# Seeing the Future (Phase I): AI-Based Measurement Prediction for Reliable High-Capacity Vehicular Connectivity in Road-Embedded Mobile Networks

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***Abstract*— Future vehicles require ultra-reliable, low-latency, and high-capacity wireless connectivity for autonomous driving and entertainment services such as XR. This paper investigates AI-based measurement prediction for proactive handover in road-embedded mobile networks, training models on simulated mobility data to minimize prediction errors. Evaluation across various test cases demonstrates measurement prediction performance and provides generalization guidelines for AI-driven vehicular inter-cell mobility.**

***Keywords*— *AI-based measurement prediction, proactive handover, vehicular inter-cell mobility, road-embedded mobile networks, vehicular connectivity, generalization of AI models***

## I. Introduction

Conventional mobility mechanisms, such as L3 handovers (e.g., basic HO, CHO) and L1/L2-triggered mobility (LTM), rely on current measurements and events to trigger cell changes, but these reactive approaches[1][2] may degrade performance in high-mobility and dense cell scenarios. As an alternative, AI-based models have been proposed to predict future signal quality or mobility events from past measurements[3]. This paper investigates AI-based measurement prediction in road-embedded mobile networks to support ultra-reliable, low-latency, and high-capacity connectivity. Experimental results demonstrate the feasibility of measurement prediction using diverse driving datasets and provide guidelines for achieving generalization.

## II. Background and Related Work

3GPP has actively promoted AI/ML integration in mobile networks, including CSI prediction/compression, beam management, energy saving, load balancing, and mobility optimization [4]. For NR-based AI/ML mobility (proactive inter-cell mobility), use cases such as RRM measurement prediction, event prediction, and RLF prediction have been defined, along with evaluation methodologies, metrics, and reported performance. System-level simulation (SLS) methodologies, metrics, and results have also been presented to validate overall effectiveness [5].

If an AI/ML model can accurately predict measurement results within a specific future time interval, proactive inter-cell mobility mechanisms can be designed on top of existing reactive frameworks (e.g., Basic HO, CHO, LTM). Accurate prediction, however, requires valid training datasets, which are costly and difficult to obtain from uncontrolled real environments. To address this, simulation environments resembling real-world conditions are essential for generating effective training data. Moreover, ensuring strong generalization allows the trained models to remain robust across diverse mobility scenarios.

## III. Proposed AI-Based Prediction Framework

In a road-embedded mobile network, all measurements are performed by a UE mounted on the top of a vehicle and correspond to the Reference Signal Received Power (RSRP). The measurement methods are categorized into sliding and non-sliding approaches. In the sliding approach, Mr, Mn, and Fn are generated at the same sampling interval (e.g., 20 ms), where Mn represents the average of recent Mr samples and Fn is obtained through L3 filtering using Mn and the previous Fn−1. In contrast, in the non-sliding approach, Mn and Fn are generated at longer intervals (e.g., every 80 ms for p=5), while in both methods the initial condition is set as Fn0 = Mn0.

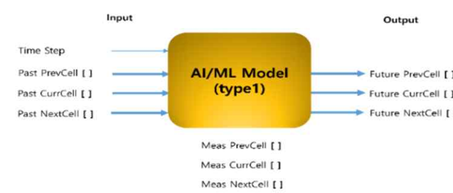


Fig. 1. AI/ML Model type1

Fig. 1 illustrates the structure of the proposed AI/ML Model Type 1. The model takes as input the time step and past measurements from the previous, current, and next cells, and outputs predicted future measurements for the same cells. In the simulation, actual future measurements are available, enabling training and evaluation based on the mean absolute error between predicted and actual values, with particular focus on the final prediction step. For example, with a 20 msec time step and an observation window of 200 msec, the input contains 11 past samples, while a 400 msec prediction window results in 21 samples for both Past and Meas cells.

## IV. Simulation and Performance Evaluation

The road for the road-embedded mobile network is a 4 km straight, six-lane highway, with three lanes in each direction. Although base stations are deployed along the entire stretch, measurements are collected only within the central 2 km segment. Vehicle (UE) speeds follow either a fixed-speed mode (dynamic driving mode, DDM = no) or a dynamic driving mode (DDM = yes), where vehicles travel at 50–120 km/h, maintain safe distances, follow lanes, and perform lane changes according to VANET highway driving algorithms. Specific simulation parameters are listed in Table I. The generated vehicle datasets (DS) are split into training (Tr DS) and testing (Te DS) sets for AI/ML model training and evaluation, with identical environments denoted by the same DS#no. Generalization Case #1 (GC#1) uses different train and test datasets, while Generalization Case #2 (GC#2) mixes data from multiple speeds (S1, S2, S3) within a single DS. Table II summarizes 12 cases of dataset usage and generalization, where cases using the same DS for both training and testing are referred to as the baseline. Figs. 2 and 3 show the CDFs of the absolute errors for all samples and the final sample, respectively.

