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# System for Continuous Multi-Dimensional Mobile Network KPI Tracking and Prediction in Drifting Environments

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***Abstract*—The usage of public mobile radio networks is steadily increasing. At the same time, the number of new and future smart city applications that rely on reliable and fast mobile data connections based on public mobile networks is rising. In particular, mission-critical smart city applications require continuous and reliable mobile network connectivity. However, the fulfillment of KPIs is not given at all locations and varies over time. Thus, use-cases like tele-operated driving profit from and, in some cases, even depend on spatiotemporal connectivity data. Indirectly, connectivity data can also be utilized to calibrate and improve network planning approaches for future network technologies, such as classical ray tracing or innovative data-driven channel modeling approaches.**

**Massive data acquisition is needed to cover vast city-wide areas like the city of Dortmund. Therefore, this paper discusses a system that enables a dedicated, continuous and systematic measurement campaign to solve this challenge. These measurements are realized by a fully automated open-source monitoring application deployed in multiple vehicles of the local waste disposal company, enabling continuous and city-wide data collection. The initial results of this measurement campaign indicate that up-to-date data is crucial for reliable data-driven services.**

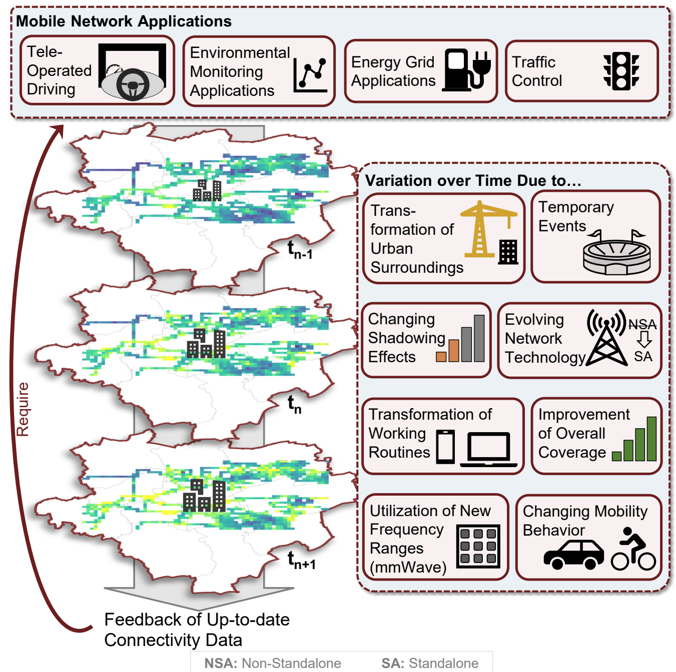


Fig. 1. Public mobile network temporal development in vital smart city environments in the area of the city of Dortmund (Map data: © OpenStreetMap contributors, CC BY-SA).

## I. Introduction

Emerging mobile network applications require exact knowledge of the achievable Key Performance Indicators (KPIs) at specific locations and times to guarantee mission-critical services. Some, like Tele-Operated Driving (ToD), are even directly impacting human life if mobile network-based challenges are not handled appropriately, e.g., necessitating emergency braking. Use cases like environmental monitoring, traffic control and critical energy grid applications need their portion of the mobile spectrum, too, in order to work correctly. The available network resources are shared between all mobile cell users and applications. Thus, the utilization on the one side and the forthgoing extension of the mobile network on the other side must be considered to assess probable compliance with required KPIs. That is why these applications need to be supplied with current Radio Environmental Map (REM) data to consider changes in demand and network expansion before deployment.

Mobile networks are exposed to many influencing factors; thus, predicting KPIs of mobile networks is a challenging task with many possible inputs. As shown in Fig. 1, these are not only location-based and utilization-dependent. Rather, mobile network KPIs change over time. This change includes technical aspects such as frequencies used and available technologies, but also user density and user behavior. Mobile Network Operators (MNOs) strive to ensure an ever-improving mobile network quality dependent on user behavior and keeping costs minimal. While new cell towers are constructed, existing cells are upgraded to be capable of 5th Generation of Mobile Communication Networks (5G) Non-Standalone (NSA). Even 5G Standalone (SA) networks are available in some locations. With the introduction of millimeter-Wave (mmWave) frequencies, even higher data rates than with current frequency range one cells could be reached within a comparably small distance to the corresponding cell.

