How Road and Mobile Networks Correlate: Estimating Urban Traffic Using Handovers

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***Abstract*— We propose a novel way of linking mobile network signaling data to the state of the underlying urban road network. We show how a predictive model of traffic flows can be created from mobile network signaling data. To achieve this, we estimate the vehicular density inside specific areas using a polynomial function of the inner and exiting mobile phone handovers performed by the base stations covering those areas. We can then use the aggregated handovers as flow proxies alongside the density proxy to directly estimate an average velocity within an area. We evaluate the model in a simulation study of Luxembourg city and generalize our findings using a real-world data set extracted from the LTE network of a Luxembourg operator. By predicting the real traffic states as measured through floating car data, we achieve a mean absolute percentage error of 11.12%. Furthermore, in our study case, the approximations of the network macroscopic fundamental diagrams (MFD) of road network partitions can be generated. The analyzed data exhibit low variance with respect to a quadratic concave flow-density function, which is inline with the previous theoretical results on MFDs and are similar when estimated from simulation and real data. These results indicate that mobile signaling data can potentially be used to approximate MFDs of the underlying road network and contribute to better estimate road traffic states in urban congested networks.**

***Index Terms*— Mobile network, cellular, traffic state, traffic flow theory, macroscopic fundamental diagram.**

I. Introduction

MOBILE networks are ubiquitous. Today there are more than 6 billion mobile subscribers worldwide that are continuously online [1]. Those users produce an unprecedented amount of information that can be used to study various aspects of our everyday life. Over the past decade there have been various research efforts to extract useful knowledge from this data. More recently, research challenges have been launched providing access to large datasets that have been released by telecommunication operators [2], [3]. In their survey on the analysis of data from mobile networks, Calabrese *et al.* [1] identify numerous topics of interest and open challenges in this domain. They include the analysis and understanding of human mobility patterns, such as the usage of mobile phone data as a complementary source for estimating dynamic traffic conditions. Their list of open challenges includes characterizing the interplay between mobile networks and the actual mobility of users, as well as privacy and data anonymity considerations. An important work discussing the feasibility of using mobile phone data to estimate traffic states was proposed by Rose [4] back in 2006, in particular using *handovers*, i.e. the transfer of a phone's connection between base stations. While highlighting the potential of mobile phone data for traffic applications, Rose discusses the need for a systematic assessment of the quality of the data from various radio access technologies.

This gap was closed by Becker *et al.* [5], who show the stability of handover patterns with respect to road, weather and hardware conditions, and Gundlegård and Karlsson [6], who compared the utility of 2G and 3G handover patterns for travel time estimation and showed the superiority of 3G for this purpose.

Generally speaking, the newer radio access technologies (i.e. 3G and 4G/LTE), which significantly increase the density of cells and the volume of data traffic, thus improving the granularity of the mobile network data and making it a viable alternative (or complement) to traditional *Traffic Information Systems* (TIS). Although it has been shown that mobile data provides a good indicator to estimate and predict traffic states on highways [7], finding accurate predictive traffic models in urban networks remains a challenging task to due to the highly dynamic nature of traffic.

Naboulsi *et al.* [8] confirm this fact in their recent extensive survey of mobile data analytics, in agreement with the earlier survey work by Steenbruggen *et al.* [9].

From a traffic flow theory perspective, urban network traffic states can be described in an aggregated form by the so-called *Macroscopic Fundamental Diagrams* (MFD), or often also called *Network Fundamental Diagrams*, as described by Geroliminis and Daganzo [10] and Mahmassani [11], [12]. MFDs serve to describe the flow, density and velocity relationships of the cumulated data from multiple detector sources within a partition of the network, provided that traffic states and road capacities are relatively homogeneous. These models therefore allow the estimation of traffic conditions for partitions of the network and enable traffic management techniques such as perimeter or coordinated intersection control [13], [14] and gating [15], [16].

