPL PROPAGATION LOSS DATASET FORMAT

NODE POSITIONS

- Tx Node Coordinates
- Rx Node Coordinates

OPTIONAL DATA

- Throughput

PROPAGATION LOSS

- Propagation Loss (Path Loss + Fast-Fading)

- Rx Power

- Tx Power
- Antenna Gains
- Channel Frequency & BW

- SNR
- Noise

- Tx Power
- Antenna Gains
- Channel Frequency & BW

DECOMPOSITION OF PROPAGATION LOSS

- Decompose propagation loss L_i into path loss PL_i + fast-fading FF_i
- Assuming fast-fading modeled as statistical distribution with μ = 0

PATH LOSS

$$\boxed{PL_d = \mu_d}$$

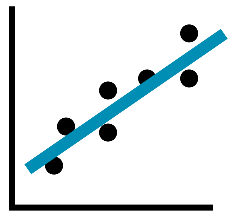
Mean propagation loss for distance d

FAST-FADING

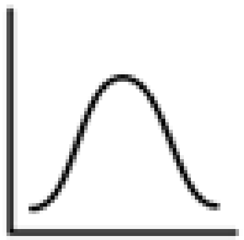
$$\boxed{FF_i = L_i - PL_i}$$

Difference between total propagation loss and path loss

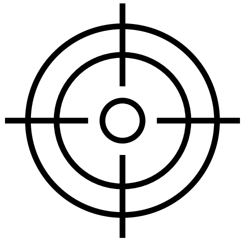
P-MLPL MODEL PRECISION



PATH LOSS
PRECISION



FAST-FADING
DISTRIBUTION PRECISION



P-MLPL
PRECISION

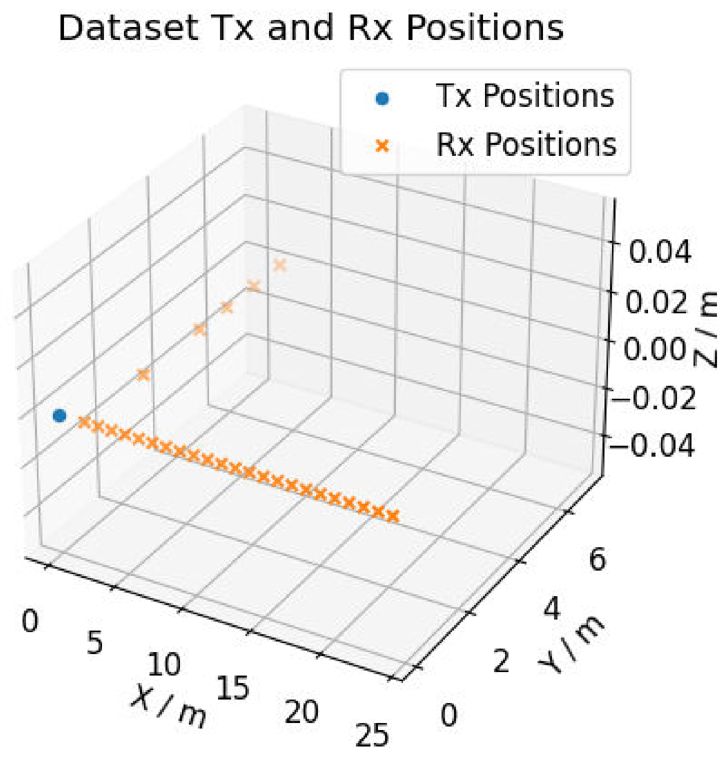
NS-3.37 SIMULATION SET-UP AND PARAMETERS

WIRELESS NETWORK

- IEEE 802.11a
- Tx Power: 1 dBm
- Antenna Gain: -7 dBi
  (3 dBi gain – 10 dBi attenuator)
- Channel: 5220 MHz (20 MHz)
- MAC Rate Adaptation: Minstrel

SCENARIO & MODELS

- 1 Fixed Node + 1 Mobile Node
- 54 Mbit/s UDP Constant Bitrate
- Packet Size: 1400 Bytes
- Warehouse Environment
- ML Models: SVR and XGBoost
- Train Set: 80% | Test Set: 20%



