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

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***Abstract*—As autonomous driving becomes increasingly feasible, the German government has introduced a legal framework to enable the operation with Level 4 automated driving functionality. A key requirement is the maintenance of a continuous connection between such vehicles and a remote technical supervisor. If this link is lost, the vehicle must transition into a safe state by bringing itself to a controlled stop. To mitigate the risk of connection loss, accurate forecasting of mobile network availability along routes is essential. This paper presents an Exploratory Data Analysis (EDA) based on 38 measurement runs collected over ten months along a rural 64 km route in Germany. The dataset includes passive mobile network signal quality parameters, Global Navigation Satellite System (GNSS) position and precision data, as well as contextual features, such as speed, driving direction, day of the week, weather, and distance to the connected base station. Although mean values capture overall tendencies for areas with consistently good or poor coverage, they fail to capture the variability necessary for reliable prediction on a per-trip basis. Notably, some route segments show high variance in signal quality across different measurement runs. This variability is assumed to result from changing environmental influences, such as weather or traffic conditions at different times. Our analysis reveals weak but statistically relevant correlations between several contextual features (e.g., temperature $\approx$ -0.2) and network quality indicators. The inclusion of weather parameters or the day of the week has been shown to lower the Mean Absolute Error (MAE) compared to a prediction based only on measurements from the past. These findings underscore the importance of contextual information and localized modeling to predict network availability for safety-critical systems, such as autonomous vehicles.**

***Keywords-autonomous driving; mobile network; connectivity forecasting; signal quality indicators; rsrp.***

## I. INTRODUCTION

Even though recent forecasts are more cautious regarding the future proliferation of automated driving vehicles, it is evident that they will gradually become part of everyday life as technology evolves [1]. In this context, emerging automated driving functions and Vehicle-to-Everything (V2X) communication systems highlight the growing importance of robust and reliable vehicular connectivity [2].

A key motivation for this work comes from recent regulatory developments in Germany. According to legislation, automated vehicles classified under Society of Automotive Engineers (SAE) Level 4 (high driving automation [3]) must maintain a permanent connection to a technical supervisor (§ 1e para. 2 Nr. 10 StVG [4]). This supervisor must receive real-time status information and can intervene, for example, by enforcing a safety stop or assisting in complex scenarios [4]. One such case involves construction zones, where the vehicle may need to cross continuous lane markings, an action typically prohibited by internal rules.

Network connection quality is influenced by various dynamic factors, including environment, time of day, and vehicle motion. Open areas near base stations usually offer strong coverage, while remote or forested areas do not. To investigate this variability, 38 test drives along a predefined 64 km rural route, recording passive mobile network parameters and Global Navigation Satellite System (GNSS) data, were conducted. During post-processing, additional context, such as weather conditions and metadata, was integrated.

This paper identifies contextual parameters that influence mobile network quality. Through feature selection and an Exploratory Data Analysis (EDA), metrics with predictive power for future Machine Learning (ML) applications are uncovered. The overall goal is to forecast network conditions along a planned route prior to the trip. Such capabilities would enable automated vehicles to make informed decisions, such as rerouting to avoid areas with weak or volatile connectivity.

We examine how spatial location, temporal factors, weather conditions, and vehicle motion affect signal metrics. However, the analysis is based on historical measurements collected along a fixed route and restricted to linear correlations between contextual and network parameters. Urban environments and larger datasets, beyond the 38 measurement drives used here, remain for future work and are expected to further improve prediction performance.

Unlike prior studies that focused on static coverage maps, short-term datasets, or urban areas, our work presents a long-term measurement campaign on a rural route and explicitly integrates contextual factors (e.g., time of the day, ambient temperature). To our knowledge, this is among the first studies to target pre-trip forecasting of Long-Term-Evolution (LTE)/ 5G quality for Level 4 driving scenarios.

This paper is organized as follows: Section II discusses the state of the art and related work. Section III introduces the fundamentals of mobile networks and describes the target parameters. Section IV outlines the data collection process and cleaning methodology. Section V presents insights derived from an EDA. Section VI introduces our initial contextual model, demonstrating how external parameters can influence predictions of mobile network performance. Finally, Section VII concludes the paper and outlines directions for future work.

## II. RELATED WORK

Several studies have addressed the prediction and analysis of mobile network quality, particularly in vehicular contexts. These efforts vary in scope, methodology, and focus, often targeting real-time diagnostics or static coverage mapping, rather than the pre-trip forecasting required for autonomous vehicle planning.

