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System Modeling and Performance Evaluation of Predictive QoS for Future Tele-Operated Driving

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Abstract— **Future Tele-operated Driving (ToD) applications place challenging Quality of Service (QoS) demands on existing mobile communication networks that are of highly important to comply with for safe operation. New remote control and platooning services will emerge and pose high data rate and latency requirements. One key enabler for these applications is the newly available 5G New Radio (NR) promising higher bandwidth and lower latency than its predecessors. In addition to that, public 5G networks do not consistently deliver and do not guarantee the required data rates and latency of ToD.**
In this paper, we discuss the communication-related requirements of tele-operated driving. ToD is regarded as a complex system consisting of multiple research areas. One key aspect of ToD is the provision and maintenance of the required data rate for teleoperation by the mobile network. An in-advance prediction method of the end-to-end data rate based on so-called Radio Environmental Maps (REMs) is discussed. Furthermore, a novel approach improving the prediction accuracy is introduced and it features individually optimized REM layers.
Finally, we analyze the implementation of tele-operated driving applications on a scaled vehicular platform combined with a cyber-physical test environment consisting of real and virtual objects. This approach enables large-scale testing of remote operation and autonomous applications.

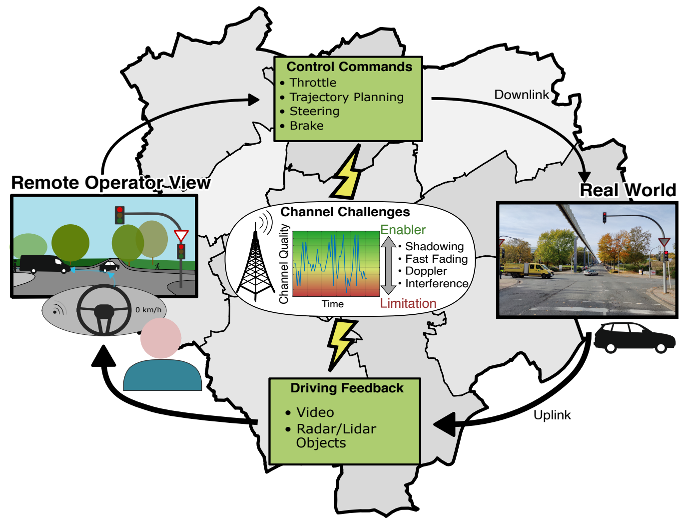

Fig. 1. System overview of tele-operated driving applications in the context of mobile networking. (Map: © OpenStreetMap contributors, CC BY-SA)

I. Introduction

Tele-operated Driving (ToD) can be seen as the next step towards automated driving and might even prevent possible driver shortages in industries like truck-based logistics as seen recently in Great Britain. Teleoperators might aid drivers or autonomous vehicles in challenging situations and ToD could be coupled with platooning. Several challenges concerning the sensors and actuators in the vehicle, but also regarding the mobile network enabling the teleoperation, need to be addressed. ToD presumes high data rates and low latency in addition to other requirements [1], [2]. That is why some kind of predictive QoS or even network quality guarantees are needed for teleoperation to work correctly [1].

Based on the current channel conditions, the mobile network channel can either be an enabler or a limitation, as demonstrated in Fig. 1. Due to mobility-dependent impact factors such as shadowing, fast fading and interference from other users, the QoS can be severely diminished. It is of crucial importance to predict this limitation of the channel to preserve the Quality of Experience (QoE) of the user remotely steering a vehicle [2]. Based on the information of video or object data transmitted via the mobile network, the operator can directly control the vehicle or set trajectories, which the vehicle independently follows. These commands must be executed reliably and immediately.

The contributions of this paper are summarized as follows:

- Derivation of a **system model** and development of an evaluation approach for ToD and autonomous driving.
- Elaborate key **performance requirements** for ToD and performing a 5G Non-Standalone (NSA) **measurement campaign** as a base for further investigation.
- Utilization of **multi-dimensional REMs** to proactively enable end-to-end predictive QoS.

The remainder of the paper is structured as follows. After discussing the related work in Sec. II, the system modeling of ToD and methodological aspects from a predictive-QoS perspective are shown in Sec. III. In Sec. IV, detailed results concerning end-to-end data rate predictions via REMs are provided. Finally, an approach to systematically evaluate autonomous driving in a cyber-physical area is discussed.

