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Context-Aware Forecasting of Mobile Network Quality for Autonomous Vehicle Connectivity

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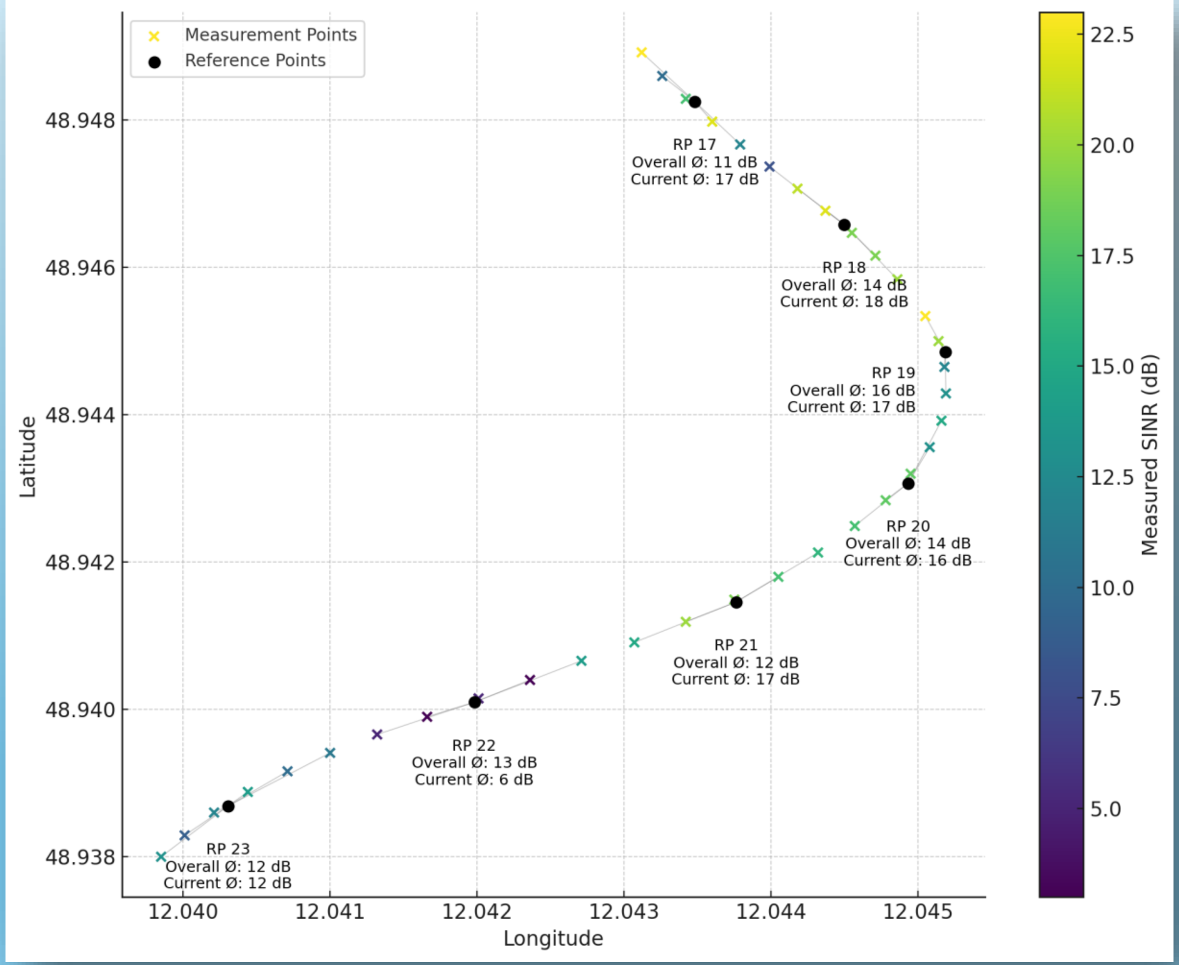
- Ph.D. Student CarSec-Lab at OTH Regensburg
- Research focus on Automated Vehicle (AV) communication
- Other topics:
    - Intrusion Detection Systems (IDS)
    - Global Navigation Satellite Systems (GNSS)