Torres et al. [5] propose a method to forecast congestion in LTE networks using data analytics and ML techniques. Their model supports Self-Organizing Network (SON) optimization for real-time traffic management, but it does not incorporate contextual factors, such as weather or time of day, nor is it designed for trip-specific predictions.

Madariaga et al. [6] adopt a time series perspective, demonstrating that meteorological conditions significantly affect mobile Quality of Service (QoS). By combining ML models with temperature, humidity, and rainfall data from crowdsourced Android measurements, they show that context-aware models outperform purely historical averages, particularly in urban areas. In another related work, they address the spatial aggregation of signal strength data through advanced interpolation methods [7]. Their approach produces statistically robust spatial estimations in urban environments. However, their studies are restricted to this setting and do not consider long-term temporal variability or predictions along rural routes.

Sahin and Sathya [8] present a classification model that estimates mobile network quality in a given area using only Global Positioning System (GPS) data. While computationally lightweight, their model omits dynamic environmental influences, such as weather or time, limiting its utility for predictive, context-aware applications. Similarly, Rahman et al. [9] use reinforcement learning with Unmanned Aerial Vehicles (UAVs) to detect mobile coverage holes in urban environments. Their infrastructure-focused approach is not intended for vehicle-specific planning or prediction.

Hultman et al. [10] introduce a route planner, which selects navigation routes based on static mobile signal coverage maps derived from publicly available data. Although useful for high-level connectivity-aware navigation, their approach lacks the temporal and contextual sensitivity required for dynamic, real-world scenarios.

More recently, Schippers et al. [11] introduced the DoNext dataset, a large-scale open-access 5G measurement campaign. Designed to support ML research, the dataset includes multiple regions and contexts. However, the focus lies on general-purpose mobile network analysis, rather than route-specific forecasting or context-weighted trip planning. As their study confirms, the signal quality can vary significantly at the same location depending on the time, e.g., signal degradation during rush hours due to network congestion from many connected devices.

Prior work has addressed many important parts of mobile network prediction, including data aggregation, spatial modeling, and urban QoS forecasting. Nevertheless, these studies often neglect the specific requirements of autonomous driving. Furthermore, most previous research is either limited to urban areas or lacks incorporation of temporal and environmental context. In contrast, this study combines:

- contextual modeling with signal metrics,
- spatiotemporal pre-trip forecasting on fixed vehicular routes,
- and a long-time measurement campaign over several months.

## III. BACKGROUND AND FUNDAMENTALS

To support our analysis, this section introduces key mobile network concepts and signal quality metrics used in LTE and 5G systems.

### A. Principles of Mobile Networks

Mobile communication networks consist of wireless links between User Equipment (UE) and base stations, which connect to a core network. The transition from LTE to 5G enhances bandwidth, latency, and reliability [12], which are critical for autonomous driving applications [13]. LTE provides high data rates and reduced latency through techniques such as Multiple Input Multiple Output (MIMO), handovers, and advanced radio resource management [14]. 5G builds on LTE by adding capabilities, such as beamforming and network slicing. It operates across low-, mid-, and high-frequency bands, including millimeter waves [15]. Research has also investigated the fundamental performance limits of millimeter-wave systems for cooperative localization, underlining the relevance of advanced 5G [16]. Moreover, 5G offers even lower latency and increased capacity supporting safety-critical automotive applications [13]. In both LTE and 5G networks, signal quality plays a central role in determining the performance and reliability of a connection [17].

### B. Mobile Network Signal Quality Metrics

Signal quality in LTE and 5G networks is assessed using a set of key radio frequency indicators. These metrics help to evaluate the reliability and performance of the wireless link between the UE and a cellular base station [18]. The most commonly used parameters are as follows:

- Received Signal Strength Indicator (RSSI) represents the total received power observed by the device within the channel bandwidth [17]. This value includes not only the desired signal but also background noise and interference from neighboring cells. Measured in decibel-milliwatt (dBm), RSSI serves as an indicator of signal presence but lacks specificity for signal quality [19] [20].
- Reference Signal Received Power (RSRP) quantifies the average power of reference signals transmitted by a serving cell [17]. Unlike RSSI, it excludes interference and noise, offering a more accurate measure of usable signal strength. RSRP is expressed in dBm and is used by UE for tasks, such as cell selection, handover decisions, and radio link monitoring [19].