On the practical side, obtaining data that exhibit MFD characteristics is difficult, and the traffic flow theory community

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has recently launched a challenge to compile suitable empirical data for MFD modeling [17]. In this context, we see potential for mobile phone data, in particular signaling data provided by mobile network operators, to contribute to detect and quantify urban mobility patterns. With the latter type of data, we can follow the intuition that the mobile network observes flows in the form of handovers, similar to the way conventional traffic sensors do. By linking the mobile network as data source to the concept of MFDs, we can address two of the challenges identified by Calabrese *et al.* [1]: 1) we characterize the interaction between road and mobile networks, and 2) we preserve user privacy as we estimate aggregate flows via aggregate data sources.

In this work, we want to exploit the correlation between the road traffic state and the observed behavior of the mobile network in analogy to the concept of MFDs, i.e. we want to approximate MFDs from mobile network signaling data. In previous work we have shown that urban mobile network clusters exhibit MFDs if vehicles can be identified from mobile networks users [18], [19]. In those works, we simulated handover information (vehicles only) and showed that they are a good proxy for traffic flow estimation. More recently in [20], we showed the feasibility of traffic state estimation using a real cellular data set provided by a local telecommunication operator. We proposed a model based on a common density proxy function along with a single regression model that has been applied to highway and mixed clusters. The model has been validated using *Floating Car Data* (FCD) recorded over the same period. The results show that the model works well for the highway and transit clusters but proved to lack of descriptive and predictive power for purely urban clusters.

To overcome this gap and show that MFDs can be modeled for urban clusters using cellular handover data, we will propose a novel methodology evaluated in both a simulation and a real data study. In the following of this paper we introduce the related work in this field and the necessary concepts.

II. Related Work

Mobile network handovers exist in two varieties: passive handovers of phones that are currently not in an active phone call or data session; their location is known to the network at *Location or Region Area* (LA/RA) level, encompassing potentially hundreds of mobile cells. On the other hand, active handovers of phones in a connected state provide information of the exact currently associated mobile cell.

A lot of research has been focusing on passive handovers, i.e. coarse-grained *Location Area Code* (LAC) updates which can be useful in predicting highway travel times [8]. The main work in this area is a study by Janecek *et al.* [7], who combine location updates to the handovers of active calls along a specific highway in Austria. They study the rate of LAC updates from idle mobile phones and augment this knowledge with the rate of active connection handovers to clearly identify and precisely locate the source of congestion. However, this methodology is valid for highways only and it is difficult to extract the required data for larger areas. In general, passive handovers (LAC updates) are difficult to use for state estimation in urban environments. They are better suited for long-range travels, as studied by Hui *et al.* [21]. In this work, we want to investigate how mobile network data can be used for estimating congestion within cities, by using only aggregated *active* connections. For these connections, the precise cell – rather than a large location area – is known, leading to a much higher spatial resolution even when computing aggregate statistics. In this vein, Bar-Gera [22] ran a study on using active connection handovers to predict freeway travel times, using probe mobile phones to record both the handover events and travel times and comparing the measurements to loop detector data. Again, this study focused on highways and not on urban settings.

Another limitation of cellular datasets for traffic flow estimation is that they include mobile and static nodes. To overcome this limitation, Caceres *et al.* [23] proposed a set of models to infer the volume of vehicles from the cellular data by calibrating them with data collected by loop detectors. On average their best model achieves an absolute relative error of less than 20% for highway scenarios. They conclude that cellular data can be used as a complement to traditional fixed sensors to enhance the available information for mobility monitoring. Generally speaking, there is little research regarding traffic states in urban environments, as Naboulsi *et al.* identify in their survey [8]. The main study in the urban traffic area was done by Calabrese *et al.* [24], who performed analyses of the Telecom Italia dataset for the city of Rome, in particular Erlang data (a unitless metric of the intensity of mobile network usage) alongside taxi and bus data. This allowed them to build a platform to estimate what they call the *pulse* of a city, and to compare the availability of public transportation to their estimated population location density.