At the same time, users' habits are changing over time. As digitization advances across almost all industries, more and more people work from home or on the move. This change in work routines could have an impact on the utilization of mobile networks near main traffic routes. The introduction of bike lanes and the redesign of road networks in urban areas might also change the use of mobile networks. Newly constructed roads and buildings further affect the propagation path of cellular networks by reflecting and attenuating the signal. New shaded areas could emerge, while the coverage of other areas will improve. While these changes are relatively slow, temporary events like sports competitions or music festivals have an immediate impact on the observed local Quality of Service (QoS). All these influences need to be taken into account for precise spatiotemporal prediction of mobile network performance. Therefore, a static REM, measured at a specific point in time is insufficient. Instead, there must be an update process that considers the changing environment.

The remainder of the paper is structured as follows. After discussing related work on mobile network monitoring applications in Sec. II, the approach for a holistic mobile network monitoring and prediction system is described in Sec. III. Afterwards, an overview of the methodological aspects is given in Sec. IV. Finally, detailed results of the first measurements are presented in Sec. V.

## II. Related Work

### A. Existing Measurement Approaches for the Determination of Mobile Network Quality

In the past, various studies were conducted concerning the quality of mobile networks. However, there is no comprehensive database available that can spare the process of exhaustive measurements. There are several measurement applications that can be used to measure some parameters of mobile networks. Tab. I compares several logging applications for measuring the quality of mobile networks based on their measurement capability, cost, and ability to export data.

The `Android` application `SigCap` is a free-to-use mobile network logging application that can measure passive parameters in combination with the location of the device. The measured data can be exported or uploaded to a server [1]. In combination with `FCC Speed Test`, which can perform data rate measurements, both passive and active parameters can be measured and exported [1]. However, `FCC Speed Test` is not available outside the US (status November 2022), as it is part of a project to evaluate mobile networks in North America. For German users, the German federal network agency published the `Broadband Measurement` app [9]. It is free-to-use and can measure data rate, latency and the network technology. However, it cannot export the data to an easy-to-process format, and its passive measurements are limited. Additionally, simultaneous logging with two apps in an automated measurement process is complex to control.
`Open Signal` is a free to use `Android` application capable of performing active data rate, latency tests, and passive signal measurements in one application. The acquired data is accumulated on an `Open Signal` server and can be displayed in the mobile application. However, there is no detailed Reference Signal (RS) view or an option to export data to an automatically processable format. Although the partially commercial `Android` application `Network Signal Guru` can access advanced passive logging parameters with root privileges, it is not free to use if data needs to be exported. In this case, a paid subscription is required. This application cannot perform realistic speed tests of the data rate on the application level. A free alternative for measuring passive network indicators is `NetMonster`. It is an `Android` application based on the open-source `NetMonster` library [5]. While the app can only monitor passive cell information, the library can be used to perform measurements by a custom app and exposes cell data provided by the `Android` API.

TABLE I
Comparison of selected existing mobile network measurement applications and systems.

| **Application** | **Free Use** | **Measurements Passive** | **Measurements Active** | **Data Export** |
|---|---|---|---|---|
| Broadband Measurement [2] | ✓ | (✓) | ✓ | ✗ |
| CellMapper [3] | ✓ | ✓ | ✗ | ✓ |
| FCC Speed Test [4] | (✓) | ✗ | ✓ | ✓ |
| NetMonster [5] | ✓ | ✓ | ✗ | (✓) |
| Network Signal Guru (NSG) [6] | (✓) | ✓ | ✗ | (✓) |
| Open Signal [7] | ✓ | (✓) | ✓ | (✓) |
| SigCap [1] | ✓ | ✓ | ✗ | ✓ |
| CNI-Cell-Tracker [8] | ✓ | ✓ | ✓ | ✓ |

To conclude, other than with a self-developed `Android` application [8], there is no possibility to analyze both active and passive measurements in an existing application known to the authors of this paper. That app is upgraded to be used for automatic measurements (see Sec. IV).