- Reference Signal Received Quality (RSRQ) is the ratio of RSRP to RSSI, normalized by the number of resource blocks [17]. It reflects both the signal strength and the level of interference within the channel. It is particularly useful in scenarios with heavy network load or high interference levels, where a strong signal may still result in poor quality due to congestion. RSRQ is commonly measured in decibel (dB) [19].
- Signal-to-Interference-plus-Noise Ratio (SINR) indicates the quality of the wireless communication channel by comparing the power of the desired signal to the sum of interference and background noise [17]. It directly impacts achievable data rates and overall link performance. SINR is also measured in dB and is a parameter for evaluating network efficiency and optimizing system performance [19].

TABLE I. SIGNAL QUALITY METRICS FOR LTE AND 5G NETWORKS [17]

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

Table I summarizes the value ranges for each of the four metrics based on industry standards and field experience, including recommendations provided by the applied router's manufacturer [17]. In general, higher values of these metrics correspond to better network quality and more stable connectivity.

## IV. DATA COLLECTION AND FEATURE ENGINEERING

This section describes the methodology used for data acquisition and the subsequent processing steps taken to prepare a clean and contextually enriched dataset suitable for analysis and modeling.

### A. Measurement Campaign

The dataset used in this study was collected during a series of 38 real-world measurement drives along a 64 km segment of the rural road B16 in southern Germany. The test drives were performed in both directions, ensuring a balanced spatial and directional coverage of the route. The measurement campaign extended over 10 months to capture a broad range of temporal and environmental variability. In total, about 60,000 measurement points along the route were collected.

For the data acquisition, a custom-built mobile measurement unit was used. The system consists of the hardware parts as illustrated in Figure 1.

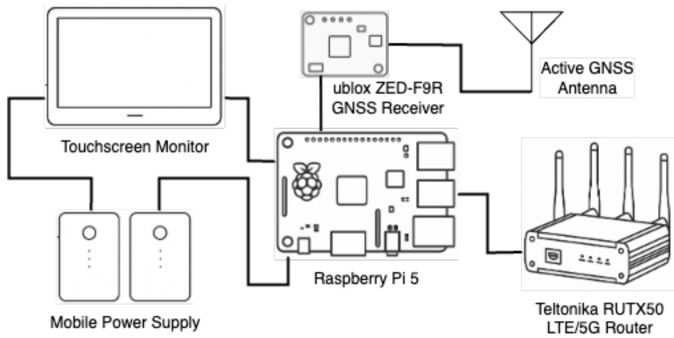


Figure 1. Setup of the custom-built mobile measurement unit

The collected mobile network parameters as presented in Section III-B were logged continuously throughout each drive. In addition, the GNSS receiver provided geographical coordinates (latitude, longitude, altitude), metrics like Position Dilution of Precision (PDOP), and the number of visible satellites. The vehicle speed and its course were also recorded to capture the motion context of the measurements.

### B. Data Cleaning and Preprocessing

In the following data collection phase, the raw measurements were processed to ensure consistency, completeness, and analytical utility. These steps were implemented using the programming language Python and applied uniformly for all drives:

- Validation and Cleaning: The routers placeholder values (-32768) were converted to Not a Number (NaN). Descriptive statistics (means and medians) and correlations were computed with pairwise deletion, which means that only valid observations are used for each metric and section. This rule keeps cell-edge situations in the dataset. They only reduce the effective sample size but do not bias the analysis by removing low-signal points.
- Merging and Structuring: All individual drive data were merged into a single consolidated dataset. A unique measurement identifier was assigned to each session to later enable distinction between the drives.
- Temporal and Categorical Features: Based on the timestamp data, additional contextual attributes like the day of the week and the week of the year were calculated. This information helps capture time-dependent variations in network performance.
- Base Station Proximity: The dataset was enriched with the distance to the connected mobile base station at each point. The base station locations were obtained from the open-source platform CellMapper [21], and distances were computed using haversine-based geospatial calculations.



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- Weather Data Integration: Historical weather data were added to each measurement point using the Open-Meteo Application Programming Interface (API) [22]. The weather attributes (e.g., temperature, wind speed, precipitation, ground fog) were matched based on timestamp and geographical coordinates, allowing for the inclusion of environmental context in the analysis process.

As a result of this process, a spatiotemporally tagged dataset that combines passive network parameters, location, and environmental conditions was created.

## V. Exploratory Data Analysis

To gain insights into the structure and variability of the collected dataset, an EDA was conducted. This analysis aims to find spatial and contextual patterns in the signal measurements and to identify the most relevant features for subsequent modeling tasks.