II. Related Work

Many previous research works have recognized the potentials of ToD for future intelligent traffic systems. However, there is no ready-proven ToD application available on a large

scale or even outside of a dedicated test environment.
One major challenge are the high data rate and latency requirements that need to be met. We summarized system requirements of several related works in Tab. I. Different related works assume varying velocities and working modes, as there is no standardization for ToD. That results in differing requirements and complicates a comparison. Furthermore, there is progress within requirement statements, as the 5G Automotive Association (5GAA) has changed its thresholds from 2020 [1] to 2021 [3].
However, all sources are consistent that a high service level requirement of over 99 % is mandatory for ToD. Also, all sources agree that a higher data rate in the uplink is needed than in the downlink because video and object data need to be transmitted in the uplink direction. Demand-based pattern usage is discussed in [4]. Differences are found in the number of cameras and the video quality settings, which result in highly varying uplink data rate requirements. While the authors of [5] state an uplink data rate requirement of 3 Mbit/s, the authors of [6] and [7] demand for up to 50 Mbit/s. In the downlink, relatively small data rates lower or equal than 5 Mbit/s are required.

TABLE I
TELE-OPERATED DRIVING MINIMUM NETWORK REQUIREMENTS

Source	V_{Max} **[km/h]**	**Data Rate [Mbit/s]**		**Service Level Reliability [%]**		**Latency [ms]**	
		DL	UL	DL	UL	DL	UL
Included in 5GAA System requirements analysis and architecture [3]							
[8]	50	0.4	32/36	99.999	99	20	100
[6]	–	5	8–50	99.999	99	10–66	10–50
[7],[9]	15	0.5	10–50	99.9	99	–	40
[10]	8	–	–	–	–	80	120
[3]	15	0.3	8–30	99	99.9	300	
Other references							
[11]	250	1	25	99.999		5	5
[5]	-	0.25	3	-	-		250

☐ : Direct Control Tele-operated Driving
■ : Indirect Control Tele-operated Driving

There are two main modes of tele-operated driving: *indirect* and *direct control* ToD [3].
With direct control, an operator directly controls the steering wheel, the accelerator pedal and other actuators. The vehicle only has to be able to sustain a lower level of automation to securely come to a halt if the connection to the teleoperator is cut. In the case of indirect ToD, the vehicle has to reach a significantly higher level of automated driving [3] because the operator can set trajectories the vehicle needs to follow. It is striking, that in this case, a control latency of only 300 ms needs to be reached compared to a latency of roughly 100 ms in the case of direct control [3]. Thus, some requirements for the network Key Performance Indicators (KPIs) are reduced.

Despite several sources specifying uplink and downlink latency requirements, the 5GAA states that only the whole Round-Trip Time (RTT) is the main determining factor [3]. In turn, the maximum allowed RTT depends on the maximum velocity allowed to operate the vehicle at [3]: Higher velocities demand even faster reaction times for braking and evasive maneuvers.
With a higher latency, precise driving operations get increasingly difficult [5]. That is a major challenge for the mobile network in the case of direct control ToD. For indirect ToD, the latency is less critical, but the high data rate that needs to be fulfilled continuously for operation is still concerning.
Sudden service interruptions during ToD could be fatal and thus need to be prevented. That could be done with the help of predictive QoS. Various related works have performed data rate predictions of mobile networks. These can either be performed instantaneous like in [12] and [13] or with the help of previously generated so-called REMs [14], [15].
Most of these predictions are based on a measurement study contributing a training set of feature vectors and labels (achieved data rate). The features are commonly a subset of real-time measured passive Reference Signals (RSs). Machine learning is used to generalize this data set to predict the achieved data rate based on new feature vectors. Many related works use tree-based regression models like Random Forests (RFs) for their predictions [16], [17], [18].
This methodology is promising to enable in advance data rate predictions for ToD with the goal to reduce service interruptions and improve the QoE.

III. SYSTEM MODELING OF PREDICTIVE-QOS FOR FUTURE TELE-OPERATED

Different operation modes of tele-operated driving set requirements for performance indicators to be met, as described in the previous section. These influence the feasibility parameters like the possible driving dynamics or the needed network coverage as demonstrated in Fig. 2. More complex operation modes demand for more sophisticated communication technology like 5G, future 6G or even a combined approach of several communication technologies in a multi-Radio Access Technology (RAT) approach. Centralized and decentralized technologies might be needed to complement their mutual strengths in an attempt to maximize coverage and user experience. While centralized approaches can reach higher data rates due to resource allocation by a central entity, decentralized solutions can also work in regions with otherwise insufficient coverage.
That is why the evaluation environment does also affect tele-operated driving. While huge competition for radio resources can be expected inside an urban environment, an overall inferior coverage might be the case in rural settings. Both pose challenges to the communication technology. Despite these challenges, data transfers need to be reliable and of low latency as independent of the channel conditions and the expected traffic as possible.

