Cellular Bandwidth Prediction for Highly Automated Driving
Evaluation of Machine Learning Approaches based on Real-World Data

Florian Jomrich[1,2], Alexander Herzberger[3], Tobias Meuser[2],
Björn Richerzhagen[2], Ralf Steinmetz[2] and Cornelius Wille[3]
[1] *Opel Automobile GmbH, Rüsselsheim, Germany*
[2] *Multimedia Communications Lab (KOM), TU Darmstadt, Germany*
[3] *Computer Science Department, Technical University of Applied Sciences Bingen, Germany*

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Abstract: To enable highly automated driving and the associated comfort services for the driver, vehicles require a reliable and constant cellular data connection. However, due to their mobility vehicles experience significant fluctuations in their connection quality in terms of bandwidth and availability. To maintain constantly high quality of service, these fluctuations need to be anticipated and predicted before they occur. To this end, different techniques such as connectivity maps and online throughput estimations exist. In this paper, we investigate the possibilities of a large-scale future deployment of such techniques by relying solely on low-cost hardware for network measurements. Therefore, we conducted a measurement campaign over three weeks in which more than 74,000 throughput estimates with correlated network quality parameters were obtained. Based on this data set—which we make publicly available to the community—we provide insights in the challenging task of network quality prediction for vehicular scenarios. More specifically, we analyse the potential of machine learning approaches for bandwidth prediction and assess their underlying assumptions.

1 INTRODUCTION

Highly automated driving vehicles will fundamentally change our personal mobility in the future. Autonomous driving will enable people to spend their time in the car with productive or relaxing tasks instead of driving by themselves. This will include office tasks like writing e-mails, having Skype calls and video conferences or relaxing tasks like streaming music and videos. Furthermore the car itself has to receive continuously updates regarding the current traffic situation to ensure the safety and the comfort of its passengers. This includes the sharing of personal sensor readings between the vehicles directly or through a data processing backend (Here, 2015), (Lee et al., 2016), (Jomrich et al., 2017b). All these services require a robust and well performing mobile data connection. However due to their mobility the vehicles are constantly experiencing a different connection quality. Reasons therefore are the varying deployed technology in the cellular network, its density and the usage related available resources of the cell towers. To ensure a reliable data connection with a high quality of service under such fluctuating conditions, different concepts and techniques have been investigated. Several researchers proposed the idea to enhance the insufficient network coverage information offered by the providers through data, which is collected by the vehicles themselves (Kamakaris and Nickerson, 2005), (Nagel and Morscher, 2011), (Kelch et al., 2013), (Pögel and Wolf, 2015). Through their own communication equipment the cars are able to sense their currently experienced connection quality. By collecting and sharing this data the network coverage maps of the cellular providers can be enhanced into so called connectivity maps, which poses a much better accuracy regarding the to be expected network quality at a certain location in the map.

Besides this concept further approaches try to predict specific key performance parameters of the overall network quality in a near real time fashion. Therefore those so called online estimation algorithms only measure the network quality, which is currently experienced by the vehicle and try to predict future values based on the most recent measurements. One of the most application-relevant network quality parameters is the expected future throughput bandwidth. Many scientists have developed different online prediction

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algorithms for this value.

Within this paper we now investigate the applicability of such throughput estimation algorithms for a large scale deployment in a mobile communication scenario as described by the highly automated driving vehicles. Thus in contrast to existing work (Lu et al., 2015), (Jin, 2015), (Margolies et al., 2016), we only rely on data that is easily obtainable from low cost hardware instead of relying on specialized measuring equipment or software tools. To make our obtained results comparable to the work of other researchers we rely on the public APIs of nowadays Android smartphones. Those devices can obtain the required network quality parameters in a similar timely resolution and accuracy as currently deployed vehicular communication hardware.

Furthermore we propose and examine the idea to combine both mentioned concepts (the connectivity map and the online throughput estimation) together, to achieve better throughput prediction results. Therefore we assume and analyse whether location specific historical measurement data can be used to optimize the training of instantaneous throughput estimation algorithms.

As a further contribution we give a broad overview about Related Work in the research area of connectivity maps and online throughput estimation techniques in the following Chapter 2.

The rest of this paper is structured as follows. Within Chapter 3 we first explain the general approach and the setup used to obtain the cellular measurements. Furthermore the selected highway scenario and the used measuring devices with their obtained quality parameters are described. Outgoing from the obtained measurements we evaluate the effects of a variety of investigated parameters on the overall performance of throughput estimation algorithms in the context of a mobile communication scenario in Section 4. We summarize our obtained results and give a short outlook regarding future work in Chapter 5.

2 RELATED WORK

To address the general challenge of continious adaptation regarding changing connectivity conditions while moving in traffic, different techniques have been proposed and investigated by researchers. They can be grouped into different categories based on the life time of data upon which they rely as well as their achieved accuracy and prediction horizon as described by (Bui et al., 2014). Within this work we investigate the possibilities that lie in the combination of two of such concepts (connectivity maps and online throughput estimation algorithms). Therefore we now give an overview of Related Work in those two areas of research.