Dataset adapted from: *V. Lamela, H. Fontes, T. Oliveira, J. Ruela, M. Ricardo, and R. Campos. 2019. SIMBED - Offline Real-World Wireless Networking Experimentation using ns-3. Zenodo. https://doi.org/10.5281/zenodo.2634272*

P-MLPL PROPAGATION LOSS PRECISION

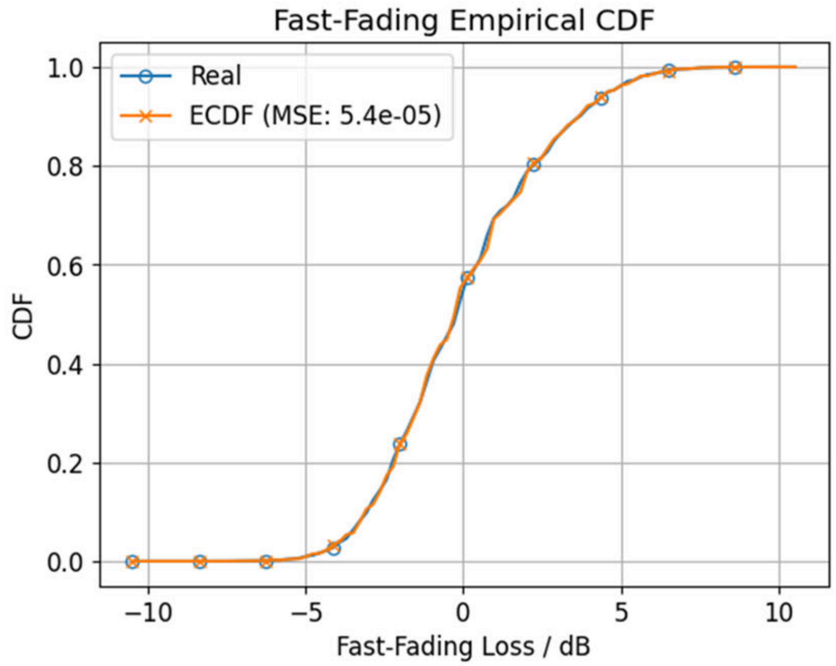
PATH LOSS & FAST-FADING RESULTS

PATH LOSS

ML Algorithm	Mean Squared Error (MSE)
SVR	1.6 dB^2
XGBoost	4.3 dB^2

Very Precise Predictions with SVR

FAST-FADING

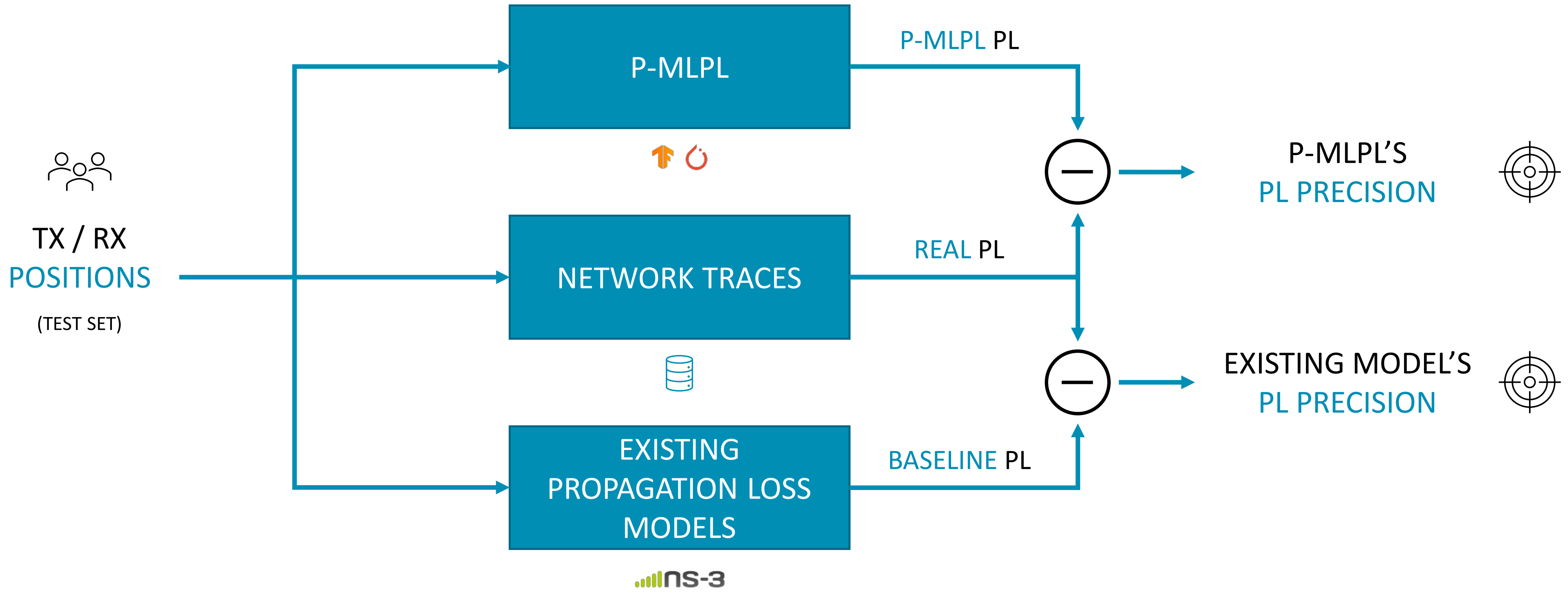