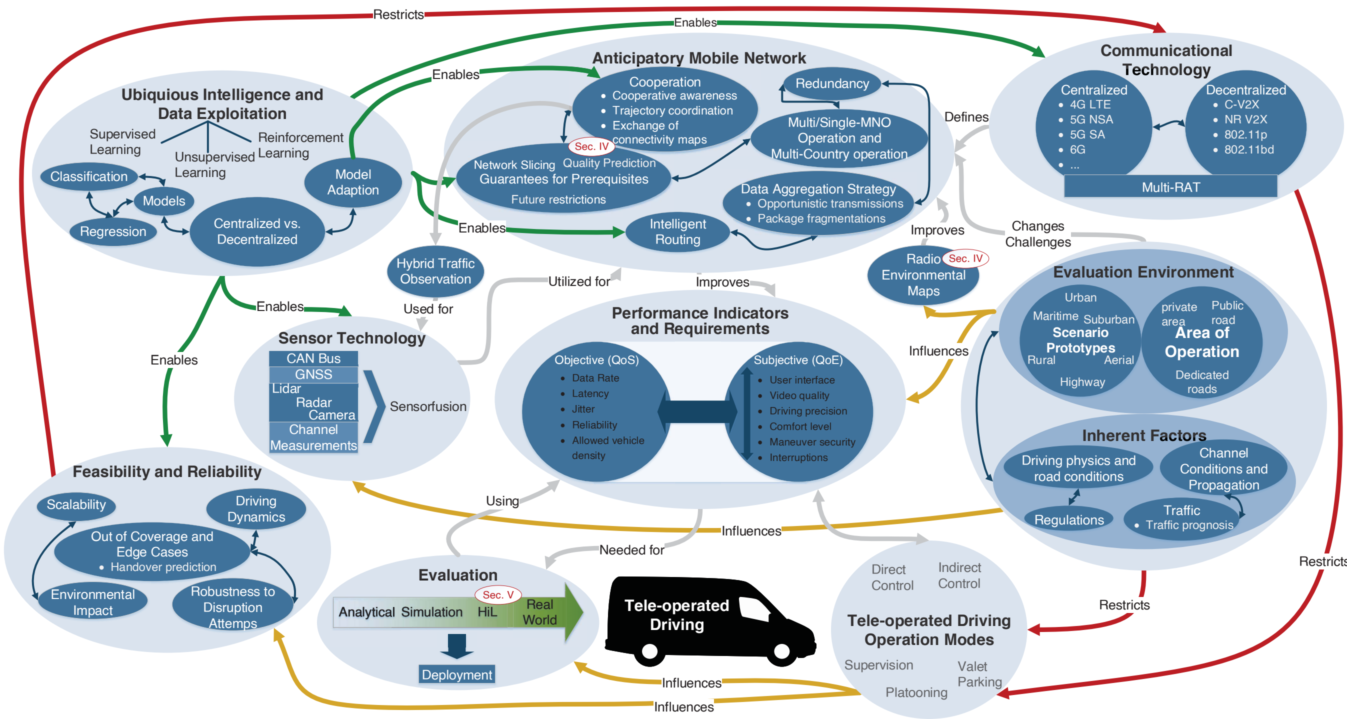

Fig. 2. Systemigram of the system architecture model for data-driven optimization of mobile traffic consisting of data acquisition, data processing and data exploitation to enable new Services in varying environments.

Network slicing and data rate predictions can be utilized to prevent and forecast inadequate network states. With the help of network slicing, network resources can be reserved and allocated to a specific user. In addition to that, multi-Mobile Network Operator (MNO) approaches can improve the coverage significantly with the help of redundant connections [13]. Based on the criticality of the data, different aggregation strategies can be used to prevent unnecessary transmissions in grim coverage situations. Data aggregation can be coupled with intelligent routing algorithms, which can also enable cooperative sensor fusion between tele-operated vehicles. The more sensor data available, the more convenient and secure tele-operated driving can be. For example, trajectory coordination combined with aggregated sensor data from several vehicles can be used to warn drivers of obstacles and driving paths, which would usually be invisible to their perspective.

Key enablers for many of these features and applications are various kinds of machine learning.
Machine learning can be divided into three categories, which can be used to solve complex challenges across multiple research areas. Different approaches in several disciplines need to be evaluated for future tele-operated driving applications.