As shown in Figure 2, the measurement route was segmented into Reference Points (RPs) based on a 200-meter radius clustering approach. Each recorded data point was assigned to its nearest RP. This segmentation enabled consistent spatial comparisons by aggregating measurements at the same location. For each RP, average values of the target parameters were calculated. This helps to mitigate the influence of measurement noise and to improve the robustness of comparisons between different test runs.

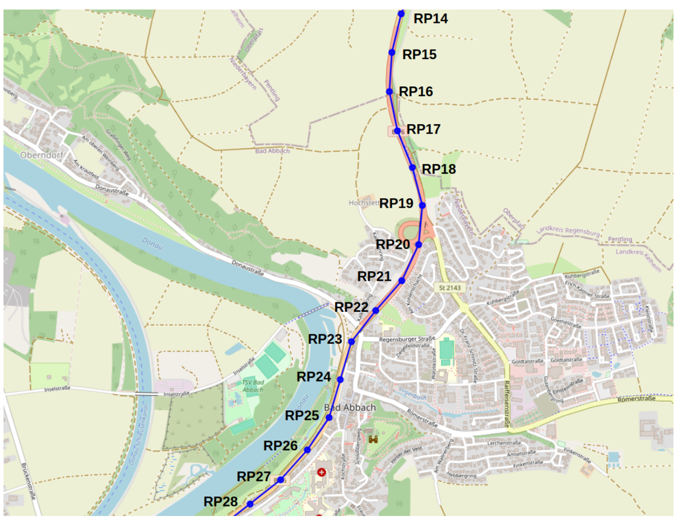


Figure 2. Clustering of the route into reference points

An initial analysis confirms observations also noted in the related work discussed in Section II. While the spatial location is a dominant factor, the measured mobile network parameters vary significantly between different test drives at the same location. The largest fluctuations were observed at locations with average reception quality. In contrast, spots with consistently high or consistently poor connectivity showed lower variability from time to time. These findings show the importance of incorporating additional contextual features into predictive modeling for signal quality.

### A. Correlations with Contextual Factors

To improve the prediction of mobile network performance indicators, especially in areas with weak or inconsistent coverage, it is important to account for environmental and temporal context. It could be identified which contextual parameters affect which signal metrics, and to what extent.

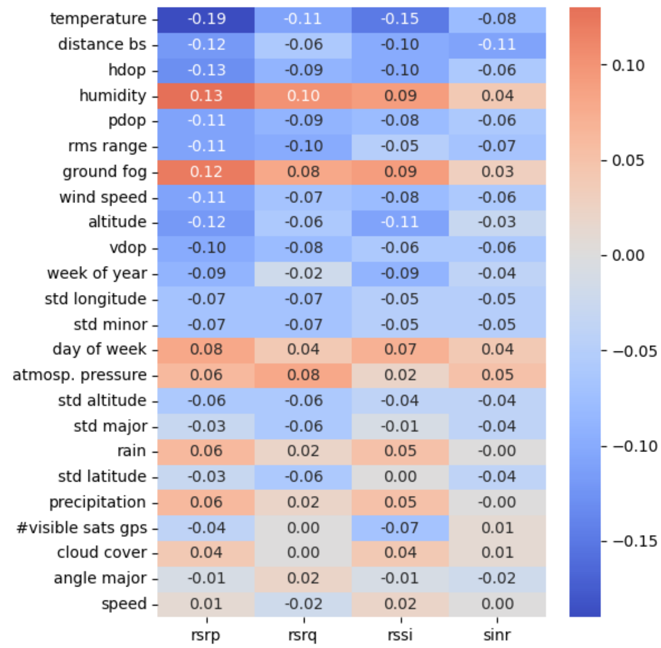


Figure 3. Heatmap showing the correlations between environmental parameters and the received signal quality metrics

Figure 3 presents a correlation heatmap between contextual features and the four target signal metrics. The variables include weather data, temporal features, distance to base station, GNSS precision metrics (e.g., PDOP, number of visible satellites), and speed of the vehicle.