Perfect Representation of Fast-Fading

P-MLPL PROPAGATION LOSS PRECISION

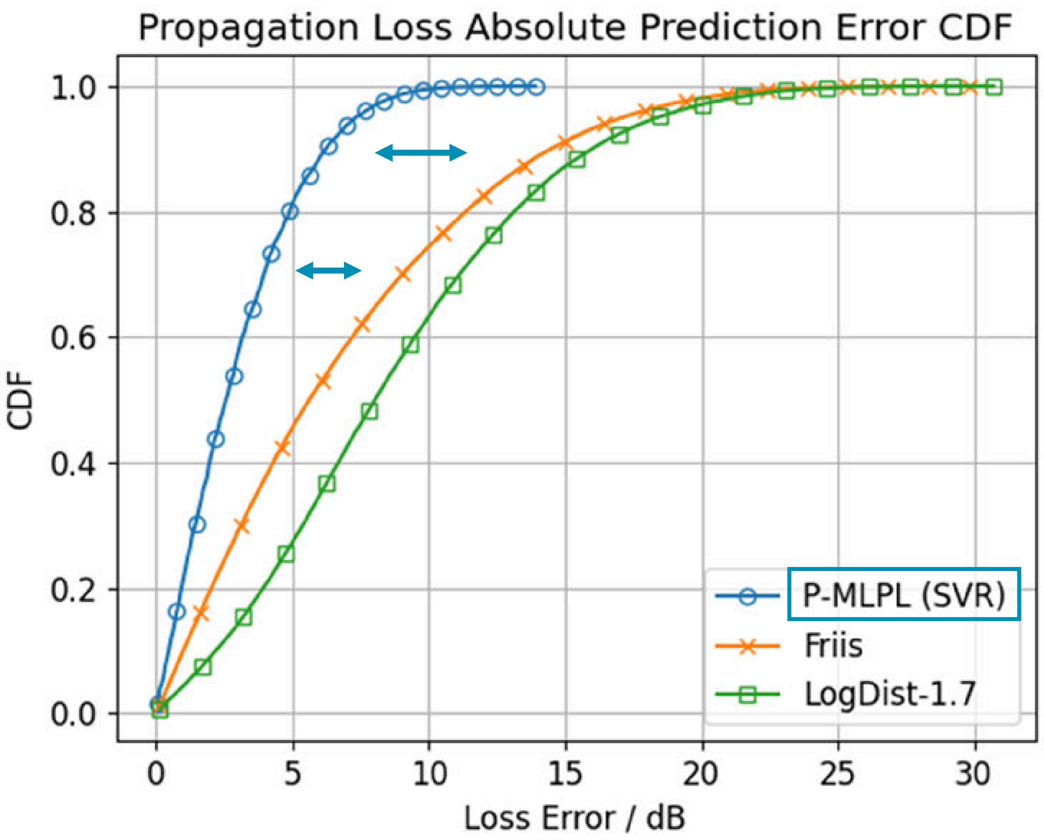
PROPAGATION LOSS METHODOLOGY

COMPARE PROPAGATION LOSS (PL) ESTIMATIONS WITH REAL AND BASELINE



P-MLPL PROPAGATION LOSS PRECISION

PROPAGATION LOSS RESULTS



- P-MLPL most precise model
  - Precision up to 2.5 dB
  - Error up to 0.5x compared to baselines
  - SVR similar to XGBoost (not shown)
  - Neither optimistic nor pessimistic
- Friis and Log-distance
  - Too optimistic
  - 90% of losses above real values