- `Supervised Learning` is based on previously labeled data. A machine learning model is trained on this data to find patterns and be able to generalize onto unseen data. This kind of machine learning is arguably the most common type.
- `Unsupervised Learning` can be used to autonomously extract hidden patterns in unlabeled data and cluster them.
- `Reinforcement Learning` rewards an entity based on its actions. Based on the rewards, the entity changes its strategy with the goal of getting as much reward as possible for its actions taken.

All these classes of machine learning are applied in one or more parts needed for tele-operated driving, like challenges in routing relying on reinforcement learning, supervised learning is used for predictive QoS and unsupervised leaning can be used for trajectory planning and coordination. Not only centralized approaches but also decentralized approaches are necessary to adapt existing models appropriately.
Based on the type of the label, the machine learning models try to predict the process is called `Classification` or `Regression`. Classification means predicting a set of classes, whereas regression means the closest possible accurate approximation of a number.
Machine learning models can be trained on a central computation entity or decentralized on many devices. Data needs to be directed to the central entity to be able to centrally train a model. That may conflict with local authorities or be impossible due to the inherent data transfers generating too much traffic [19].

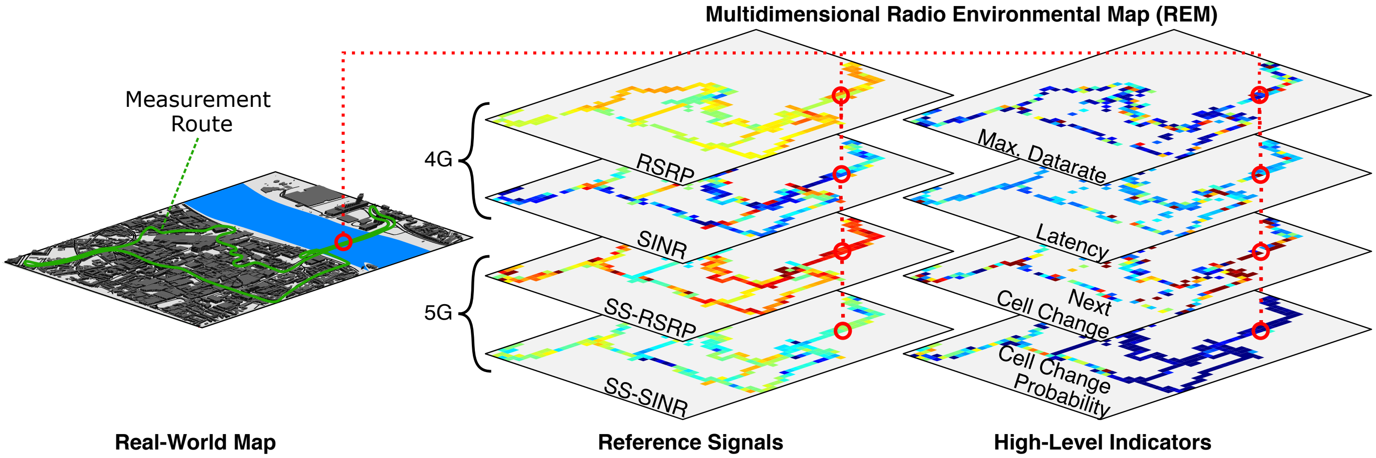

Fig. 3. Real-world map and radio environmental map of the city center of Cologne with a cell width of 50 m consisting of reference signals for 4th Generation of Mobile Communication Networks (4G) and 5G mobile networks and combined or higher-level indicators. (Map: © OpenStreetMap contributors, CC BY-SA)

For predictive QoS applications, supervised learning models are most commonly used in a regression configuration.
In this paper, the python library `scikit-learn` [20] is used for machine learning.

With the goal of deploying a real-world capable tele-operated driving application, an evaluation process has to be gone through, starting with analytical calculations. These can be used as a base for simulations and later hardware in the loop experiments. During this process, repeated tests of compliance with performance indicators and requirements need to be done. Only then, real-world evaluations can be conducted. These consist of pre-tested individual parts of the tele-operated application that are composed into one system.

Geospatial aggregation of network context information with Radio Environmental Maps (REM): As stated by the 5GAA [3], predictive QoS is a key enabler for ToD, as it can ensure service availability and user experiences. One method to achieve in advance network quality predictions is based on REMs [14], [21], [22].
REMs consist of a predefined multidimensional grid containing aggregated reference signals or performance metrics based on geographical locations [18]. These are commonly aggregated over several measurements of one person or a crowd-sensing approach [23]. However, it is also possible to calculate a REM utilizing simulation methods such as ray-tracing. The REM can then be used as a digital twin of the radio domain in a specific area. An example of a REM with a cell width of 50 m can be seen in Fig. 3. Passive RSs like the Reference Signal Received Power (RSRP) and the Signal to Interference and Noise Ratio (SINR) are utilized.
In addition to passively measurable 4G and 5G RSs, high-level indicators resulting from active measurements or further processing of raw measurements are integrated. It has to be noted that additional parameters like the Reference Signal Received Quality (RSRQ) are also used inside REMs, but these are not shown due to clarity and space considerations.