### B. Model Drift and KPI Prediction in a Mobile Network Context

Machine Learning (ML) depends on the quality and generalizability of the training data. If the association between features and labels changes, but also if the distribution of dependent or independent variables changes, the performance may decrease or the model may even become unusable. In this case, additional or another training of the model is needed [10]. Changes in the distribution of the data used in an ML model can lead to **model drift**. Model drift can be distinguished into **concept drift** and **data drift**. While concept drift is a change in the distribution of the observed data [11], data drift reflects the change in the independent variables of the model. Therefore, it is important to recognize data drifts [10], [12].

In [8], the cross-scenario performance of data rate predictions was analyzed. An ML model was trained using

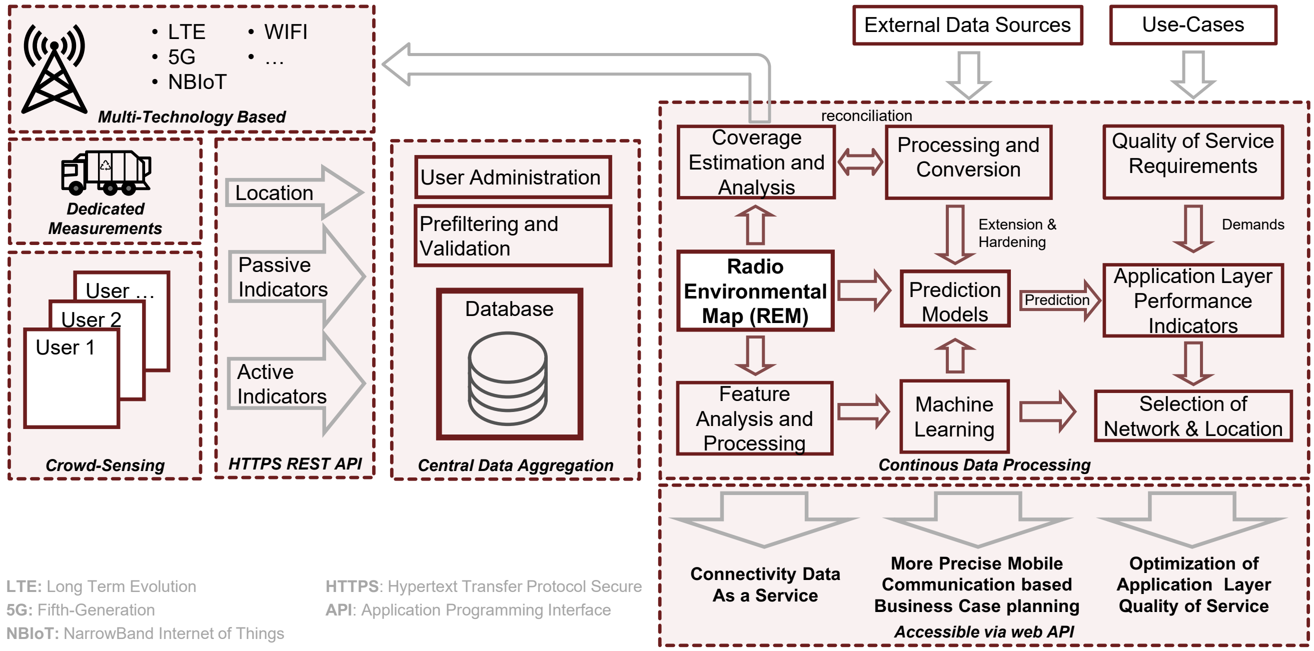


Fig. 2. Developed measurement system used to measure and continuously monitor 5G mobile network performance in the area of the city of Dortmund.

data from one scenario at one site. In the second step, the trained model was used to predict the achieved data rates in another scenario. The results show that the cross-validated model usually performs better than a model trained on another scenario. This observation suggests that the data distribution is different at different locations, leading to a deterioration in the performance of the model. Despite this effect is not due to time-related model drift, it shows that KPI prediction models for mobile networks have limited generalizability. Thus, model drift might also significantly influence mobile network data rate predictions.