The correlation between road traffic states and the observed reaction of the mobile network is an interdisciplinary topic, connecting transportation and telematics. It is therefore sensible to rely on concepts from traffic flow theory such as the Macroscopic Fundamental Diagram (MFD), which describes the traffic profile of an urban area from a macroscopic, aggregated perspective. MFDs are synthetic but powerful metrics that quantify and explain the interaction between road capacity, travel and driving behavior-related parameters such as routing/rerouting, as well as characteristic vehicle speeds and car following behavior. It postulates that if a sufficiently large amount of data about traffic states in a network is collected, and the (sub) road network topology has a sufficient level of regularity in terms of route flow distribution, then state variables such as vehicle density and the total network throughput are clearly related by a concave function. This function expresses the transition between uncongested conditions to congested states, characterized in urban systems by frequent conditions of queue blocking and gridlock phenomena. Theoretical and empirical studies contributing to gain insight into the properties of MFD focused on deriving relations starting from analytical and simulation-based Dynamic Traffic Assignment theory [11], on assessing the impact of traffic control [25], and on capturing hysteresis phenomena in congested networks [26].

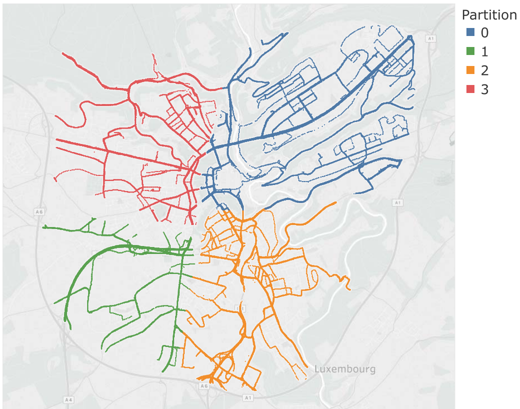

Fig. 1. Luxembourg City road network partitions used in both simulation and real data study.

III. Methodology

In this work we estimate traffic flows from a 4G mobile network dataset. The dataset is composed of two components. The first one is the position of LTE base stations (eNodeBs) and the corresponding cell identifiers hosted on each base station. The second component is the number of handovers of active connections between any given cell pair per hour.

In the remainder of this paper we will refer to the handovers within a set of cells as *inner flows* (i) of that set, and to the handover count leaving a set of cells as its *exiting flows* (o). Both metrics are scaled into $[0, 1]$ with respect to their daily maxima. We will also refer to the *traffic state* ν as the space-mean of the ratio between actual velocity and the legal speed limit $\left(\overline{v \div v_{limit}}\right)$. Further details on the different datasets used will be provided in Sections IV-B and V-A.

We want to establish a model in the form of $v = q \div k$, i.e. the fundamental flow-density relationship for partitions of the road network, in analogy to the concept of MFDs. Since in mobile networks the phone's precise serving cell is only known during an active data or call connection, we cannot access the density of mobile phones directly (as the majority of them typically are in a passive, disconnected state). Thus, we propose a three-stage approach: first, we partition the road network in areas that are large enough to capture the traffic dynamics of MFDs. Next, we model each partition's density using handovers within and from the partition. Finally, we use linear regression to estimate the traffic state from exiting flows and approximated density, thus optimizing the regression coefficients globally for all time intervals and partitions.

A. Stage 1: Network Partitioning

In this article, we will focus on theoretically and empirically studying the traffic and mobile networks of Luxembourg City[1]. Fig. 1 shows the partitioning we opted for, which we will use both in the simulation and real-data studies. The study area covers approximately 45 km^2. According to Geroliminis and Daganzo [10], MFDs emerge in areas larger than 10km^2. Thus, we opted for 4 partitions, representing the main geographical zones of Luxembourg City, i.e. physically separated plateaus, independent from the number of flows. Note, however, that road network partitioning can also be done algorithmically and depending on the flows, e.g. using the normalized cuts [27] or spectral clustering algorithms [19], or be based on data concerning mobile phone calls [28], [29].