Motivation

- Why is context-aware network forecasting relevant for autonomous driving?
  - Level 4 autonomous vehicles must maintain continuous connectivity with a remote supervisor (required by German law)
  - Connection loss → vehicle must perform a controlled stop
  - Reliable mobile network availability forecasting is critical to ensure uninterrupted connectivity
  - Environmental and temporal factors strongly influence this highly dynamic system of a vehicle moving along a route

Problem Statement

- Mobile network quality varies due to spatial, temporal and environmental influences
- Existing coverage maps fail to capture real-time variability
- Goal: Develop a context-aware prediction model for mobile signal quality



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Related Work (examples)

- Torres et al. (2017): LTE congestion forecasting - *no contextual parameters*
- Madariaga et al (2018): Weather impact on QoS - *no dynamic or route-based modelling*
- Schippers et al. (2025): 5G measurement dataset - *urban focus and no consideration of weather features*

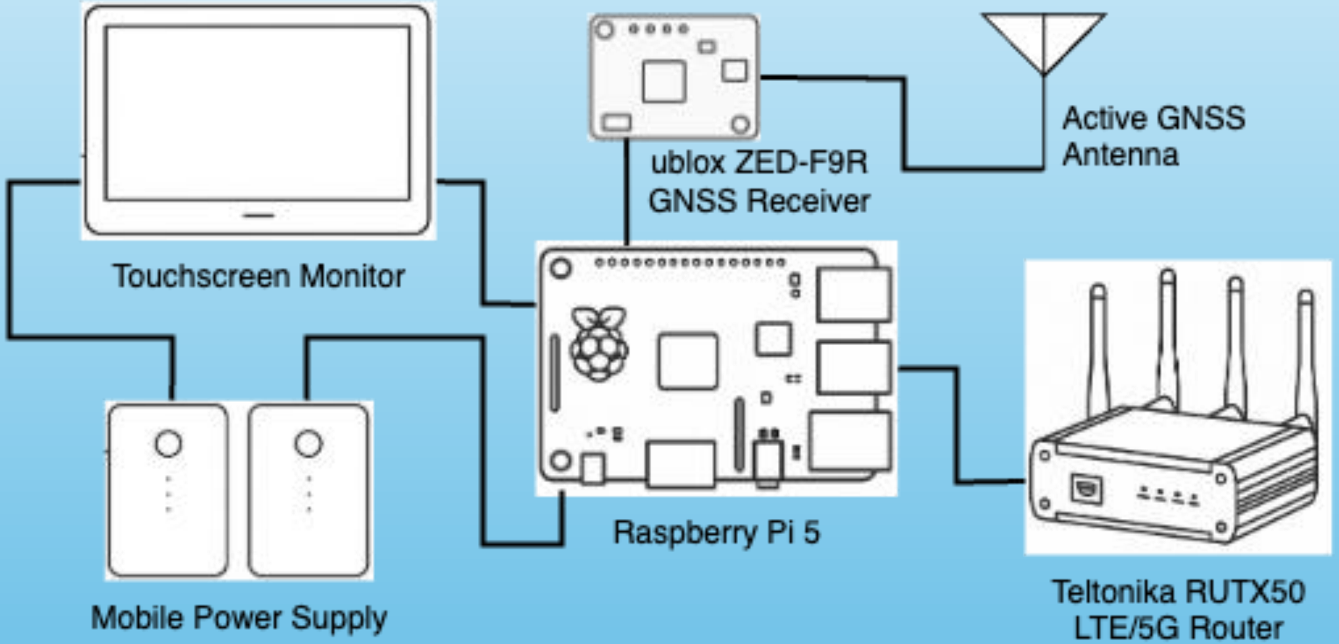
→ This study: long-term, rural, context-aware forecasting

Background: Mobile Networks

- LTE and 5G technologies form the backbone of vehicular communication
- Passive signal parameters (shown right) indicate performance and stability
  - **RSSI**: Total received power
  - **RSRP**: Average power of reference signals
  - **RSRQ**: Ratio of RSRP to RSSI
  - **SINR**: Defines link quality and achievable data rate