The following trends can be observed in the heatmap:

- Temperature shows a negative correlation with RSRP and RSSI, indicating that higher temperatures may be associated with reduced signal strength.
- Distance to base station, PDOP, and Horizontal Dilution of Precision (HDOP) also exhibit negative correlations with signal strength indicators. This aligns with the expectation that increasing distance and positioning uncertainty can degrade radio wave propagation.
- Humidity and ground fog show moderate positive correlations with RSRP, RSRQ, and RSSI, potentially indicating the energy absorbing effects of water in the air.
- Temporal features like day of week and week of year also show small but consistent correlations, suggesting time-dependent network load or usage patterns. The effect is likely to increase with a better timely distribution of measurements.
- Speed seems to have no relevant influence on the signal parameters.

Beyond environmental effects, fluctuations in signal quality often coincided with serving-cell handovers. Sections with more frequent handovers (normalized per 1000 measurements) tended to show higher run-to-run variability, supporting the view that cell transitions contribute to the variance observed in average-quality zones, although the overall correlation remains weak.

### B. Correlation with Ambient Temperature

To further investigate the influence of temperature, Figure 4 illustrates the average RSRP values across different temperature bins, separated by connection type. A clear degradation in signal strength with increasing temperature is observed. However, LTE connections appear to be more sensitive to temperature increases than 5G-Non Standalone (NSA).

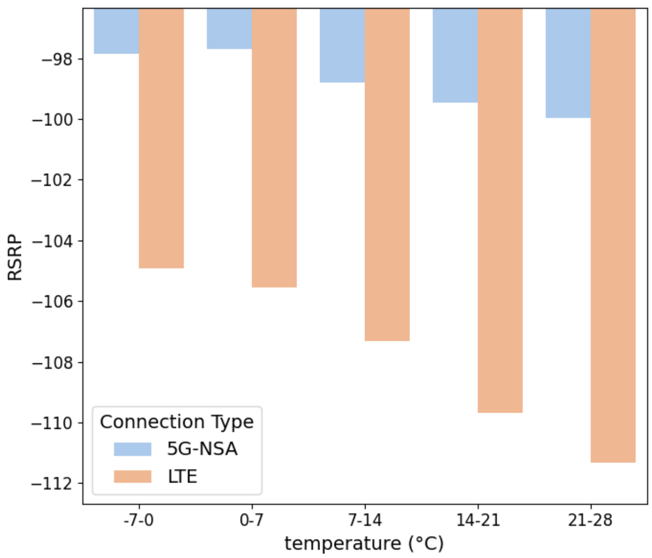


Figure 4. Influence of the ambient temperature on the RSRP value separated in 5G-NSA and LTE measurements

These results support the hypothesis that weather conditions can differentially affect radio wave propagation, and that newer network technologies like 5G may offer enhanced resilience under varying environmental conditions.

## VI. Prediction Model

The discussed correlations provide a foundation for feature selection and motivate the inclusion of contextual parameters in the predictive modeling efforts described in this section. The Mean Absolute Error (MAE) was used to assess the influence of contextual features on the target parameters. MAE is chosen for its interpretability and robustness to outliers, as it provides a direct average of absolute errors in the same units as the target variable, making it especially suitable for this purpose. The MAE is defined as:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{1}$$

where $y_i$ denotes the true value, $\hat{y}_i$ the predicted value, and $n$ the number of samples [23].

As mentioned in Section III-B, RSSI and similar metrics are expressed in dB or dBm, which are logarithmically scaled. Therefore, even small changes in the MAE can have a significant impact on signal quality [19].

### A. Context Parameter Scaling

To investigate how external context parameters affect mobile network signal quality, a modeling approach that adjusts the section-wise signal predictions based on environmental deviations was developed. The baseline model predicts the expected target parameters for every RP along the route only using the mean value from historical measurements. This section explores whether incorporating individual context parameters can improve the prediction by reducing the MAE.

For each context parameter, a linear model was trained using the deviation between a parameter's current value and its historical section average. This deviation was multiplied by a scale factor to model the resulting shift in signal behavior. The prediction was then computed by adding this adjustment to the baseline section average. To identify the optimal scale factor, values ranging from -5.0 to 15.0 in increments of 0.1 for each context parameter were tested. The scale factor that minimized the MAE on the test measurement was selected. The goal was to quantify how strongly each context parameter contributes to prediction accuracy and whether any of them provided consistent improvements over the baseline.