[1]Center coordinates: 49.611634, 6.129451

B. Stage 2: Traffic State and Density Models

We want to define density and flow proxy functions to predict the traffic state in analogy to the fundamental equation of traffic flow ($v = q \div k$). The goal is to obtain an estimate of the current traffic state ν, the velocity factor relative to free-flow conditions, within the partition. To this end, we use each partition's scaled exiting flows (o) and a density proxy function characteristic of it – referred to as $k(i, o)$ below – so as to gain an expression of the traffic state akin to the fundamental equation of traffic flow. We can obtain this expression by using a linear regression with a logarithmic transformation of the variables, turning the sum into the desired ratio:

$$log(\nu) \sim a\ log(o) + b\ log(k(i, o)) + c \tag{1}$$

$$\nu \sim \frac{o^a}{k(i, o)^{-b}}\ exp(c) \tag{2}$$

In the formulation in Eq. 2, we require as a last component a density modeling function $k(i, o)$ based on the scaled inner and exiting flows ($i,\ o \in [0, 1]$) of a partition. We propose to express this relationship using a parsimonious model, a polynomial with interaction between inner and exiting flows $i,\ o$ of the partition. The degrees $(p_i, p_o, p_{ix}, p_{ox})$ and coefficients (c_i, c_x, c_o) are the model parameters characterizing the behavior of each partition:

$$k(i, o) := c_i\ i^{p_i} + c_x\ i^{p_{ix}}\ o^{p_{ox}} + c_o\ o^{p_o} \tag{3}$$

Thus, we have three global parameters that are shared between all the partitions ($[a, b, c]$) and need to be estimated to link the flow and density proxy functions into a traffic state:

$$\tilde{q} := o^a \tag{4}$$

$$\tilde{k} := k(i, o)^{-b} \tag{5}$$

The unit of k is $(veh.\ m^{-1})^{-\frac{a}{b}}$. An approximation of the space-mean density $\overline{\rho}$ with respect to the space-mean speed limit velocity $\overline{v_{limit}}$ is given by:

$$\overline{\rho} = \tilde{k}(i, o)\ o^{(1-a)}\ \overline{v_{limit}}^{-1} \tag{6}$$

Fig. 2 gives an overview of our full model in graphical form. The shaded circles represent observed variables (in the training set) and the unshaded circles are latent estimated parameters or dependent variables in the case of k. For each of the N partitions, we estimate the parameters of the polynomial density model k, i.e. the p and c parameters. Its inputs are the scaled inner and exiting handovers i and o for each interval. The density k is then used alongside o as input for the linear regression model, that is globally parameterized (i.e. for all partitions and across the entire time range T) by its coefficients a, b and c. Essentially, we approximate density, then use the flow-density relationship to estimate the traffic state.

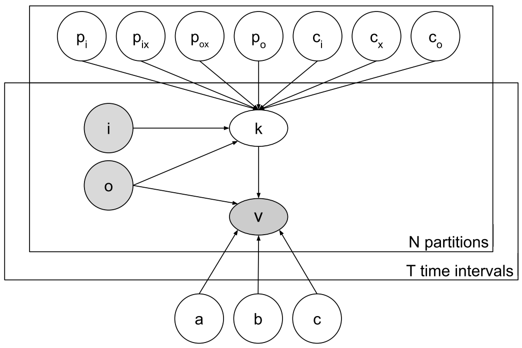

Fig. 2. Graphical representation of the model: p and c are characteristic of each partition, $[a, b, c]$ are common parameters.

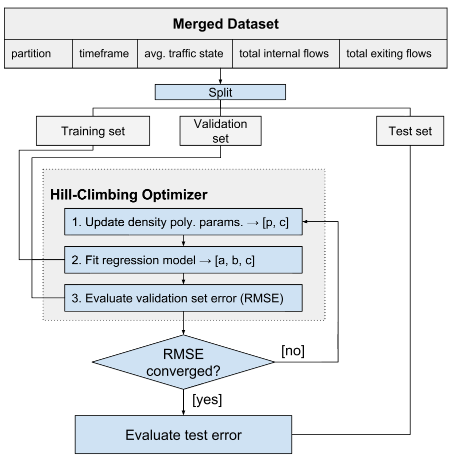

Fig. 3. Parameter estimation: hill-climbing optimizer.