P-MLPL PERFORMANCE IN NS-3 SIMULATIONS

THROUGHPUT
PRECISION

COMPUTATIONAL
PERFORMANCE

HARDWARE & SIMULATION SET-UP

UBUNTU
22.04 LTS

8 CPU CORES
16 GB OF RAM

10 SIMULATION RUNS
95% CONFIDENCE INTERVAL

NS-3.37
OPTIMIZED PROFILE

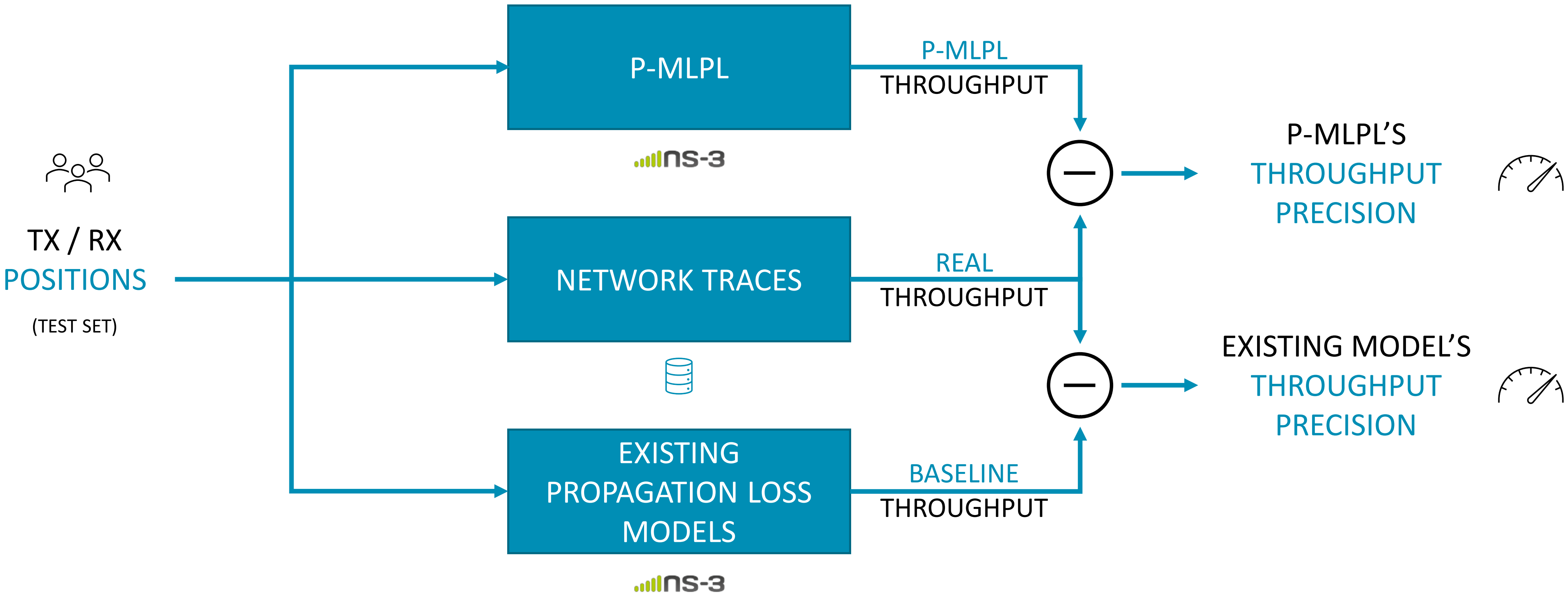
UDP CBR 54 Mbit/s
1 s INIT. + 5 s PER POSITION