Parameter	Unit	Range	Quality Interpretation
RSSI	dBm	-120 to -30	> -65: Excellent -65 to -75: Good -75 to -85: Fair < -85: Poor
RSRP	dBm	-140 to -60	> -80: Excellent -80 to -90: Good -90 to -100: Fair < -100: Poor
RSRQ	dB	-20 to -3	> -10: Excellent -10 to -15: Good -15 to -20: Fair < -20: Poor
SINR	dB	-20 to +30	> 15: Excellent 10 to 15: Good 5 to 10: Fair < 5: Poor

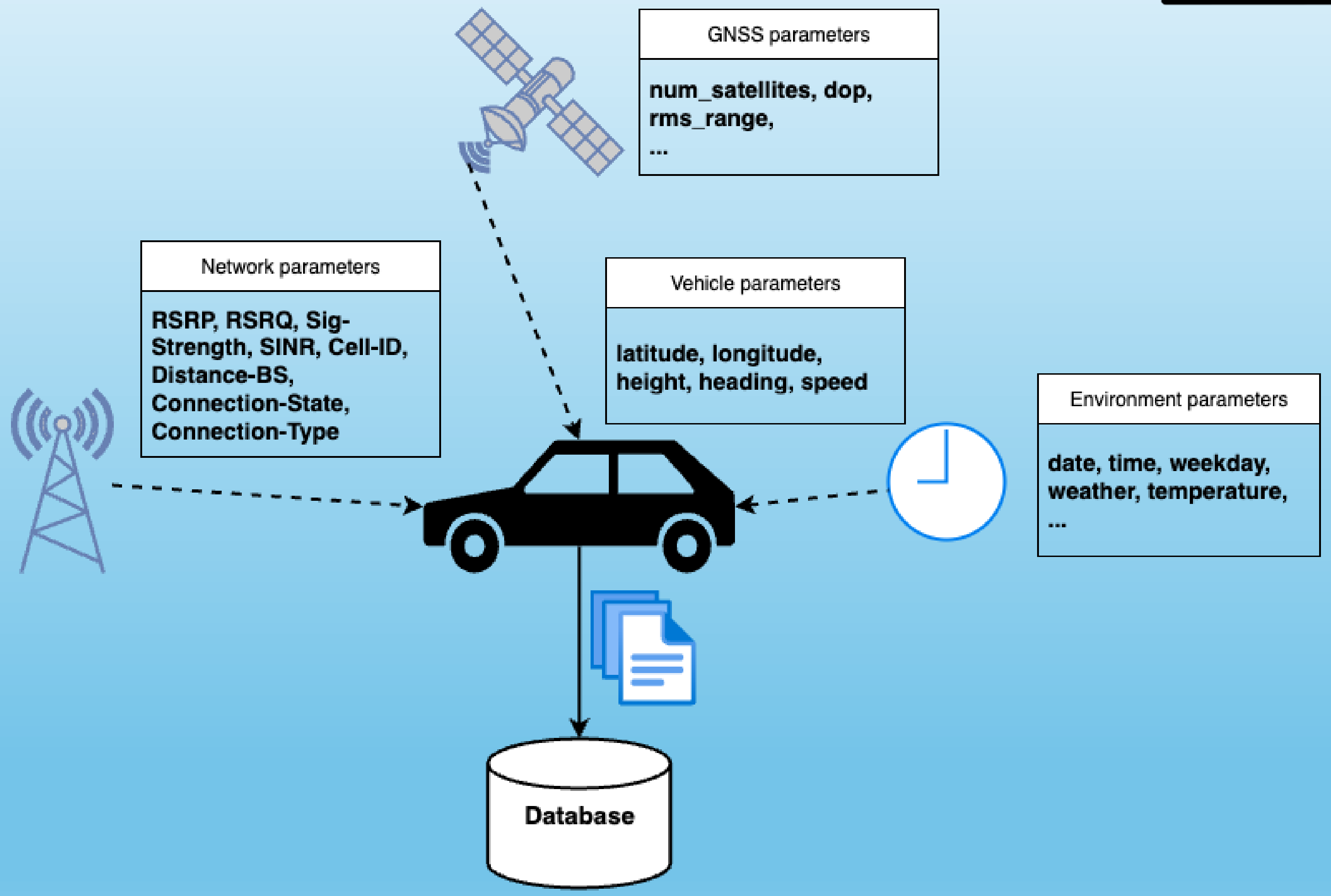
Measurement Device Setup



Data Collection

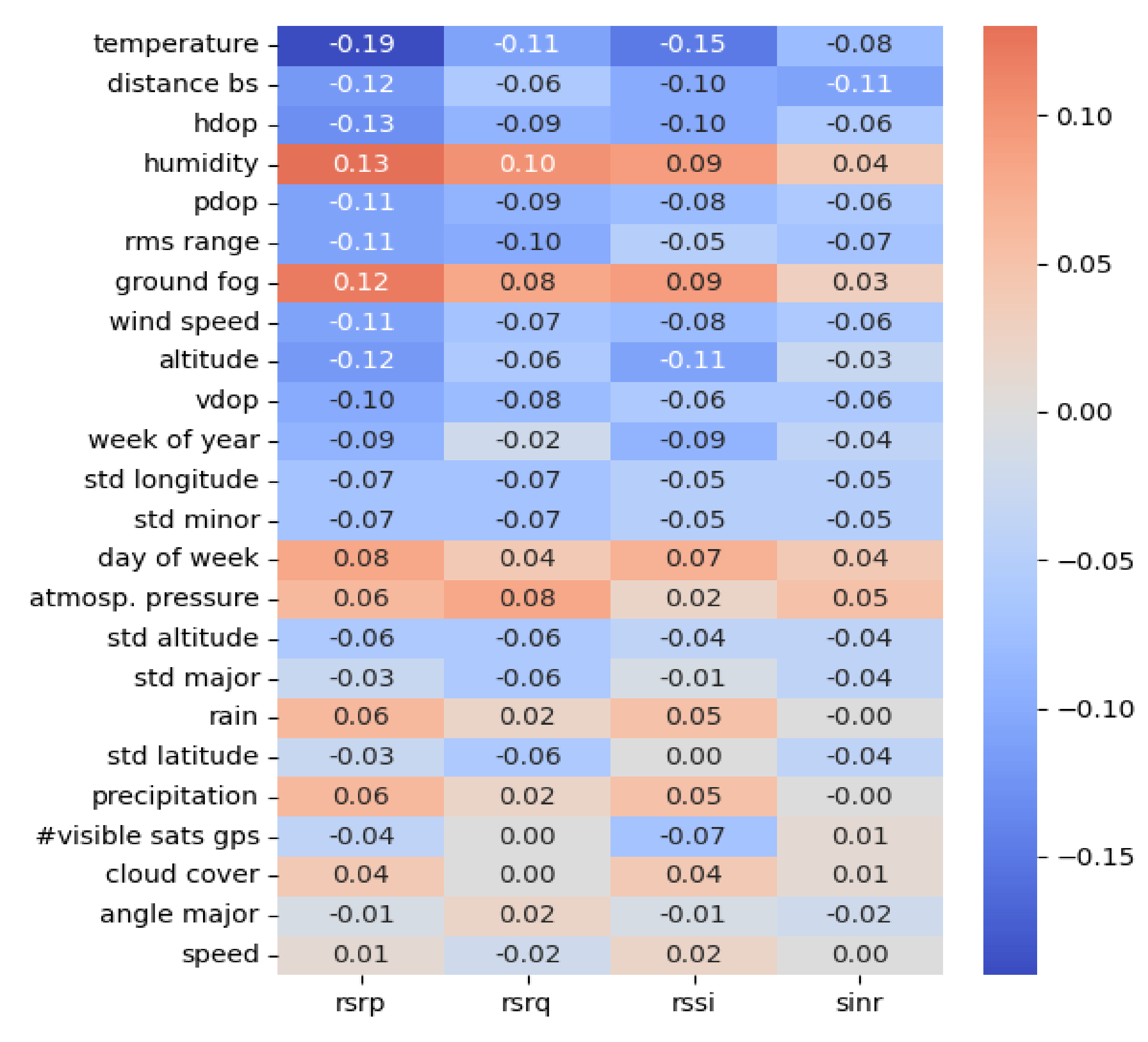
38 measurement drives over 10 months along a 64 km rural route (B16, Germany)