C. Parameter Estimation

In order to estimate the parameters $(p_i, p_{ix}, p_{ox}, p_o)$ and coefficients (c_i, c_x, c_o) of the density proxy polynomial of each partition (Eq. 3) we implemented a hill-climbing optimizer.

Fig. 3 shows how the data set is used in this approach. We start from a random vector of density polynomial parameters in $[0, 2]$. During each iteration, we update the density parameter by adding a random offset sampled from $Uni[-0.01, 0.01]$ to a single parameter. Next, we run linear regression on our model (Eq. 2) and evaluate the resulting *Root Mean Square Error* (RMSE) of the validation set. The goal is to find the density proxy polynomials of each partition that allow the best regression performance. We accept parameter updates that lead to a lowering in validation RMSE, and that yield $a > 0$ and $b < 0$ in the linear regression step. The latter conditions are to assert that the density model can be interpreted as intended, i.e. $k(i, o)$ is a directly proportional proxy of the true density and $\tilde{v} = \tilde{q} \div \tilde{k}$ is respected.

D. Validation Techniques

In order to validate the model, we evaluate its predictive power on test data sets. We use the same methodology – i.e. partitioning and prediction model – for both a simulation and a real-world study so as to be able to compare them, and to be able to quantify the impact and limitations of the simulation.

IV. Simulation Study

A. Simulation Environment

The simulation scenario we base our study on is the LuST scenario by Codecà *et al.* [30] for the microscopic traffic simulator SUMO [31]. The scenario provides 24 hours of calibrated mobility consisting of almost 300000 vehicle trips in a wider area around Luxembourg City (155 km^2). As we are studying urban environments only, we limit our study to the inner city (within the highway ring), approximately 50km^2. We opt for this validated scenario in order to be able to compare our results to the corresponding real data.

The VeinsLTE framework by Sommer *et al.* [32] and Hagenauer *et al.* [33], realizes the connection between the microscopic road traffic simulation SUMO and the communication network simulator OMNeT++ [34], simulating the LTE connectivity of cars or their drivers.

Through VeinsLTE, the SUMO simulation is synchronized with the OMNeT++ communication simulator [34] to reflect the mobility of vehicles inside the mobile phone network. That means that SUMO simulates the movement of vehicles, while OMNeT++ computes signal strengths, connectivity and communication of the moving vehicles. More precisely, the LTE network is simulated using the SimuLTE library [35], to which we added a simplified implementation of handovers based on Signal-to-Noise Ratio (SNR). On the other side, SUMO provides the traffic demand and microscopic modeling and we use it to generate *Floating Car Data* (FCD) for validation purposes. The identifiers of vehicles are matching between both simulators and thus allow to map signal strengths by routes taken. The LTE network configuration consists in mapping 113 eNodeBs (LTE base stations) to the simulation coordinates. The original coordinates of the eNodeBs (with small noise offsets) were provided by POST Luxembourg. Note that each eNodeB hosts multiple cells, but that the simulation does not account for the precise associated cell since we have no information regarding the different cell coverage directions and areas. The simulation framework, LuST-LTE, is published in [18].

B. Artificial Datasets

From the SUMO simulator, we obtain vehicle positions and velocities, i.e. simulated floating car data. This information is augmented with the currently connected cell, allowing us to compute the *Space-Mean Traffic State* $\nu = \overline{(v \div v_{max})}$ within the coverage area of a set of mobile base stations.

From OmNET++ and SimuLTE, we extract the number of handovers between cell pairs observed. Since we know the mapping between base stations and road partitions, we can compute the inner flows (i) and exiting flows (o).