Analogously to instantaneous measurements, network quality predictions can be based on the features located inside the REM: To predict a data rate at a specific location, the corresponding feature vector stored in the REM is extracted and fed into a trained machine learning model [14], [23].
The quality prediction based on REMs has further advantages in addition to the ability to predict future data rates. Due to the accumulation of measurements, over-fitting to specific radio channel situations can be prevented [23]. With the help of predicted data rates, the energy consumption and the spectrum usage can be improved [22] if the driven trajectory is known or can be predicted, and delays of the transmission can be tolerated [14], [21]. Furthermore, appropriate trajectories for ToD can be chosen based on REM information [24].
One key factor of REMs is the cell width c of the underlying grid [23]. Not only the spatial resolution and thus the precision and occupied memory of the REM is affected. If the REM is built by measurements, care must be taken to ensure the REM is without gaps. Otherwise lookup misses occur, which need to be treated separately. As the rate of misses is dependent on the cell width, the probability of misses rise with a higher spatial resolution of the REM. As a result, the cell width has to be adapted to minimize the prediction error [23].

IV. Real World End-to-End Data Rate Prediction and Evaluation using Radio Environmental Maps

As described in the previous section, one method to reduce the impact of fluctuating data rates of public mobile networks on the QoE of tele-operated driving applications is REMs-aided in advance data rate prediction. Large-scale real-world measurements are needed to evaluate this setup.

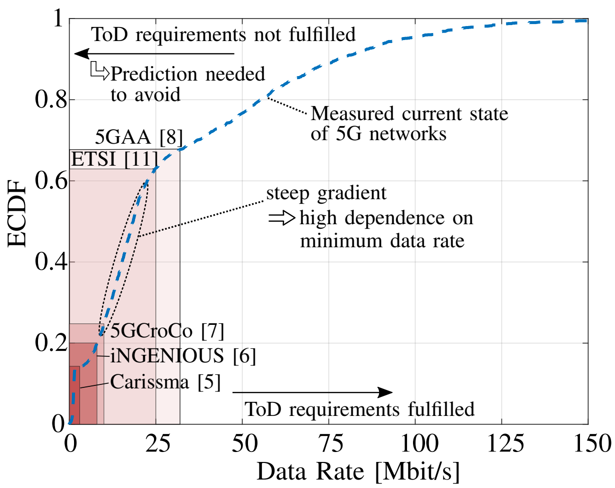

Fig. 4. Empirical Cumulative distribution function (ECDF) of the measured data rate with the Samsung Galaxy S21 5G using the UDP protocol in the uplink direction and the minimum uplink data rate to enable tele-operated driving according to related work. The raw measurements are available at [25].

Over 7000 data rate and 35 000 RSs measurements have been conducted in several areas in the German federal state of North Rhine-Westfalia using the Samsung Galaxy S21 5Gin a public 5G NSA mobile network. In the NSA mode, an existing 4G core network is used instead of a dedicated 5G core network. Major cities like Cologne, Bonn and Dortmund, highways and also suburban and urban areas are covered. A dedicated `Android` application developed for this purpose has been utilized, first used in [15]. The open-source software `iperf 3.9` was used internally to conduct the data rate measurements.

In this work, the measurements using the User Datagram Protocol (UDP) protocol in the uplink direction with a payload size of 5 MB to 10 MB for each individual measurement are utilized to emulate ToD video streaming and object data transmission. The raw measurements and the used `Android` application are publicly available under this link [25].

An Empirical Cumulative Distribution Function (ECDF) of the achieved UDP uplink data rates is shown in Fig. 4. On top of this, the minimum uplink data rate requirements of several related works are displayed. All data rate requirements are below 50 Mbit/s. In 75 % of all measurements, a data rate lower than 50 Mbit/s is reached. Around and below this data rate, the gradient of the ECDF is steep. Consequently, slightly varying data rate requirements have a significant impact on the number of places where ToD would be feasible with the current 5G technology. In the case of the most challenging requirements of 30 Mbit/s, in over 60 % of the measurements, ToD would not be possible. In the case of the least challenging requirements, in over 80 %, ToD would be possible. That results in over 40 % of the measurements being located in a range where it is uncertain if ToD is possible. Independent of the proposed needed data rate, at a significant part of the measurements, ToD would not be possible.