2.1 Connectivity Maps

The general idea behind the connectivity map is to collect and store information about the network quality, which is experienced at certain areas of the map. For example this can include parameters like the received signal strength, the experienced latency and the measured throughput bandwidth of the network. In the context of vehicular communication the cars are considered as probes to generate such a connectivity map. They measure the network with their personal communication equipment and share such information with a data collecting backend server. This gathered data set within the server is than used to predict the future network quality of a vehicle based on its current location and driving direction. Most commonly this is achieved by taking the average of the historical data for equally sized areas of the map and considering those average values as the most likely to be experienced value in future.

One of the earlier works, which proposed the concept of a connectivity map is done by (Kamakaris and Nickerson, 2005). Within their work the authors investigated the correlation between the Received Signal Strength Indication (RSSI) and the measured throughput values within WiFi networks. In their work the authors addressed the short average lifetime of predictions that can be achieved by the connectivity map based on its stored measurements. This is due to the highly dynamic variations of the overall network quality over time. The data contained in the map therefore gets quickly outdated and has to be constantly updated by remeasuring the current situation. The authors state that the reasons therefore are manifold, for example the fluctuation of actual users in the network and thus the current network load, but also environmental influences like buildings.

Kelch et al. (Kelch et al., 2013), Lu et al. (Lu et al., 2015) and Pögel et al. (Pögel and Wolf, 2012), (Pögel and Wolf, 2015) specifically focus on the creation of a connectivity map of the cellular network and its possibilities for vehicular usage scenarios. A similar kind of connectivity map is also considered to be established in our contribution.

In the work of (Kelch et al., 2013) and (Lu et al., 2015) both authors independently from each other investigated the usability of connectivity maps to optimize the overall experienced network quality of 3G HSDPA cellular networks. Therefore both authors suggest to correlate the so called Cellular Quality Index (CQI) [1] with the achieved throughput rate at different locations of a map. The CQI is a parameter derived from the different measured signal strength parameters (Reference Signal Received Power - RSRP, Reference Signal Received Quality - RSRQ and Received Signal Strength Indication - RSSI) to indicate the overall channel quality. While driving a vehicle Kelch et al. periodically executed the download of a large file via the HTTP protocol using the TCP transport layer protocol to fully utilize the present channel and to measure the maximum achievable bandwidth. The Channel Quality Indicator (CQI) was collected in parallel by polling it each second from the used cellular modem via an AT-command.

In a similar way (Lu et al., 2015) send data for a consecutive time of 60 seconds via the UDP protocol to obtain active measurements of the currently present HSDPA cell. They used Nexus 5 smartphones as measuring devices. The CQI values were retrieved with a high precision timely resolution of 2-8 ms by connecting those smartphones to the so called Qualcomm eXtensible Diagnostic Monitor (QXDM) [2] framework.

As a result of their investigation both authors suggest the Channel Quality Indicator to be a good value to predict the achievable throughput. They state this as possible, as an exact mapping of the Channel Quality Indicator onto the reserved resources and the used modulation scheme of the celltower is possible. Those two parameters than directly specify the granted available bandwidth. Such an exact mapping however is not possible any more in the more advanced 4G/LTE networks[1], which are investigated in our work. Furthermore the achievable network speeds in 4G networks are far larger than the speeds obtained by Kelch et al. and Lu et al., being limited in the peak to only 7,2 Mbit/s. This makes the predictability more difficult as larger variations in the achievable throughput rate are possible. We argue that although we expect the CQI as well to be an important parameter in the throughput prediction, it should not be considered as sufficiently enough. Thus we investigate further parameters (see Section 3) in our personal work, which describe the overall network quality and can be stored within the connectivity map as well. The work of (Lu et al., 2015) further relies on the highly accurate CQI values obtained via the QXDM toolset. This hinders an actual large scale deployment, as such software requires expensive licenses and might not be easily deployable on low cost hardware, as used in our work.

(Pögel and Wolf, 2012) also investigate the possibilities of a connectivity map to predict certain network parameters in the vehicular context. This includes the next cell tower, to which a future handover of the current connection will be performed, as well as the future to be experienced bandwidth. In a further work (Pögel and Wolf, 2015) this gathered information is than used to improve a variety of network services like adaptive video streaming and the handover between different network technologies (2G, 3G networks). Similiar to (Kelch et al., 2013), (Pögel and Wolf, 2012) collected active measurement data from a productive HSDPA network by performing drive tests. Furthermore both approaches only rely on historical collected data without taking into consideration currently measured quality parameters of the moving vehicle. (Pögel and Wolf, 2012) stated this as a future work in their research, however did not further investigate it in (Pögel and Wolf, 2015).

In conclusion of this section it can be summarized that the connectivity map is capable to improve the overall network experience of vehicles by leveraging its historic data to plan future network transmissions accordingly. However due to the high timely fluctuation of the overall network quality as described by (Kamakaris and Nickerson, 2005), we argue that the data stored within the connectivity map should not be considered sufficient enough. In addition instantaneous measurements of the currently experienced network quality should be taken into account, too. A variety of contributions, which only rely on those instant values, are presented in the following Section 2.2.