-90 dBm RSSI
PREAMBLE DETECTION

P-MLPL THROUGHPUT PRECISION

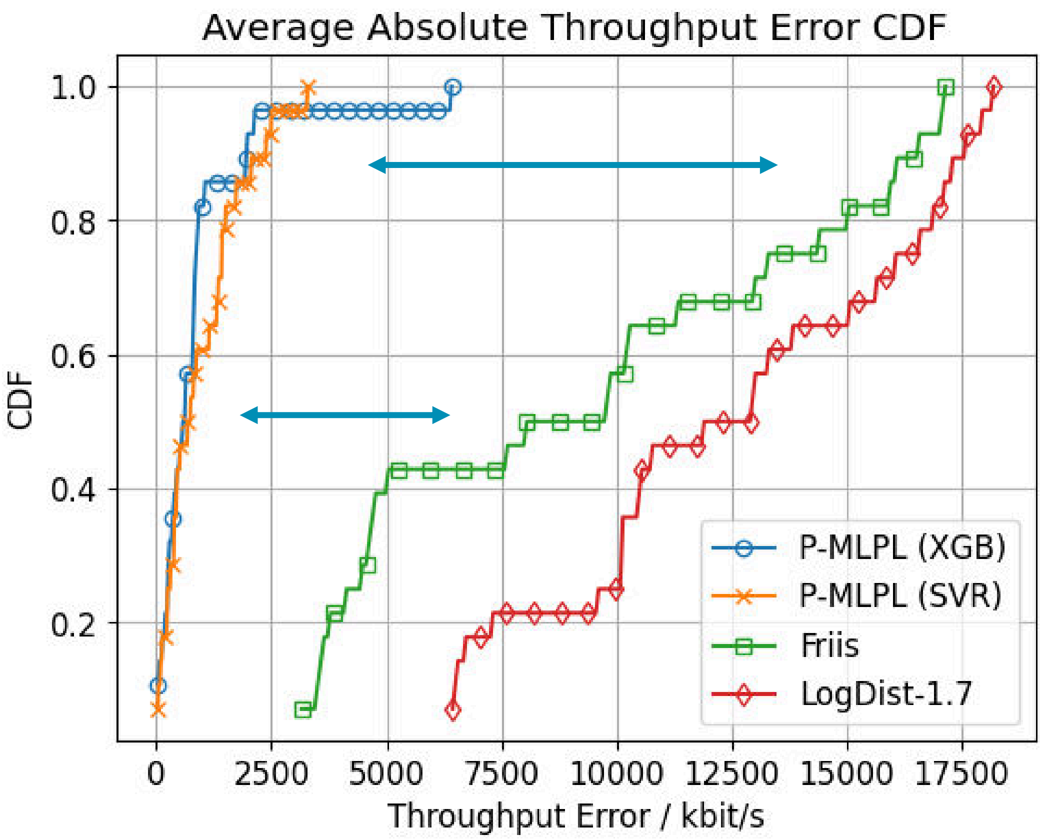
METHODOLOGY

COMPARE THROUGHPUT OBTAINED IN NS-3 SIMULATIONS



P-MLPL THROUGHPUT PRECISION

RESULTS



- P-MLPL
  - Accurate reproduction of experimental throughput
  - Precision up to 2.5 Mbit/s
  - XGBoost with slightly better precision
- Friis and Log-Distance
  - Optimistic throughput estimation
  - Precision up to 17.5 Mbit/s