This observation further underlines the criticality of the prediction of where ToD would not be possible to prevent frequent service interruptions.

However, the achieved data rate depends not only on the coverage, bandwidth and network technology at a specific location but also on resource competition with other users. Based on one indicator alone, an accurate forecast of the data rate is not possible, because multiple factors influence the achieved data rate. That is why data rate prediction is a demanding task, which needs to be based on a set of multiple indicators, including network, application and mobility context parameters.

Not all influencing factors like the activity of other users can be measured directly. However, the User Equipment (UE) can measure a set of RSs giving insight into the current channel conditions. For example, the signal quality represented by the RSRQ can indicate a crowded radio channel and thus an expected lower data rate.

REM-based and Combined Prediction: In Fig. 5, the prediction error of different REM configurations is compared to instantaneous predictions based on real-time channel measurements. One REM setup considers only the passively measured RSs. A second REM also utilizes high-level and advanced features to predict the UDP uplink data rate. Lastly, a combined approach both using real-time measured data and REM data is evaluated. For the REMs a grid size c of 50 m is used.

A Random Forest (RF) machine learning model consisting of 560 trees and a maximum depth of 40 is trained on each configuration. 10-fold cross-validation is used to prevent overfitting. In addition to that, the learning process is repeated ten times with random initialization to get more reliable results.

It can be seen that REM-based data rate predictions can keep up with instantaneous data rate predictions. Based on the chosen scenario, REM-based predictions can even outperform real-time predictions. If REM data is available in addition to real-time RSs – Combined Approach –, data rate prediction can be improved in all scenarios. In addition to that, based on the configuration, significant improvements can be reached by using additional parameters in the REM (Multidimensional REM). This observation is consistent with the results of the authors of [12] for instantaneous data rate predictions. However, the improvement is dependent on the scenario and the added features.

The cell width c is another design factor affecting the data rate prediction performance of REMs, as previously mentioned in Sec. II. To analyze the impact of the cell width on 5G NSA data rate predictions, REMs with different cell widths are created with a set part of the measurements (training set). On this training data set, an RF is trained. Then a data rate prediction on a distinct test set is performed. This approach is repeated ten times for every scenario, to get more reliable

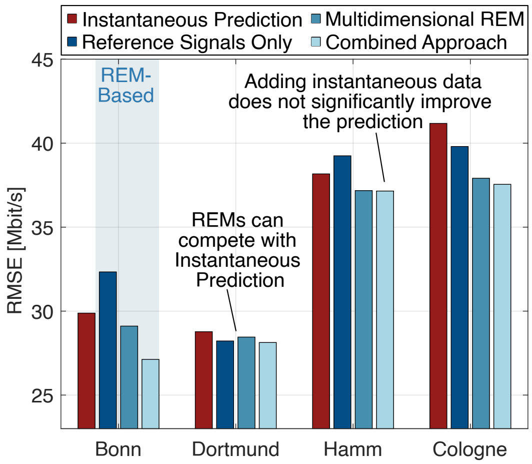

Fig. 5. Data rate prediction performance comparison: Two REM approaches with a cell size of 50 m, one instantaneous prediction approach as the baseline and a hybrid approach using both the instantaneous and the REM data, are examined. The results are evaluated on different scenarios.

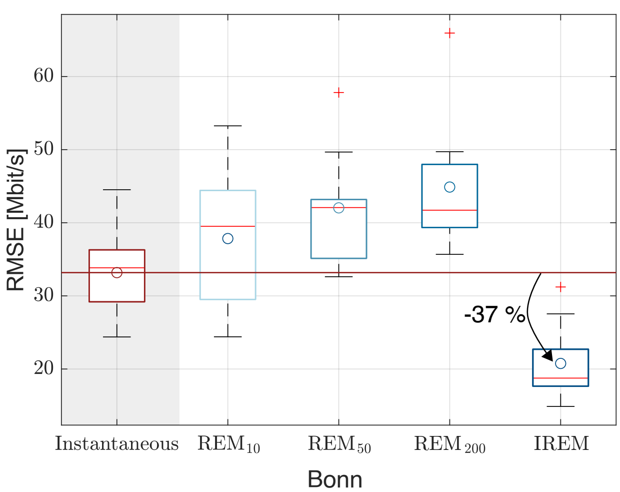

Fig. 6. Data rate prediction performance comparison between REMs with a constant grid size, an optimized REM with individually tuned grid sizes for every feature (IREM) and an instantaneous prediction as the baseline. The results are exemplarily evaluated at the Bonn scenario.

results. All available features are used in the REM and the same cell width is set for each feature in a REM. The results are shown exemplarily for the Bonn scenario.