2.2 Online Throughput Estimation

As one of the earlier contributions within the field of instantaneous throughput prediction (Xu et al., 2013) develop PROTEUS, a system interface, which collects instantaneous network performance parameters, such as throughput, loss rate and one way delay of 3G networks to predict the future network performance. The authors did not investigate the performance of their approach regarding the more advanced 4G/LTE networks as it is the case in our contribution. PROTEUS relies on Regression trees to enable the improvement of services such as VoIP, video conferencing and online gaming. To realize its future network predictions PROTEUS only relies upon the last 20 seconds of experienced network performance and completely avoids any form of previous offline training.

(Liu and Lee, 2015) addressed this gap by relying on previously driven trace data of 3G networks to train their online throughput estimation approach. The estimator itself relied upon 60 average through-

[1] www.sharetechnote.com/html/Handbook_LTE_CQI.html

[2] Diagnostic Monitor. http://goo.gl/ibV7g1

put samples of 5 seconds long data transmission (300 seconds in total). This data is then used to predict the following 300 seconds of future throughput. The authors did not specifically investigate a mobile scenario, in which the measuring probes are moving, they still support our assumption regarding the significant impact of locality by stating that their obtained results have been different for varying locations, where the measurements have been performed. As a small disadvantage their approach has to rely upon information gained by initially transmitting data to be able to predict the remaining transmission quality. This approach might not be feasible for only short term transmissions of small amounts of data as it is the case in many automotive scenarios like sensor data uploads from the vehicles or map updates for highly automated driving vehicles as described in our previous works (Jomrich et al., 2017b), (Jomrich et al., 2017a).

(Jin, 2015) are one of the first works, who investigated 4G/LTE cellular networks for instantaneous throughput prediction. The authors used ensemble learner to predict the future throughput and also relied on the QXDM toolset described previously. Thus they were able to obtain a large set of precise network parameters (e.g. the number of assigned Resource Blocks for each client), which would otherwise not be available. The authors share our opinion, that relying on the QXDM toolset makes a current large scale deployment not possible as considered by our approach. The currently available devices (October 2017) do not provide such values "out of the box".

(Margolies et al., 2016) investigate the influence of so called "slow-fading" on the obtained channel quality of 3G networks, which is experienced specifically by mobile nodes (e.g. vehicles), which are moving between different cell towers. Instead of predicting the future achievable throughput (as it is the case for our work) the authors try to predict the position of the vehicle without relying on GPS sensors. The current location of the vehicle therefore is predicted based on the experienced short term history of signal quality. In a second step the estimated position segment, in which the car is currently residing, is than queried from a connectivity map to provide the averaged throughput value of this specific segment for further transmission planning. Thus the approach does not include any kind of online estimation for the future throughput value. Similar to previous work all the measurement values have been obtained in a fine granular resolution of only some milliseconds by using the QXDM tool set.

Ide and Wietfeld et al. (Wietfeld et al., 2014), (Ide et al., 2016) propose a predictive Channel-Aware Transmission scheme (pCAT), which tries to identify so called connectivity hot spots of good network quality based on measuring the experienced current and historic Signal To Noise Ratio (SINR) to improve the overall network performance, especially the required energy consumption for each data transmission. Although the authors do not predict the actual achievable throughput, they propose in their first work (Wietfeld et al., 2014) an approach that combines historical measured SINR values stored in a connectivity map and currently measured values together to identify the connectivity hot spots. Thus the general concept is similar to the investigated idea within our work. In their second work however the authors then focus only on location-independent connectivity data to feed their channel-aware transmission scheme. Also only the Signal To Noise Ratio (SINR) is investigated as an influencing factor of the channel quality. In our work we take additional quality parameters into account.

(Samba et al., 2017) present another approach to predict the currently achievable throughput bandwidth in current 4G networks. Therefore they rely on the usage of Random Forest classification trees. In contrast to the work of Ide and Wietfeld et al. the authors also consider further parameters like the Received Signal Strength Indicator (RSSI) and the Reference Signal Received Quality (RSRQ) in their approach. They also take the context of their performance measurements into consideration, e.g. the current distance between the device and the cellower and its moving speed, but they do not include the exact location. As a result they do not provide location specific training data sets to their machine learning classifier like it is the case for our work. Additionally to the information collected by the device the authors further rely on a data set provided by a cellular network provider, which offers further details about the radio access network. Samba et al. show, that this information in combination with the achieved data from the end user devices improve the estimation results. However we argue that such information should not be expected to be shared on a common basis between the network providers and vehicles. Thus a general deployment of a predicition approach that relies on such data is questionable. Furthermore the authors obtain their measuring data from a crowdsourcing campaign in which 30 different users performed a total of 5700 measurements in 350 different cells. This results in a large diversification of different locations. For our measurements we narrow our measurement campaign to only a small part of the German highway A60 to achieve a significant high number of measurement results in a small amount of cells as described in Section 3.2.

Our personal contribution is now described in the following Section 3. We present our findings regarding a throughput estimation algorithm to be used in a purely mobile context. Therefore we investigate possibilities to combine both presented concepts together: the connectivity map with its historic data set regarding future locations and the online estimation algorithms with their measurements of latest achieved network quality to predict the future experienced throughput.