P-MLPL COMPUTATIONAL PERFORMANCE

METHODOLOGY

DURATION OF NS-3 SIMULATIONS

- Time to finish simulation

MEMORY USAGE OF NS-3 SIMULATIONS

- ns-3 + ns3-ai + External ML framework
- Manually observed with *htop*

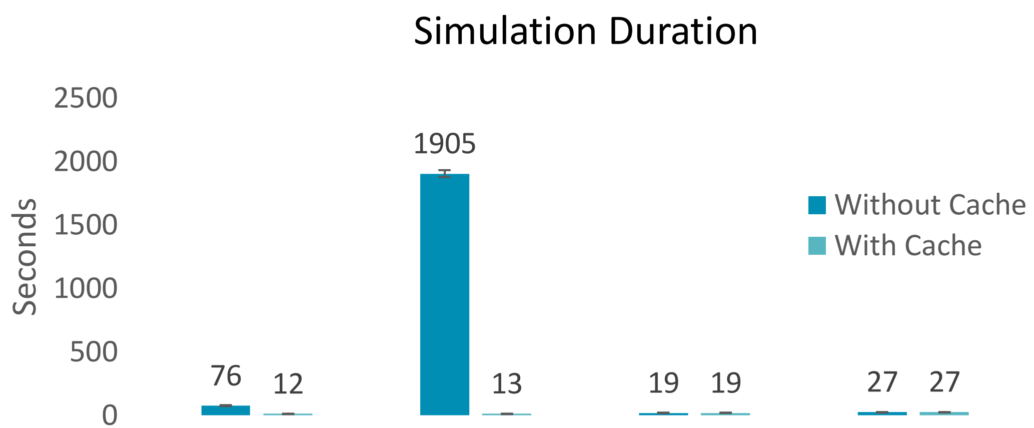
P-MLPL (CACHE)

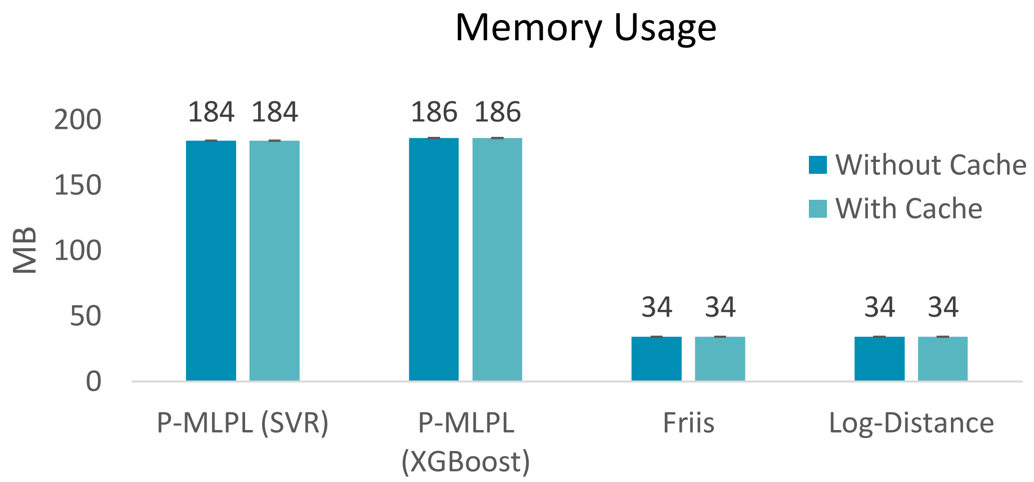
P-MLPL (NO CACHE)

EXISTING PROPAGATION LOSS MODELS

P-MLPL COMPUTATIONAL PERFORMANCE

RESULTS





- Simulation Performance
  - SVR 25x faster than XGBoost (without cache)
  - P-MLPL (with cache) faster than baselines by 1.6x (Friis) and 2.3x (Log-Dist.)
  - P-MLPL higher memory usage

- Cache Performance
  - XGBoost 147x faster | SVR 6.3x faster
  - Negligible memory usage
  - Mitigation of ML query overhead
  - Simulation performance improvement

CONCLUSIONS

- Position-based ML Propagation Loss (P-MLPL) Model for ns-3
  - Enables digital twin of experimental wireless environment
  - Trained with experimental network traces
  - Repeatable, reproducible and flexible

- More accurate than MLPL and ns-3 existing models
  - Considers absolute node positions and traffic direction
  - Especially in dynamic and asymmetric scenarios

- Cache improves performance and mitigates ML overhead

FUTURE WORK

- Explore using neural networks for path loss model
- Evaluate P-MLPL with obstacles and asymmetric links
- Explore caching technique in ns-3 propagation loss models

- Publish in ns-3 App Store
  - Module already available on GitLab

E. N. Almeida *et al.*, *"ML Propagation Loss Model for ns-3"*, 2023

https://gitlab.com/inesctec-ns3/ml-propagation-loss-model

QUESTIONS?

Position-Based Machine Learning Propagation Loss Model Enabling Fast Digital Twins of Wireless Networks in ns-3

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E. N. Almeida *et al.*, *"ML Propagation Loss Model for ns-3"*, 2023. https://gitlab.com/inesctec-ns3/ml-propagation-loss-model

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