As can be seen in Fig. 6, different cell widths result in varying Root Mean Squared Errors (RMSEs). A large cell width of 200 m mostly results in the worst RMSE compared to the other REM approaches due to the lack of resolution. However, the smallest cell width of 10 m does not always yield the best RMSE: At this cell width, less averaging gains are achieved and more lookup misses occur than at a cell width of 50 m [23].

Indicator individually optimized REMs: The explained results pose the question, if the prediction accuracy improves, if some features have a higher resolution, while other features are more locally averaged. Some features might have a more pronounced local dependence than others. That is why, an optimized REM with individual cell widths for each feature is created — so-called IREM. This REM is optimized using a random search approach for the cell width (10, 20, 50, 75, 100, 200 and 400 m are considered) with the goal of minimizing the RMSE of the data rate prediction. 2000 iterations of the random search are performed to ensure, the search space is sufficiently covered.

It can be seen in Fig. 6, that the IREM does not only exceeds the prediction performance of REMs with a set cell size, but also outperforms the instantaneous predictions. A gain of up to 40 % is reached compared to the instantaneous prediction.

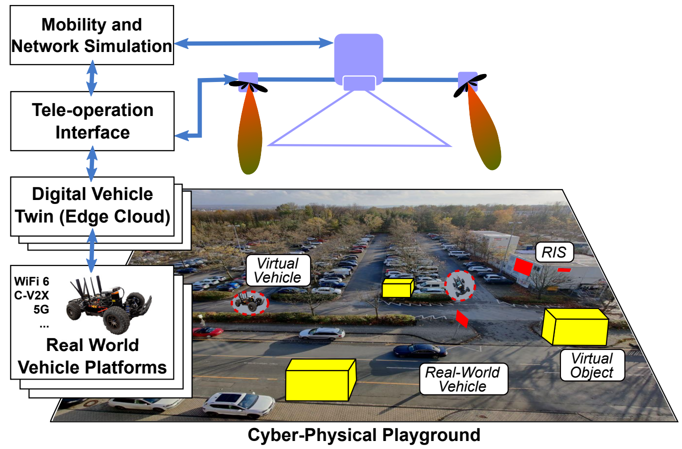

Fig. 7. Cyber-physical playground consisting of real vehicles with respective digital twins in a ToD operation configuration.

V. Towards Systematic Evaluation of Autonomous Driving

The evaluation and scalability analysis of ToD use cases is a crucial development stage. It needs to preserve a high grade of realism and a high reproducibility of drive tests to underline the significance of the results. As shown in Fig. 2, evaluation methods range from analytical models over simulative approaches towards the integration of Hardware-in-the-loop (HiL) and, finally, real-world experiments.

Although HiL setups take place in a controlled laboratory environment, scalability is often realized by traffic shapers, and thus, is not suitable to figure the actual characteristics and dynamics of ToD scenarios. Nor do cabled setups offer the possibility to carry out a parallel evaluation of the resulting QoE. On the other hand, real-world trials can overcome this constraint and provide a complete end-to-end tele-operation but also come at full costs, especially in the case of scalability analyses.

A combination of both approaches in a cyber-physical playground can overcome these issues, as demonstrated in Fig. 7. Teleoperated real-world vehicles interact with several

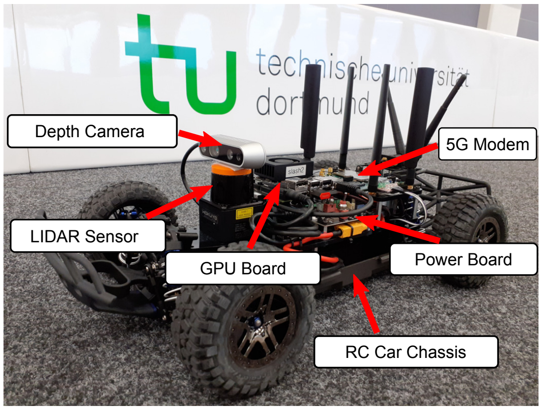

Fig. 8. Scaled vehicular platforms provides a cost-effective opportunity for scalability analyses in controlled environments to evaluate novel approaches.