3 CONCEPT

As the main contribution of this work we want to investigate the possible performance of online throughput estimation algorithms in a future large scale deployment. Therefore we let our investigated throughput estimation algorithms only rely upon network quality parameters, that can be collected "out of the box" from currently available (October 2017) public APIs and end customer hardware instead of relying on expensive diagnostic toolsets or special hardware as frequently used in the presented Related Work. The exact setup is described in the following.

3.1 Measuring Setup

To make our measurement results and achieved estimation performance comparable for other researchers, we used Android smartphones as measuring probes. Such devices are able to provide a similar amount of different network quality parameters in a timely granularity, that is also achieved by current built-in communication systems, but instead are freely available for easier comparison.

Most of the contributions presented in the Related Work investigated their personal concepts by probing older 3G UMTS and HSDPA networks. In contrast to them we focused our measurement campaign purely on active measurements of the current 4G/LTE network. In contrast to the work of(Samba et al., 2017), which also investigated 4G networks, we used newer devices of the LTE category 6 (Samsung A3) and 9 (Samsung S7), which are able to rely on new technological features like Carrier Aggregation or 4x4 MIMO. The measurements of those devices were compared with a device of category 4 (Google Nexus 5), which cannot rely on those technical features.

To collect the required quality indicators for the estimation algorithms, we developed an Android application as described in our previous work (Jomrich et al., 2017a) that logged all available network parameters, which we could obtain from current Android OS systems, while performing our throughput measurements. Those pairs of passive obtained network quality parameters and active throughput measurements were then used as data for our investigation of throughput prediction with state of the art machine learning techniques as presented in chapter 4. Depending on the specific device type different network quality parameters could be obtained via the usage of the Android API. The Samsung A3 and the Samsung S7 devices could provide the same feature set. The Nexus 5 device in contrast provides only a reduced feature set as described in the Table 1.

Table 1: Obtained measurement parameters of the different devices for network quality estimation.

Device type	used features for training
Samsung A3 / S7	Signal Strength Level, Timing Advance, RSRP, RSRQ, CQI, RSSNR, average speed of vehicle
Nexus 5	same as A3 and S7, but no Timing Advance, CQI and RSSNR

Based on the provisioning constraints of the Android OS all described network parameters were obtained with a timely resolution of up to one second. This is a rather coarse timely resolution in comparison to the specialized tooling software like Qualcom's QXDM, which is used frequently in other Related Work and can obtain the data within only some milliseconds granularity. Thus we expect less accurate prediction results.

Similar to the Related Work of (Lu et al., 2015) we used the UDP transport layer protocol to perform our throughput measurements. Therefore we modified the described application in (Jomrich et al., 2017a) to be able to execute continuous measurements. We selected the UDP protocol as our transport layer protocol, as we wanted to be able to perform our measurements as quickly as possible without wasting any costly cellular traffic data. UDP in contrast to the TCP protocol does not rely upon protocol specific control mechanisms like slow start and congestion control. Thus by using UDP we could probe the upload and download speed right from the beginning of our measurement transmission. To verify, that our application was able to congest the available cellular connection, we used the LTE network sniffer Imdea OWL developed by (Bui et al., 2017) as a ground truth. Within their work Bui et al. could verify that smartphone applications can reliably measure the available throughput by decoding the LTE control channel and correlating the transmitted packets of the measurements with the decoded results. We tested different probing set-

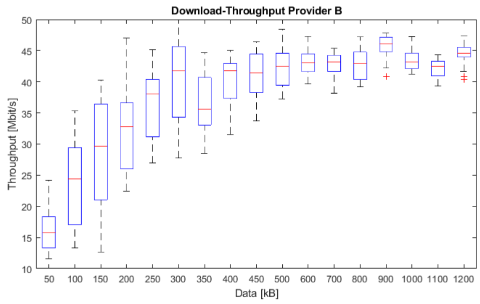


Figure 1: Investigation of the amount of data that saturates the bandwidth of one single LTE cell in the download. Within this picture the obtained results for Provider B are shown. They are similar for Provider A.

Table 2: Measurements executed for two different providers with three different devices of different categories.

	Provider A		Provider B	
Device	Samsung S7 (Cat. 9)	Google Nexus 5 (Cat. 4)	Samsung A3 (Cat. 6)	Samsung S7 (Cat. 9)
Amount of measurements	36775	12834	9166	15513
Amount of data [GB]	27,58	9,63	6,87	11,63

tings to conduct our measurements as data efficient as possible. Besides data efficiency also measuring accuracy was ensured by verification through Imdea OWL. The achieved results of this investigation are presented in figure 1.

As a concluding result we conducted our further measurements throughout the testing campaign by sending a packet train of 750 Kilobyte of data to a dedicated server and receiving the same amount of data via download from it. We ensured the server to be sufficiently connected with around 500 MBit/s of transmission speed in both directions. In total an amount of 74.468 upload and download speed measurements could be collected. The distribution of the measurements is indicated by Table 3. We collected measurements for two different providers, which could provide 4G/LTE connectivity along our complete test track. The collected data set will be made publicly available on GitHub [3]. We hope this way to provide a new benchmark data set for further future approaches of related scientific work.