≈ 60,000 data points recorded in both driving directions



Correlations with Contextual Factors

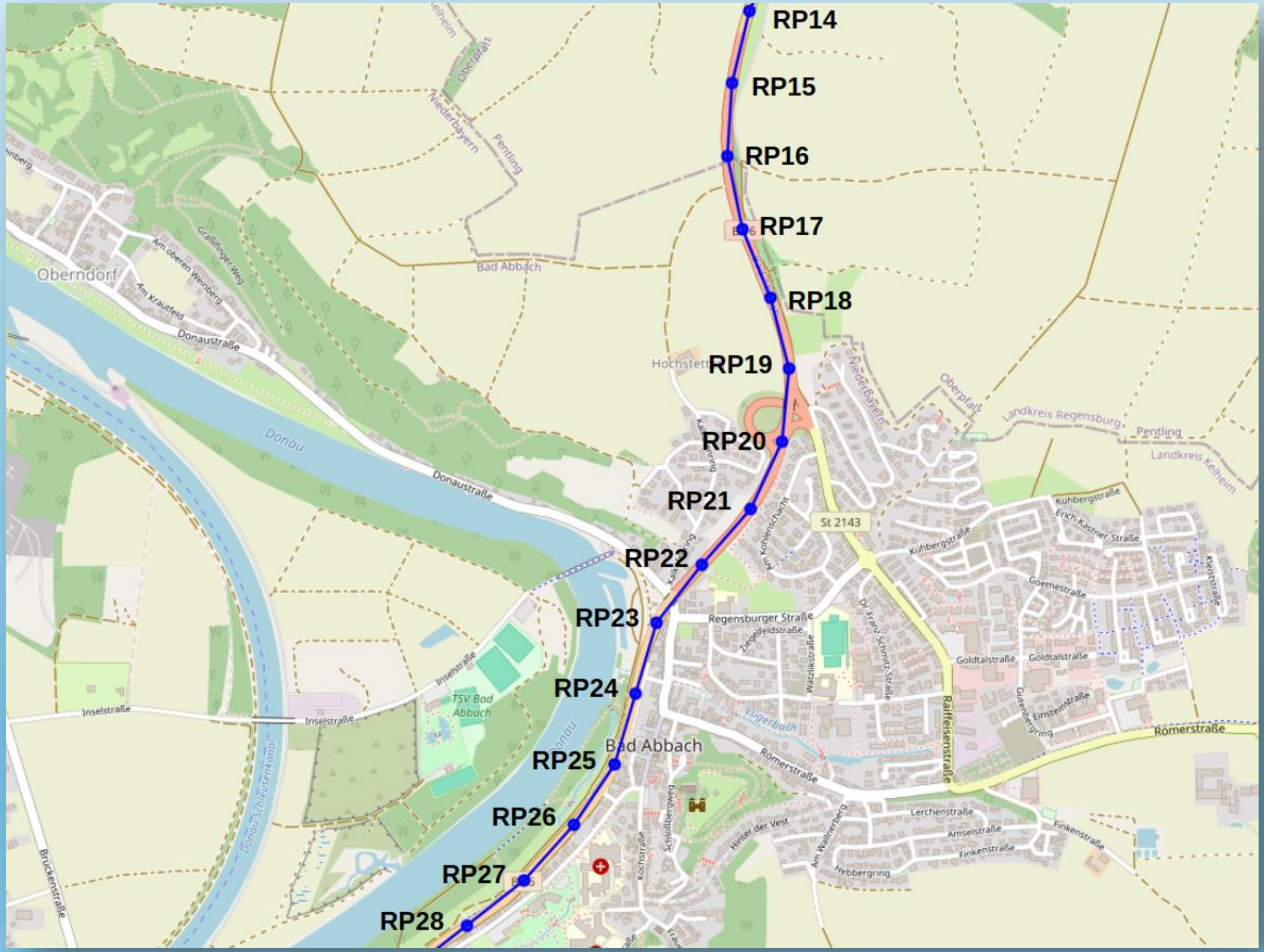
- Several environmental and temporal factors show measurable correlations with signal quality metrics
- Higher temperature → lower connection quality
- Base station distance → weaker signals
- Speed → no relevant influence



Exploratory Data Analysis (EDA)

- Route segmented into 200m reference points for comparison
- Location dependency but high variability between runs