## III. Approach to the Measurement System Architecture

A complete measurement system has been developed from mobile network data acquisition to server-based automated evaluation. The system overview is illustrated in Fig. 2. Measurement data based on crowd-sensing sessions or dedicated and systematical measurements are transferred to a dedicated database. The measurements can include passive indicators like RSs (e.g. Reference Signal Received Power (RSRP), Signal to Interference and Noise Ratio (SINR)), general cell information and active measurement results like the achieved data rate and latency. Furthermore, the location, velocity, bearing angle and device-specific information are transmitted. The measurement devices can be smartphones, dedicated measurement kits or even NarrowBand Internet of Things (NBIoT) devices. Different measurement users legitimate themselves at the database server with a username and password combination, which is mandatory to upload data. The upload is implemented via an HTTPS link only when no active measurement is performed. To further protect the database from erroneous data and falsification attacks, the data is filtered before it is inserted into the database. Additional steps against falsification attacks described in [13] could be implemented in another validation iteration.

Based on the collected data, REMs are repeatedly generated and updated. These form the basis for further data studies like coverage estimations and reconciliation with given coverage maps. Due to the REMs containing passive and active measurements, prediction models for the active parameters, like the data rate can be built with the help of ML. To accomplish this, passive features must first be analyzed to understand the needed spatial feature resolution [14] and individual feature importance [8].

In the second step, the obtained knowledge can be used to select locations for future network-dependent applications or restrict the area of use by predicting the QoS requirements of the individual use cases. For example, ToD or the tele-operation of drones requires a fixed minimum data rate and a maximum tolerable latency for the video feed and the control channel [14]. Both could be predicted based on previous measurements in the target area. Feasible routes with a reliable data connection could then be pre-planned [15]. Missing measurements in the mission area could be at least filled with the help of ray tracing or DRaGon [16] based systems that can be calibrated on the measurement data.

To ensure the quality of the collected data and even improve its accuracy, external data sources are used to re-conciliate the obtained data. One example of external data sources are the `OpenData` portal of the city of Dortmund [17] and the `Bundesnetzagentur` [9], both providing location information for existing mobile cells.

To sum up, the developed setup allows for new business cases like connectivity data as a service, speeding up the

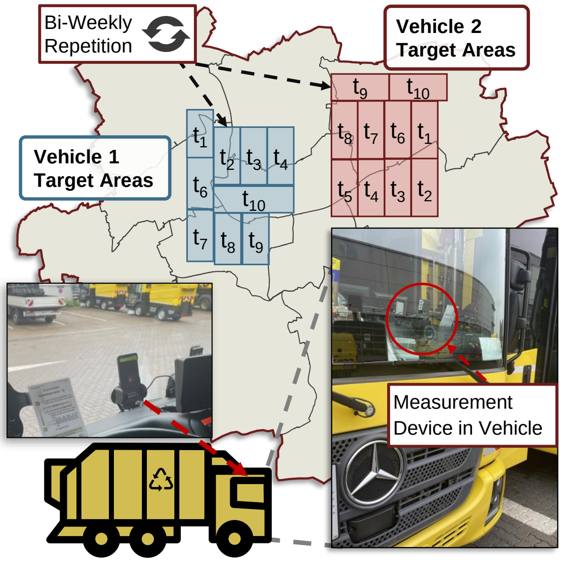


Fig. 3. Measurement device attached to the windshield of a garbage collection vehicle of the Dortmund waste collection company and exemplary repeating daily target areas (Map data: © OpenStreetMap contributors, CC BY-SA).