[3]https://github.com/florianjomrich/cellularLTEMeasurementsHighwayA60

3.2 Scenario Description

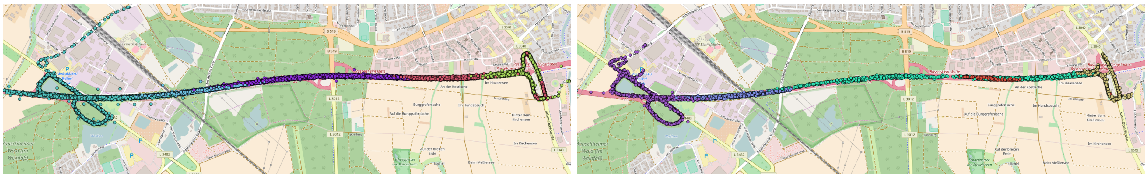
In contrast to most of the presented Related Work, we focused our measurement campaign specifically on a mobile scenario. Highly automated driving is currently developed with a major interest regarding the initial deployment on highways. To investigate the possible usage of our concept for such a communication scenario, we selected a short section on the Germany highway A60 for our test measurements as shown in Figure 2. Throughout this track the smartphones have always been connected to 4G/LTE network cells. At certain segments even 4G+ connectivity, which indicates the availability of Carrier Aggregation, was available for the A3 and the S7 devices. The measurement campaign was conducted for a period of 3 weeks. Within the campaign we compared the networks of two German providers, in the following named A and B. As an interesting side constraint all the cell towers of Provider A operated in the LTE Band 20 at frequencies of 800 MHz. For provider B the situation was contrary. Nearly all it's cell towers (with only one exception) operated in the LTE Band 3 at frequencies of 1800 MHz. The different cells to which the smartphones have been connected are colourised in Figure 2 with different colours.

3.3 Investigation of Machine Learning Algorithms for Use in Evaluation

As an initial investigation, before executing our evaluation we compared different Ensemble Learner algorithms with each other, regarding their overall performance on our data set. Namely we investigated Gradient Boost a boosting machine learning algorithm, as well as the Random Forest as one of the representatives for the bagging technique. Throughout our investigation we could not identify a certain advantage off one of the algorithms over the other. Therefore to be comparable with the newest Related Work of (Samba et al., 2017) we decided to further rely in our evaluation upon the Random Forest algorithm. The presented results in the following Section 4 therefore have been obtained by using the Random Forest regression algorithm for the prediction of the throughput value.

4 EVALUATION

We now present the obtained evaluation results gained from our three weeks long measurement campaign. To ensure a representative timely distribution in our dataset we performed our test drives each day of the



(a) Provider A (b) Provider B

Figure 2: Selected driving scenario for the measuring campaign. Measurements of different cells are coloured differently. ©OpenStreetMap contributors.

Table 3: Median of achieved throughput values for both providers.

	Provider A		Provider B	
Device	S7	Nexus 5	A3	S7
Median upload speed [Mbit/s]	13,40	13,47	13,48	13,37
Median download speed [Mbit/s]	29,25	30,88	34,32	35,69

week, separated into two different time slots, a morning part (from 8 till 12 o'clock) and an afternoon part (13 till 17 o'clock).

4.1 General View on the Collected Data

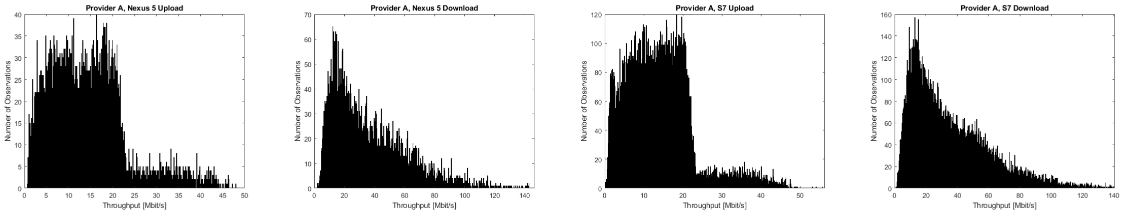
As the first step of our evaluation we did a check of the distribution of obtained throughput measurements in the upload and download direction. Therefore we separated the data in further sub sets accordingly to the three different devices for each of the two different operators, which networks have been used in the campaign. The resulting histogram plots are presented in Figure 3. With respect due to space constraints, we only show the results obtained for Provider A. The plots for Provider B however are very similar and the achieved median throughput values for the upload and download direction of both providers is shown in Table 3. Based on those values we could not identify any specific advantages of the newer devices with LTE category 6 (A3) and 9 (S7) compared to the older category 4 devices (Nexus 5). The medians of the upload and download are nearly the same for the devices used for each provider. Provider B could only achieve a small performance advantage of around 5 Mbit/s in the median in the download compared to the same device used in Provider A's network. These findings support the statement of (Jin, 2015), in which the authors identified the providers to compensate certain technical disadvantages of older devices through a fair scheduling trade off between old and new devices. Older devices get assigned more resource blocks throughout a transmission and therefore achieve comparable data transmissions like newer devices.