In order to construct the data set, we ran the scenario with 50% re-routing probability of vehicles and 300 second re-routing interval, which were the most realistic parameters according to the validation by Codecà *et al.* [36]. The penetration rate of vehicles in active calls was defined as 1%,

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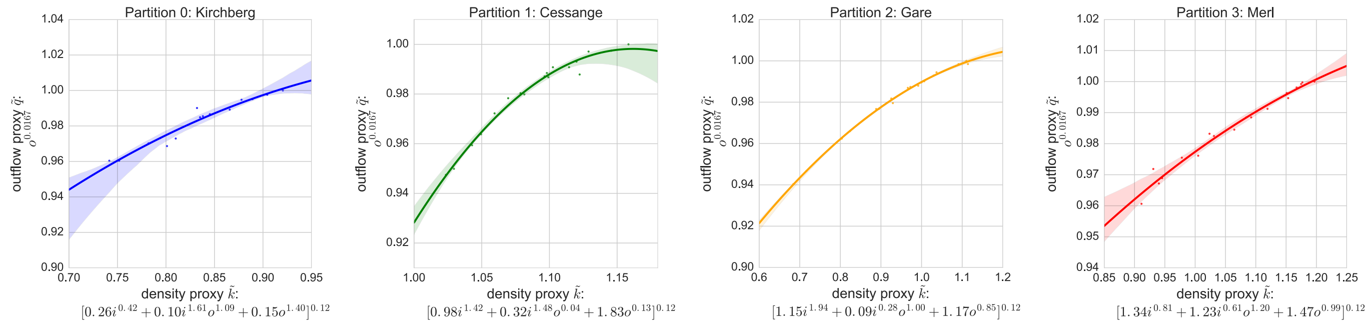

Fig. 4. Simulation study mobile network macroscopic fundamental diagrams: flow-density relationships by partition.

which is in line with a previous study by Caceres *et al.* [23]. The data set split was defined as a 50-50 split of the data, where validation and training sets both make up 25% and the test data is 50%. We opted for this split because otherwise modifying the demand and running an additional simulation day would have made the prediction error directly dependent on the degree of modification of the demand distribution.

As temporal scale, we chose 1 hour, yielding sufficient number of training and test data points (48 of each, i.e. 12 hours with 4 partitions), and matching the real data that we will study in Sec. V.

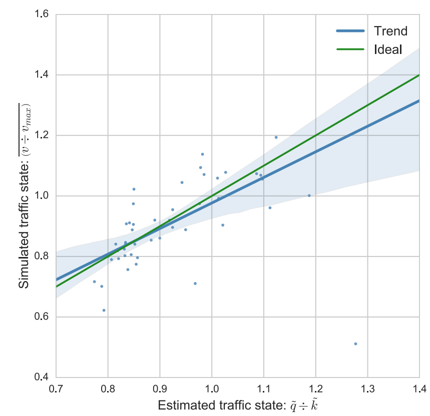

Fig. 5. Simulated mobile data-based traffic state predictions vs ground-truth simulated floating car data (12 hours of test data for 4 partitions).

C. Results

As described in Section III-C, we estimated each partition's density proxy polynomial functions and the regression coefficients jointly using a hill-climbing optimizer.

1) Mobile Network MFD Proxy: Figure 4 shows the flow-density relationship resulting from the parameter estimation (as described in Sec. III-C). We can see that Partitions 0, 1 and 2 show a tendency of saturation, and similar profiles in general. The resulting density proxy polynomials, however, differ strongly between the partitions, meaning that different ratios of inner-to-exiting handovers are characteristic of their traffic state profiles. The MFD of Partition 3 on the other hand, exhibits a quasi-linear flow-density relationship, indicating that this partition does likely not reach critical capacity and thus there is no reduction in flows caused by congestion. Thus, we do not observe the descending branch of the flow-density relationship, as we do for the other partitions. Overall, we do not observe the very harsh congestion MFD profiles that would be produced by grid-lock phenomena, but this is not the case in Luxembourg City, and is in line with other real-world results from other cities. The fact that these smooth, low-variance profiles result from our methodology is a first encouraging result, as they match the expected MFD shapes.