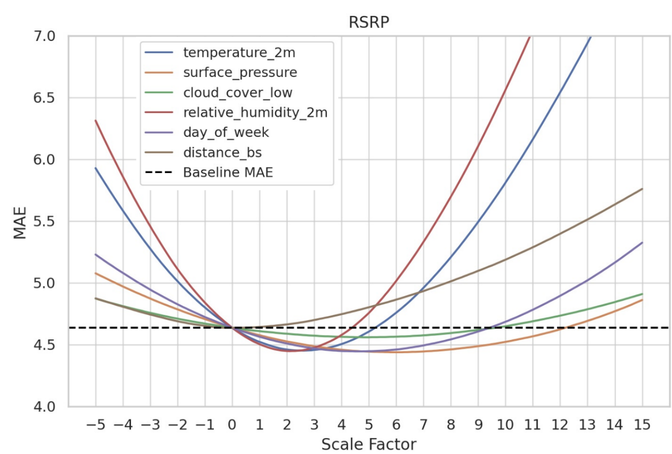


Figure 5. Influence of the context parameters with different scale factors on the MAE compared to the baseline MAE without context

Figure 5 shows the results of the scale factor optimization for the signal parameter RSRP. Each curve in the plot represents the MAE progression as a function of the scale factor applied to the respective context parameter. In all cases, the MAE initially decreases with increasing scale factor, reaches a minimum, and then increases again. The findings show that several context parameters can improve prediction accuracy compared to the baseline. However, the improvement varies between the parameters.



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### B. Combining Context Parameters

The aim of this section was to investigate whether the prediction accuracy of mobile network parameters could be further improved by simultaneously incorporating multiple context parameters. Building on the results of the individual analyses, it was examined whether combining two context parameters, each with its own scale factor, could reduce the MAE even further. Therefore, all possible pairs of the five most relevant context parameters (temperature, surface pressure, relative humidity, ground fog, and day of week) were systematically evaluated. For each pair, a linear model was trained using the deviation of each context value from its corresponding section average. A grid search over scale factor combinations in the range -5 to 15 (in steps of 0.1) was conducted. The goal was to identify the combination that minimized the MAE on a separate test measurement.

However, the results in Table II show that none of the tested parameter combinations yielded significantly better performance than the single context parameter. For RSRP and SINR, the MAE even increased when using two parameters instead of one.

TABLE II. MAE COMPARISON OF BASELINE, BEST SINGLE FEATURE, AND BEST FEATURE COMBINATION

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

This finding suggests that the influence of context parameters on mobile network measurements cannot be adequately described by a simple linear superposition. Another explanation may be the multicollinearity among weather variables, which adds redundancy and inflates linear model variance. For example, temperature and relative humidity are often negatively correlated [24]. It is likely that complex interactions or nonlinear relationships exist between the context features, which are not captured by the linear model. As a result, more advanced modeling techniques may be necessary to identify and leverage synergistic effects between context features. The current findings highlight the importance of targeted feature selection and expose the limitations of linear modeling approaches in the analysis of context-sensitive measurement data.

The results of our research confirm that mobile network quality is not only dependent on geographic location but is also significantly influenced by contextual factors, such as environmental conditions and temporal variation. However, some limitations must be acknowledged. First, the current analysis is based on a linear correlation approach, which limits the ability to capture complex or nonlinear relationships between contextual features and mobile network metrics. Second, robust prediction across a spatial route may require even more measurement campaigns under diverse conditions.

## VII. Conclusion and Future Work

Future work will address these limitations by applying advanced ML models capable of learning nonlinear relationships and feature interactions (e.g., gradient boosting, random forests, or neural networks). Such models could uncover hidden patterns and provide more accurate predictions of mobile network performance based on complex environmental context. Further measurement campaigns are also planned to expand the dataset in terms of spatial coverage and seasonal variability. This will not only enhance model training but also allow the inclusion of additional features, such as traffic density or infrastructure obstacles (e.g., forests, bridges, buildings). Finally, incorporating GNSS precision metrics may further improve the contextual understanding of signal fluctuations in dynamic, real-world vehicular environments.

This paper presents a comprehensive data collection and analysis approach to investigate the environmental influences on mobile network signal quality for automated driving. Based on 38 measurement drives along a fixed route, it was demonstrated that mobile signal quality varies even at identical locations, depending on weather and temporal conditions. Through an EDA, we showed that contextual parameters, such as temperature, humidity, GNSS precision, and day of the week correlate with key mobile network metrics. These findings underscore the value of integrating environmental context into signal prediction models. The insights from this study lay the foundation for advanced modeling aimed at enhancing the connectivity awareness of automated vehicles. Future work will focus on the development of advanced models trained on enriched datasets to improve pre-trip signal quality forecasting and to support more reliable network connections for Level 4 vehicles.

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