4.2 Correlation between Training Data Size and Prediction Accuracy

The correlation between the size of the used training data set for the machine learning approach and the resulting prediction accuracy was one of the first questions, which we wanted to investigate. Within all the presented Related Work this factor has not been discussed. It however is an important question for scientists or companies, who want to perform similar measurements and to ensure the reliability of our obtained results. We investigate how the prediction accuracy is related to the actual used training data set size and whether this correlates as well with the specific type of the device, the provider or the direction of the data transmission. To answer this questions we selected randomly a subset of all our measurements, which have been conducted by the device for the certain provider and applied the Random Forest Algorithm for regression on it. To ensure the significance of these results we repeated the process of random selection and algorithm application for 30 times. In Figure 4 the obtained results are presented as box plots. Interestingly the variance and the prediction accuracy of all the different trained models saturated between 1500 and 2000 measurements used for training, independent of the specific device under consideration or the provider under test. The further improvements regarding variance reduction and increasing the prediction accuracy, which could be achieved by using more training data (up to 10.000 measurements), were only minor.

4.3 Comparison between Upload and Download Prediction Accuracy

Most of the presented Related Work focused on the prediction of the throughput in the download direction to optimize the user experience of applications, which are receiving data on the users device. The most frequently used example are adaptive video streams. Future autonomous driving vehicles however won't be only consumers of data. They will be providing relevant personal sensor information to central



(a) Nexus Upload (b) Nexus Download (c) S7 Upload (d) S7 Download

Figure 3: Distribution of achieved throughput measurements in the network of Provider A.

backend servers. This data will then be processed and shared between all traffic participants to further enhance the overall safety while driving. Furthermore the passengers inside the vehicle might also request different kinds of services, which require a certain upload throughput, for example for Skype video calls. To also support such applications we measured the achievable throughput in the upload and in the download direction throughout our measurement campaign.

The achieved results for the different transmission directions are presented in Figure 4. The plots show the achieved prediction accuracy of the Random Forest algorithm trained for regression learning. To be comparable with the Related Work we used the same metric like (Samba et al., 2017), the R^2 value. R^2 is defined as described by Formula 1, where $\bar{y}$ is the average of all considered throughput measurements, y_i is the current throughput estimation and is $\hat{y}_i$ the predicted throughput value.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(\bar{y} - y_i)^2} \tag{1}$$

We have to state, that with our obtained measurement data set we were not able to reproduce the overall achieved performance of the Random Forest Algorithm's estimation accuracy as stated by (Samba et al., 2017). The most likely reason therefore might be the difference in the overall transmission time between our two different approaches. Samba et al., as stated, conducted a download measurement by transmitting 4 MB of data. In a former work of them (Samba et al., 2016), the authors stated that in average one of their data transmissions took about 8 seconds of time. Within our current work however, we wanted to keep the data transmission time as short as possible, as due to the mobility of the vehicle the cellular network quality is also constantly changing and influencing the obtained measurement result. Thus we only transmitted an amount of 750 KByte of data per measurement to still ensure a congestion of the data channel as described in Section 3.1. In a stationary scenario transmitting more data over a longer period of time possibly compensates the short term fluctuations of the network, when calculating the overall throughput. Thus the machine learning might become more reliable, as only a long term average throughput is being used for learning, which contains less fluctuation. This however might not be a feasible approach in a pure mobile context, as investigated within our work, in which changing quality effects due to the mobility of the vehicle play a much more important role. A possible trade off between those two noises to achieve a higher precision of the throughput prediction in our mobile context will be investigated by us in future work. Another possibility to improve the achievable performance could be to improve the timely resolution of obtained network quality parameters, to get a more accurate impression of the timely behaviour of the network (e.g by relying on QXDM). For our current approach however this is not possible, as the interval for receiving quality parameters is limited by the Android OS.

Still the achieved results show, as expected, that the actual value of the obtainable download speed is more difficult to predict, than the corresponding one for the upload speed. This holds true for all devices and both investigated providers. The most probable reason therefore is the more diverse distribution of achievable download throughput values compared to the distribution of the upload values (see Figure 3). Due to a wider range of possible outcome values the prediction of the machine learning approach becomes more difficult. This especially holds true for modern 4G networks, which achieve a higher bandwidth than older 3G technology. Further possible reasons might be the higher modulations schemes, which can be used in the download direction or the usage of the MIMO antenna technique for the download data stream. Both factors might influence the overall consistency of the signal quality during the execution of the measurement.