→ Motivation for adding contextual parameters to prediction



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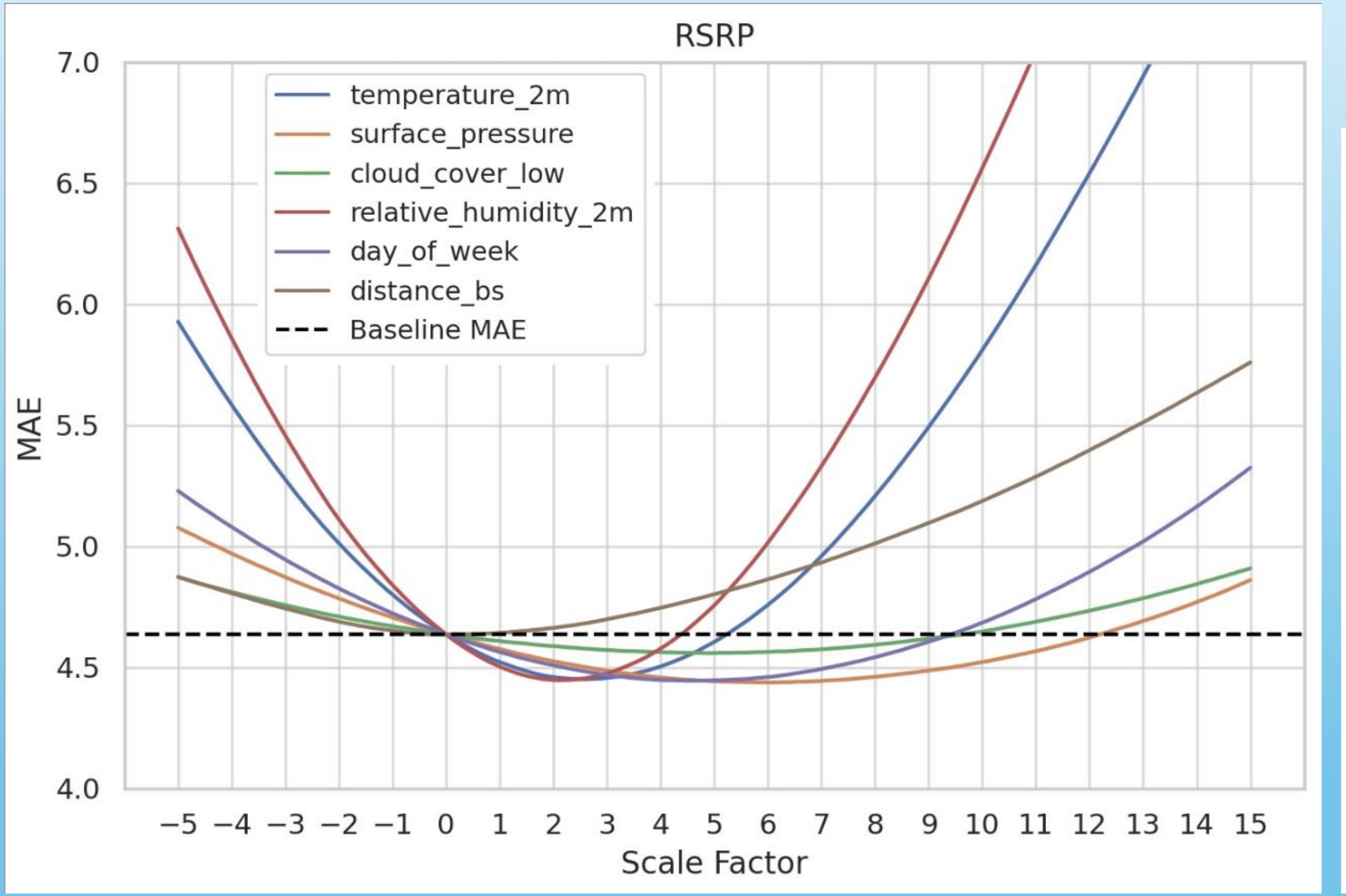
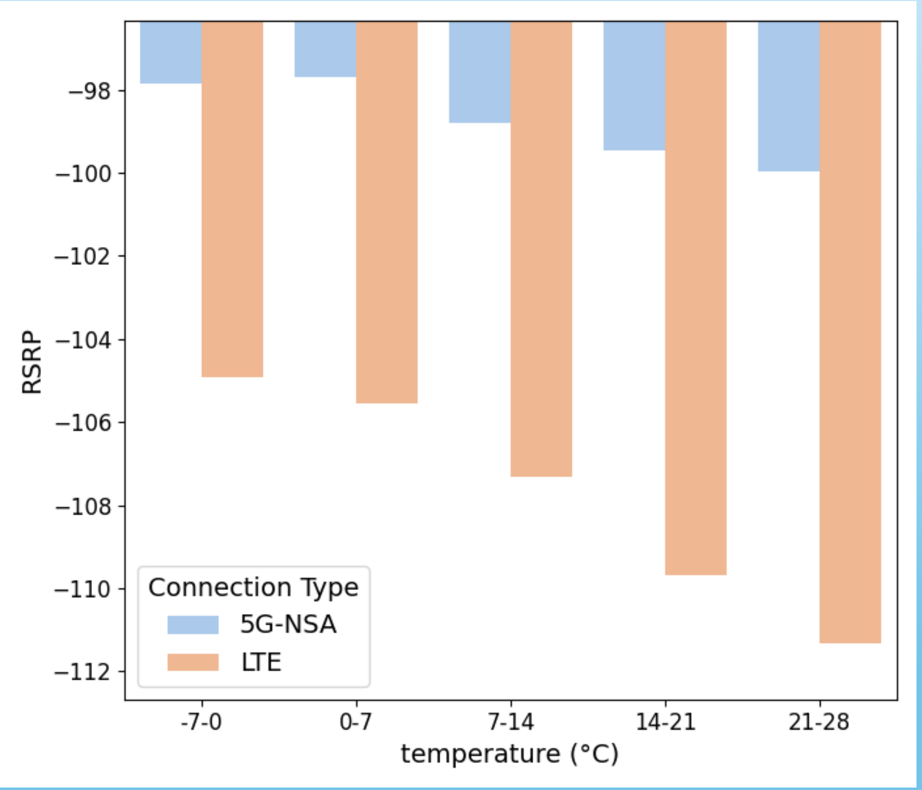
Prediction Model