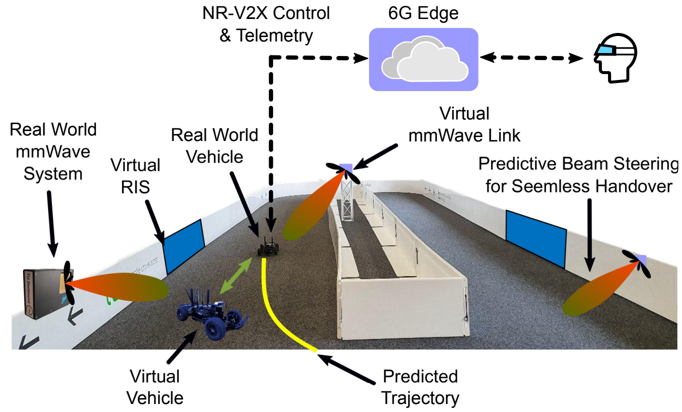

Fig. 9. A cyber-physical playground can be used for tele-operated driving evaluation with scaled vehicular platforms connected via a 6G network and V2X connectivity, including trajectory prediction and virtual Reconfigurable Intelligent Surfaces (RISs).

real objects and thus experience real behavior and physics. However, all real objects also exist as digital twins. In addition to that, further virtual objects utilizing the 5G communication technology can be introduced, to which the vehicles need to adapt. These can act as obstacles or restrictions. The reaction of vehicles to these can be observed and improved. As a result, real-world physics with the repeatability of laboratory experiments can be achieved.

To improve scalability, lower the cost, but maintain the end-to-end aspect of the teleoperator, this setup can be sized down to be used with scaled vehicular platforms. The used vehicle is built in alignment with the *F1/10* project [26] and consists of the ground chassis of a consumer radio-controlled car, which is further equipped with communication equipment, sensors, and computation entities.
A detailed picture is shown in Fig. 8. Besides the chassis and original drive train, a motor controller is equipped to enable smooth steering of the brush-less motor and servo actuators through networked tele-operation.
Further, there are two main computation units. An *NVIDIA Nano NX* adds powerful graphical processing capability. Although it was originally installed for autonomous driving use cases, it can also be utilized to compute complex machine learning algorithms locally. A parallel *Raspberry Pi* orchestrates the 5G connectivity over *Quectel RM500Q* modules and is, in the long-term, to be extended with other communication technologies to support multi-RAT approaches. A high-resolution depth camera in the front of the car delivers rich visual material. In extension to this, the Light Detection and Ranging (LIDAR) senses the environmental information to enhance the teleoperator's perception.
These F1/10 based scaled vehicles can be used to enable large-scale tele-operated driving at indoor and outdoor test sites. Before non-scaled vehicles are ready for testing, complex maneuvers can be driven using the real-world radio channel. This way, the development of ToD platforms can be accelerated in an effective and relatively cost-effective way. In addition, trials with a scaled vehicular platform do not pose a potential danger for test personnel that would need to be in a tele-operated vehicle for emergency halting.

The described evaluation setup has the potential to be used beyond 5G, for example, to test Reconfigurable Intelligent Surfaces (RISs), which are a key enabler of future 6G networks. A playground for these F1/10 vehicles based on 6G Millimeter-Wave (mmWave) and V2X technology is shown in Fig. 9. The trajectories of the real-world vehicles are prognosticated to enable predictive beam steering for seamless handovers. To test the system, virtual RISs can be introduced, while a teleoperator controls the F1/10 vehicle, driving through the environment consisting of real and virtual objects and vehicles. That way, teleoperation with 6G mmWave technology can be tested in different challenging virtual environments.

VI. Conclusion

For tele-operated driving, multiple individual systems need to interact with each other. Various challenges from several research directions need to be overcome to enable ToD smoothly and safely. One part of this system is the mobile network part. Different data rate requirements are specified in related work. The current 5G NSA mobile network can not always fulfill these. That is why in advance predictive QoS is a key enabler of ToD. In the case of a insufficient data rate, alternative routes can be chosen, or the velocity adapted. One method to predict in advance end-to-end data rates are so-called REMs. The results of REM-based predictions are comparable to instantaneous predictions. However, with the help of individually optimized REMs, which tune the cell size of each layer individually, the prediction accuracy can be further improved. In the future, current UE-based predictions might be further improved by network slicing and network-side-based data rate predictions [12].
Since ToD is a complex system, the evaluation of tele-operated driving systems is a challenging task. In this paper,

an evaluation approach for ToD and autonomous driving based on cyber-physical playgrounds is given. With the help of real and virtual vehicles and obstacles, real-world physical interaction similar to the final product can be achieved with the repeatability of laboratory trials. By sizing down this approach to scaled vehicular platforms, which are safer to handle, further cost reductions can be achieved.

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