4.4 Comparison between Different Devices

Throughout our measuring campaign we performed the throughput estimation with three different devices

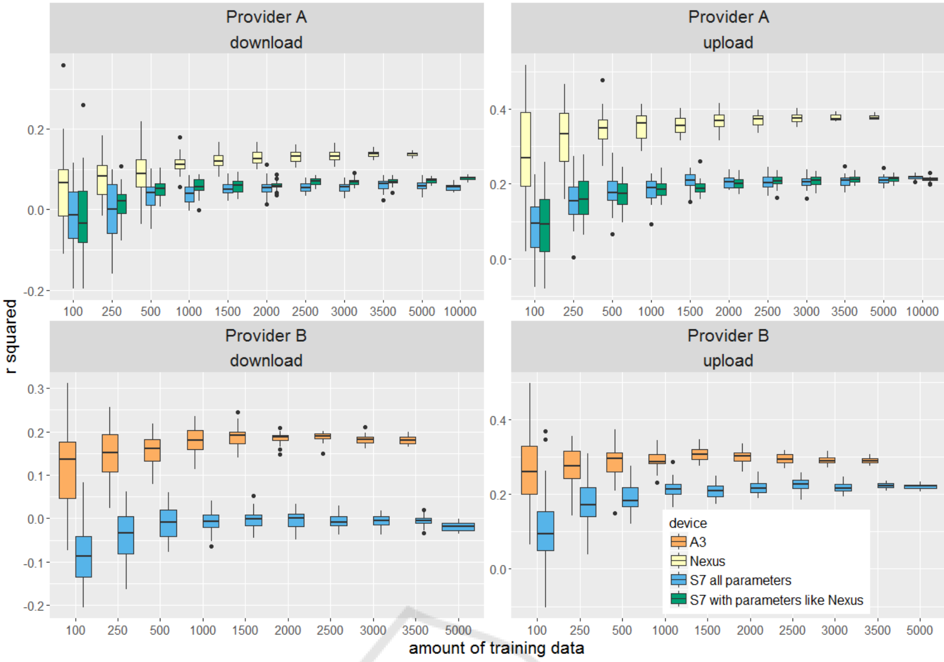


Figure 4: Comparison between the different devices for the different providers.

(Nexus 5, Samsung A3 and S7). Each device was related to a different LTE device category (4,6 and 9). The significant amount of measurements collected by each device (see Table 3) enables us to investigate a comparison between them, in contrast to most of the presented Related Work, where all devices were considered together. Although the distribution of the overall achieved throughput measurements are very similar (see section 4.1) for all the devices, the prediction performance of the Random Forest Algorithm is quite different for each of them (see Figure 4). The data provided by the Nexus 5 smartphone achieves the highest prediction performance, although the set of parameters, which the Nexus 5 can provide (see Table 1) is reduced. To investigate the possible influence of those neglected network parameters (e.g. the Channel Quality Indicator - CQI), we investigated the performance of the estimation algorithm based on a training data set of the S7 device, where those parameters have not been considered for training (see Figure 4). The obtained results therefore however are very similar to the full set of parameters for the S7. The performance of the Nexus 5 device still could not be reached. Most surprisingly the performance of the throughput estimation based on the measurements obtained from the Samsung S7 device also performed worse in comparison to the achieved results of the Samsung A3 device. Even though both devices provided us the exact same set of network quality parameters. The possible influence of Carrier Aggregation can only be considered for the comparison between the Nexus 5 device and the S7. Still it would only explain the difference for the download direction, as in the upload direction no Carrier Aggregation is used. In contrast the A3 and the S7 both relied on this technology within our measurements. In conclusion it can be stated, that the specific hardware built into each device seems to play a very important role in the achievable overall performance of the estimation, although the overall obtained measured throughput is nearly the same. An investigation, if a longer throughput measurement (as described in Section 4.3) can reduce these device dependent effects, shall be conducted in future work.

4.5 Influence of Local Training Data Compared to Global Training Data

As a further idea, which we propose in this work, we investigated if the performance of an online throughput prediction algorithm could be improved through the usage of cell tower specific/geo-referenced training data. Such a functionality for example could be realized through a connectivity map. Based on the large scale historical data contained in the map, it could provide specifically trained Ensemble Learners for each cell tower along the path of the vehicle to be used by the throughput estimation algorithm. In our opinion, instead of only relying on a generalized, non-geo referenced training set, this might possibly increase the algorithms performance. To examine this idea, we generated decision models based on the data specifically obtained from the eight cells, in which we could gather the most measurements. Those eight cells split up into four cells per provider. All those measurements have been collected with a Galaxy S7 as measuring device. Those cell tower specific decision models were than compared to decision models of equal size, which have been generated form data obtained from all the other cells in which we conducted measurements. For performance comparison both decision models (locally trained and globally trained) were than tested on separated test data, which was measured in the cell tower currently under investigation. We ensured the ratio between training data size and testing data size to be 70:30. Again we repeated the experiment for 30 times with randomly selected measurement sub sets to ensure the significance of our obtained results. This time we calculated the mean absolute error between the predicted throughput value and the actual tested throughput value as metric of comparison. Due to space we present only the plots obtained for the four cells of Provider A. The results for Provider B were similar, but due to a smaller amount of collected measurements per cell probably not as representative. We certainly agree that by comparing only eight network cells with each other no generalisation for the whole LTE network is possible. However our resulting graphs show some visible tendencies, which might become even more significant if a more precise measuring approach or network quality parameters of a finer timely resolution can be used in future work. As tendency it is visible, that in the cells where the Random Forest algorithm performed best or close to it, the decision tree with local training data could improve the overall estimation accuracy significantly. For cells, in which the algorithm did not perform very well in comparison, the influence was not significant. For one of those cells (cell D) it even performed a bit worse in the upload direction. The influences were more visible for the upload direction. This probably correlates again with the poorer prediction performance, which the Random Forest algorithm could achieve for the download speed based on our collected measurement data set as discussed in section 4.3.