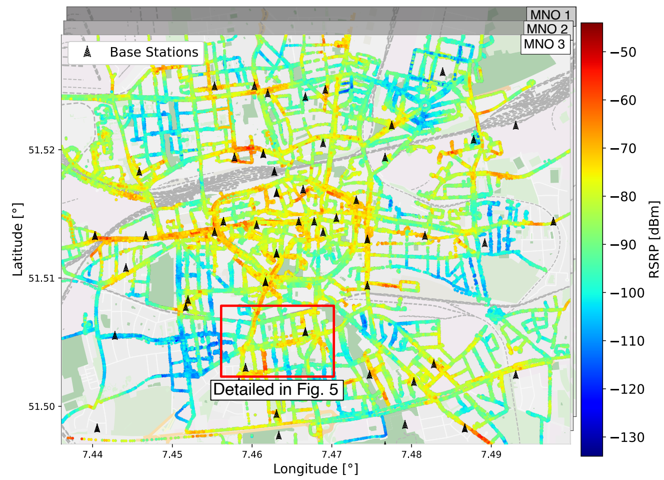


Fig. 4. Scatter plot of the measured Reference Signal Received Power (RSRP) of the first three months of the measurement campaign for Mobile Network Operator (MNO) 3 and base station locations based on `openData` of the city of Dortmund [17] and the Bundesnetzagentur [9]. The measurement devices are carried on waste disposal vehicles (Map data: © OpenStreetMap contributors, CC BY-SA).

introduction of new products and services. With the help of precise connectivity data provided by a web Application Programming Interface (API), mobile communication-based businesses could be planned more reliably. Users would benefit from the optimized QoS novel applications could provide.

## IV. Methodology of the Measurement Campaign with Dedicated Vehicles

The measurement application already introduced in [8] has been improved and updated to be used in an automated measurement setup in combination with the explained measurement system (see also Sec. II). Six Measurement smartphones with the measurement application installed are permanently attached to a garbage collection vehicle as shown in Fig. 3 to cover a wide area in Dortmund regularly. Every day, each vehicle targets a dedicated area, which repeats after two weeks. After three repetitions, the phones are switched to another vehicle to extend the measurement area. While the measurement system is capable of processing arbitrary measurements from different users, this method achieves systematic and mutually comparable measurements in a fixed area.

As the measurement smartphone is attached to the center of the windshield in the cockpit, the attenuation through the vehicle is kept to a minimum, and the crew can react to possible difficulties with the measurement process. The phone is connected to the onboard 12 V DC system. During the measurement breaks, the phone enters a low power state, which enables it to survive over approximately six days without a power supply. That is partly possible because the app can be run with device admin privileges in `lock task mode`. If the garbage collection vehicle leaves the service yard area, the measurement is automatically started utilizing `geofences`. The measurement is stopped shortly after reentering the `geofence` of the service yard. Afterward, collected data is automatically uploaded to the database via the mobile network. That prevents competing network accesses between the measurement process and the data upload.

The passive cell information is collected from three sources. First, the `Android` APIs networking classes are manually sampled regularly. Additionally, "onChange"-listeners are set up for cell information data. Finally, the observed data is merged with data provided by the `NetMonster` library [5] (see Sec. II).

The evaluation interval of passive and active parameters is configured to depend on the movement speed. That keeps the spatial measurement density per measurement session constant and reduces the number of energy-intensive active measurements. These would otherwise be unnecessarily stressing the network, the measurement smartphone and the server infrastructure. Furthermore, the logging interval is increased, depending on the time, since the measurement smartphone has moved significantly. The increase is designed to be low if the movement break is short and increases quadratically with time, as it becomes increasingly unlikely that the smartphone will start moving again. Finally, logging stops if no movement is detected for an extended time and the recorded data is uploaded to the server.

## V. Results: Impact of Drifting Mobile Network Environments

The running measurement campaign, in cooperation with the local waste collection company, results in continuously new measurement data.

A sample trace of a day in the measurement campaign from one MNO looks as follows. After the vehicles have reached their target area of waste disposal, the area is systematically