The prediction rankings for Case IDs in Table II (Fig. 2 and Fig. 3) are generally consistent. Performance for the final sample in Fig. 3 is lower than that for all samples in Fig. 2, indicating decreasing accuracy for longer forecast horizons. In the baseline, where a DS was split into training and evaluation sets, prediction was highly accurate. Lowest performance was observed for C005 and C008, due to limited generalization of models trained on S1 (60 km/h) or mixed DS when applied to DDM VS test DS. Conversely, C011, trained on DDM VS DS, achieved superior accuracy on the S3 (100 km/h) test DS, reflecting typical highway speeds (90–110 km/h) and scarcity of low-speed data.

## V. Conclusion

This study investigated AI-based measurement prediction for proactive inter-cell mobility in road-embedded mobile networks. Achieving high prediction accuracy is challenging when using only mixed fixed-speed datasets in real-world scenarios. Constructing dynamic driving mode datasets that realistically mimic vehicle behavior, including not only typical scenarios but also various worst-case situations such as traffic congestion, significantly enhances model training and prediction performance. These results highlight the importance of designing realistic and comprehensive datasets to improve AI-driven vehicular mobility support.


## Aknowledgment

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## References


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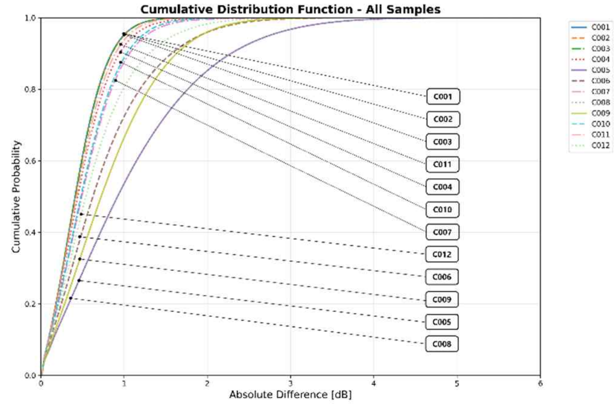


Fig. 2. CDF of all predicted samples in the future prediction sequence

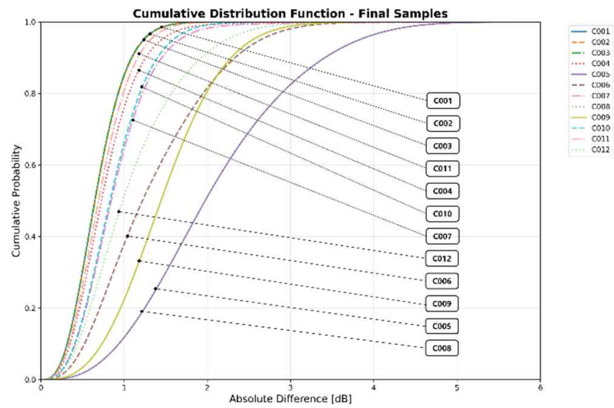


Fig. 3. CDF of the last sample in the future prediction sequence

TABLE I. Simulation Parameters

| Parameter | Value |
|---|---|
| Channel model | UMi (Urban Micro) [6] |
| Frequency | 30 GHz (FR2) |
| Bandwidth | 80 MHz |
| Subcarrier spacing | 120 kHz |
| ISD (deployment) | 200m (one-sided upper) |
| BS power | 46 dBm |
| Measurement method | sliding |
| Measurement object | RSRP |
| L1 average sample number | 5 |
| L3 filtering coefficient (*k*) | 19 |
| Observation Window Time (owt) | 400 msec |
| Prediction Window Time (pwt) | 400 msec |
| AI/ML Model | XGBoost (type1) |
| UE (Car) Speed | DDM: no<br>- S1: fixed 60 km/h<br>- S2: fixed 80 km/h<br>- S3: fixed 100 km/h<br>DDM: yes<br>-VS: 50-120 km/h |
| UE (Car) Type | S: Sedan, U: SUV, T: Truck |

RSRP: Reference Signals Received Power, DDM: Dynamic Driving Mode, VS: Variable Speed

TABLE II. Test Cases

| Case ID | Scenario | DS#1 Tr S1 | DS#2 Tr S2 | DS#3 Tr S3 | DS#4 Tr DDM VS | DS#1 Te S1 | DS#2 Te S2 | DS#3 Te S3 | DS#4 Te DDM VS |
|---|---|---|---|---|---|---|---|---|---|
| C001 | Baseline | yes | | | | yes | | | |
| C002 | Baseline | | yes | | | | yes | | |
| C003 | Baseline | | | yes | | | | yes | |
| C004 | Baseline | | | | yes | | | | yes |
| C005 | GC#1 | yes | | | | | | | yes |
| C006 | GC#1 | | yes | | | | | | yes |
| C007 | GC#1 | | | yes | | | | | yes |
| C008 | GC#2 | yes | yes | yes | | | | | yes |
| C009 | GC#1 | | | | yes | yes | | | |
| C010 | GC#1 | | | | yes | | yes | | |
| C011 | GC#1 | | | | yes | | | yes | |
| C012 | GC#2 | | | | yes | yes | yes | yes | |

GC: Generalization Case, DS: Data Set, Tr: Train, Te: Test, S1: fixed 60 km/h, S2: fixed 80 km/h, S3: fixed 100 km/h, DDM: Dynamic Driving Mode, VS: Variable Speed (50-100km/h)