In conclusion we state that our obtained results show potential, that justifies further personal research regarding it in future work.

5 CONCLUSION AND FUTURE WORK

In this paper we investigate the possible performance of online throughput estimation algorithms for the currently deployed 4G/LTE cellular network to ensure a reliable connectivity quality for services required in the context of highly automated driving vehicles. We especially wanted to examine the possible applicability of those algorithms in a large scale future deployment on existing communication hardware currently built into the vehicles. Therefore we base our performance estimates on a data set, which is collected by using Android smartphones as comparable and low cost hardware, that can be used "out of the box" without the requirement of any further special tooling or equipment. We obtained a measurement data set of over 74.000 throughput measurement values for the upload and the download direction with correlated network quality parameters over a period of three weeks. This data set will be made publicly available to the community for further investigation in future work and as a support of other related research. Furthermore we give a broad overview of Related Work in the areas of connectivity maps and online throughput estimation algorithms to enhance the overall experienced connection quality in vehicular communication scenarios. In addition we examine the idea to combine the capabilities of both techniques together by training the used Random Forest machine learning algorithm with localized training data, in comparison to non-geographically referenced global training data. In contrast to Related Work we specifically focused our measurement campaign of the cellular network on an automotive and mobile scenario. Based on the obtained results we can show, that the throughput estimation in a mobile context is rather difficult compared to a throughput estimation predicted for a stationary scenario, as already performed in Related Work (Samba et al., 2016). A possible reason therefore might be the contradicting influence of two different noises. The general performance fluctuation within the network can be reduced by conducting measurements over a longer period of time. Unfortunately in our mobile communication context this introduces additional fluctuation through the movement of the vehicle and the correlating changing network quality. A possible tread off between those two different noises to obtain better performance results shall be investigated in future work. Furthermore we could showcase the influence of different measurement devices on the overall obtained estimation results for the 4G/LTE productive networks of two German providers. For future work we will extend the

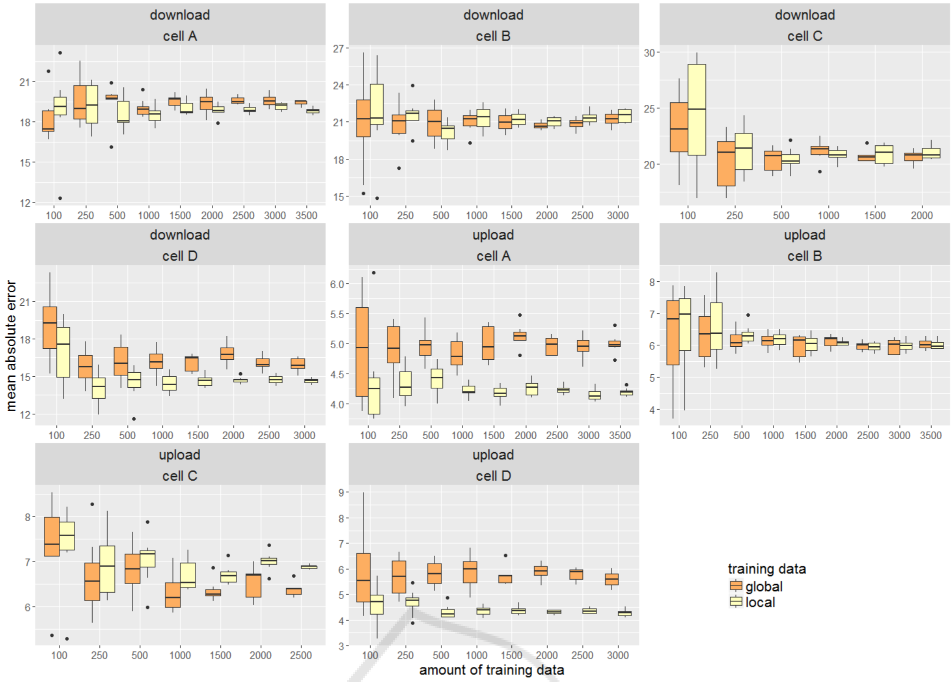


Figure 5: Comparison of the performance of local vs global training data sets of the same size.

presented work by investigating the performance of currently deployed communication hardware within the vehicles themselves and compare those achieved results with our presented results. By continuing the collection of measurement data also the investigation of timely aspects like changing network load over the day and provider specific traffic scheduling shall be investigated. Therefore normalisation techniques as described in (Gozalvez and Coll-Perales, 2013) shall be taken into consideration. Furthermore a deeper investigation of new technological effects like the overall influence of Carrier Aggregation is necessary. As the Android OS only indicates the availability of this LTE-Advanced feature, but not its actual usage, it is currently not possible to get further details to improve the prediction accuracy. Thus our current work, which only relies on the public available Android API shall be enhanced in future with more in depth analysis features.

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