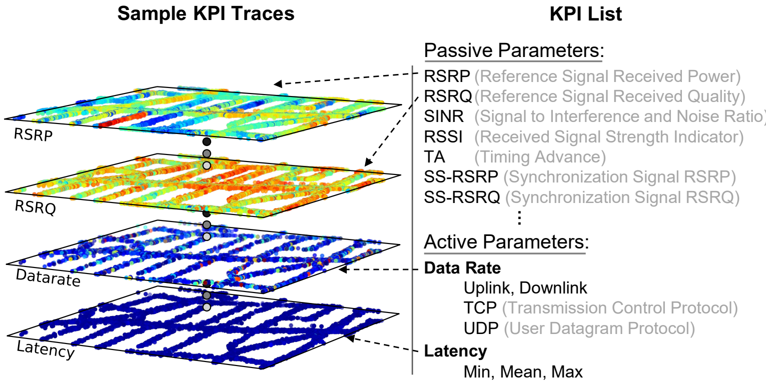


Fig. 5. Selected Radio Environmental Map (REM) layers of measured active and passive Key Performance Indicators (KPIs) for Mobile Network Operator (MNO) 3.

traversed before being unloaded. After this, the cycle starts a second time, which creates a dense cloud of measurements on almost every road in the target areas. In Fig. 4, the RSRP layer of the measured data is plotted together with base station locations from external sources [17] and [9] in the area around Dortmund city. It can be observed that even in the relative vicinity of cell towers, the received signal strength can be low due to shadowing. The measurements also show that the RSRP can be as low as −120 dBm at some places in the urban Dortmund city area. However, the RSRP is not the only captured signal. In Fig. 5, a selection of REM layers for a small portion of the area of Fig. 4 are shown. The parameters are recorded for all three considered MNOs and can be divided into passive and active. The combined information of all layers is needed to train precise models for data rate predictions.

### A. Observations From Long-Term Comparisons

In 2019, the authors of [19] measured multi-layer REMs in the area of the Dortmund city ring. These measurements can be utilized to make statements about the network expansion in the last three years and if changes can be observed. In Fig. 6, the RSRP layer of the REM measured in 2019 is compared to the data of 2022. The received power mainly remained the same in most parts of the city ring. On average, the RSRP increased by 9 dB. Minor changes could be due to different User Equipments (UEs) and measurement vehicles being used in 2019 and 2022. However, at the northeastern part of the city ring, the measured RSRP did improve by more than 20 dB. This change might be due to a new mobile cell tower, which has been built and will result in significantly higher data rates in this area. From 2019 till now, all considered MNOs put a 5G NSA network into operation. That can be modeled as another RSRP REM layer (Synchronization Signal RSRP (SS-RSRP)) in this comparison, which was not present in 2019.

### B. Performance of Machine-Learning Based Prediction of Network KPIs

In [14], data rate predictions for future tele-operated driving applications were conducted using well-tuned REMs based on

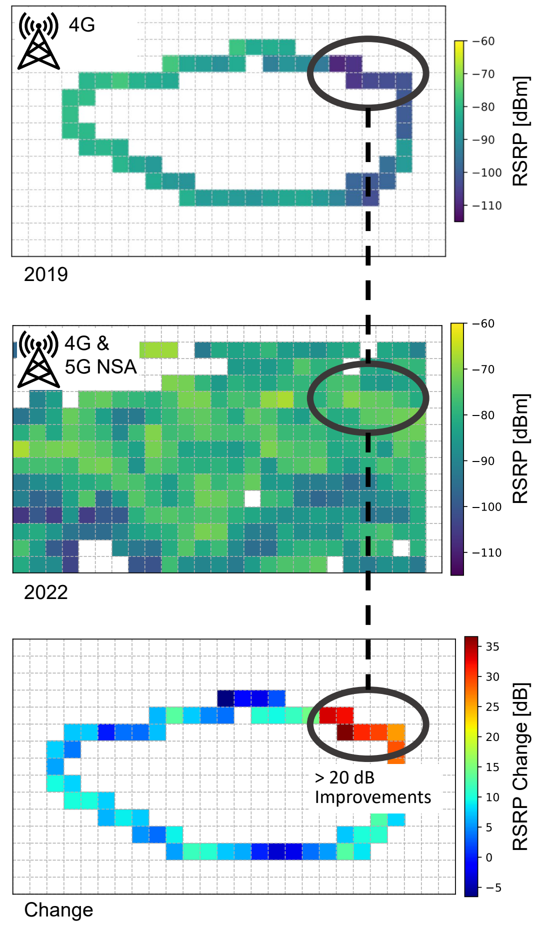


Fig. 6. Comparison of the Reference Signal Received Power (RSRP) REM layer with a cell width of 100 m measured in 2019 by [18] and in 2022 at the Dortmund city ring for Mobile Network Operator 3. It has to be noted that in addition to the RSRP changes, 5G Non-Standalone is available in 2022.

recorded passive and active measurements. The results demonstrated the feasibility of REM-based data rate predictions in several German cities. However, the setup was not automated to update the used data over time.