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Results and Insights

- Contextual information improves signal forecasting accuracy
- Correlated features lead to higher Mean Absolute Error
- Linear models capture trends but not complex interactions

Metric	Baseline	Best Feature	Best Combination
RSSI	3.684	3.556 Surface Pressure	3.548 Surface Pressure Humidity
RSRP	4.635	4.437 Surface Pressure	4.440 Surface Pressure Humidity
RSRQ	2.158	2.065 Surface Pressure	2.063 Surface Pressure Ground Fog
SINR	3.041	3.017 Temperature	3.024 Temperature Surface Pressure

Table: MAE comparison of baseline, best single feature, and best feature combination

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Conclusion and Future Work

- Incorporating contextual information improves network prediction for automated vehicles
- Context-aware prediction can support route planning and connectivity management
- Future Work:
  - Apply nonlinear ML models (e.g. gradient boosting, neural networks)
  - Extend dataset across seasons and traffic conditions
  - Integrate additional features such as traffic density, infrastructure obstacles, or environment topography

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Thank you for your attention!

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References

- P. Torres et al., “Data analytics for forecasting cell congestion on LTE networks”, en, in 2017 Network Traffic Measurement and Analysis Conference (TMA), Dublin, Ireland: IEEE, Jun. 2017, pp. 1–6. DOI: 10.23919/tma.2017.8002917.
- D. Madariaga, J. Madariaga, J. Bustos-Jiménez, and B. Bustos, “Improving signal-strength aggregation for mobile crowd-sourcing scenarios”, en, Sensors, vol. 21, no. 4, p. 1084, Feb. 2021, Publisher: MDPI AG, ISSN: 1424-8220. DOI: 10.3390/s21041084.
- H. Schippers, M. Geis, S. Böcker, and C. Wietfeld, “DoNext: An open-access measurement dataset for machine learning-driven 5G mobile network analysis”, IEEE Transactions on Machine Learning in Communications and Networking, pp. 1–1, 2025, ISSN: 2831-316X. DOI: 10 . 1109 / TMLCN . 2025 .3564239.