In Fig. 7, the impact of outdated ML models is shown. Using Transmission Control Protocol (TCP) downlink LTE speed test data from 2019 [19], a Random Forest (RF) based prediction model with the same hyper-parameters is trained to predict the data rate. Analogous to [19], the features RSRP, SINR, RSRQ, Cell Quality Index (CQI), Timing Advance (TA), cell index, velocity and payload size are used as features. If the model is ten times cross-validated, the performance is comparable to the results in [19]. The difference from the squared correlation coefficient of 0.552 in [19] to the value of 0.54 can be explained by the probably changed exact implementation of the RF model and the fact that the frequency data used in the prediction model of [19] is not available to the authors of this paper. If the old model is used to predict the new data rates, the score drops to 0.11, which is an unusable accuracy. When a new model is trained with the same features and cross-validated ten times, performance is improved by over 45 %,

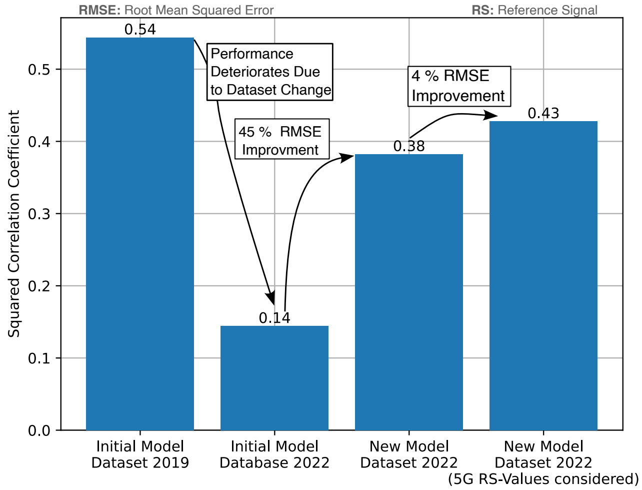


Fig. 7. Performance comparison of a model trained on data from 2019 and an updated model trained on data from 2022 evaluated on different data sets.

considering the Root Mean Squared Error (RMSE). However, the performance is worse if compared to the performance of the old model on the old data set. That is partly the case because measured data rates in the Long Term Evolution (LTE) networks of 2019 are overall lower than in conjunction with today's 5G networks. The 5G Synchronization Signals (SSs) reflect the utilization and the modulation used in the 5G part and therefore have a strong influence on the achieved data rate. A slightly higher squared correlation coefficient score is obtained if these SSs are also used. This only small increase can be explained by the RF utilizing the cell index as a substitute for the SSs. In summary, the demonstrated outdated performance of the old model highlights the need for continuous updates for spatiotemporal predictions of mobile network performance. Data and prediction models must be updated to keep track of drifting environments.

## VI. Conclusion

The capability of mobile networks has changed considerably in the last few years. Further improvements and changes are to be expected. That is why known concepts like REM-based predictive QoS that rely on measured mobile network indicators need to be based on current data that is frequently updated as changes are observed. These changes include not only the expansion to new cellular sites, but also the widespread deployment of 5G NSA, which drastically changes the feasibility of potential cellular-based applications. In order to ensure that future changes are detected in a timely manner, this paper presented a holistic system architecture. By automatically updating REMs on a server platform in combination with a systematic and regularly repeated measurement process, the current KPI of the mobile network can be monitored and predicted. This system favors the feasibility of new applications like ToD. It can also verify the availability of adequate mobile internet connectivity to the general public, identify opportunities for future improvements, and calibrate known radio channel simulation algorithms. In the future, further analysis will be conducted to fully exploit the growing amount of data collected.

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