2) Prediction: Fig. 5 shows the model predictions on the simulated data. On the y-axis, we see the actual mean traffic states of a partition during a 1-hour window, as computed by SUMO. The x-axis represents the predictions computed by the model using the simulated LTE signaling data, namely the inner and exiting flows (i) and (o) and the derived density proxy (k). The blue line shows the trend between both measures, which should ideally coincide with the green identity line. Since trend and identity lines are close, and the variance (error) appears to be stable across the range of true traffic states. We can conclude that the model fits the data reasonably well, with the exception of an outlier at the lowest tested traffic state, which is likely due to the absence of sufficient training data in that region. The *Mean Absolute Percentage Error* (MAPE) is 10.02%, which is an encouraging result given the simplicity of the proposed model and the low amount of training data.

D. Limitations

There are several limitations in the simulation study. On the road network side, there are only vehicles, no pedestrians. There are also no stationary users, that might impact mobile network handovers by moving minimal distances and triggering ping-pong handovers. As our model takes into consideration aggregated within- and exiting partition flows, short-distance pedestrian trips will mostly happen inside a partition, not between them, and can most likely be captured by the density proxy function.

On the mobile network side, there is the inherent error of our model of purely SNR-based handovers versus real handovers, that are consistently more complex in nature. Further, we only simulate the LTE network connectivity, thus omitting the other radio access technologies, which influence handover behavior as well, e.g. through interference and intra-RAN handovers.

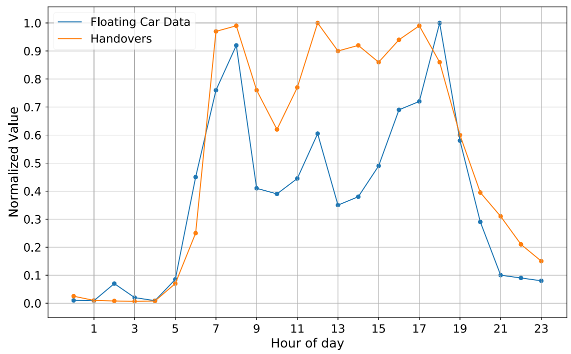

Fig. 6. Normalized number of handovers observed in the study area vs. number of floating car data entries.

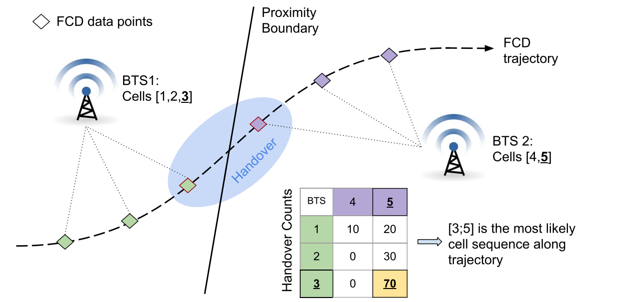

Fig. 7. Floating-car data and mobile network mapping: Every vehicle position is matched with its most likely associated mobile cell (cf. Sec. V-A3).

The fact that we only associate vehicles to eNodeBs, not cells, leads to an additional error. Most importantly, we have a static penetration rate of 1% of vehicles in an active connection. While this is a realistic percentage on average, it is dynamic in reality in the course of a day as described by Caceres *et al.* in [23]. However, for this simulation study, we focused on the general feasibility of handover-based traffic state estimation using our methodology, and not as much on the precise attainable error. Thus the limitations above should be considered but not overvalued.

Having shown the performance of the model on simulated data, we will now evaluate it using real data to show its performance without the simulation limitations.

V. Real Data Study

A. Datasets

1) Ground Truth (Floating-Car Data): As ground truth data, we use *Floating Car Data* (FCD) that was made available for a whole week at the end of September 2016. This is a set of time-stamped vehicle positions and travel speeds which were collected in the area of Luxembourg City, and consists of 600 trips and 220000 GPS data points. In particular, we are interested in *Traffic States*, i.e. the ratio between actually driven speeds and the speed limit ($v \div v_{max}$). Thus, we performed map-matching on the FCD to obtain the values of v_{limit} for every vehicle GPS data point.

2) Mobile Data (LTE Handovers): The mobile dataset contains aggregate data from 436 LTE (4G) cells within Luxembourg City. The data consists of the number of handovers between cell pairs per hour. The data was made available for the same time period as the FCD. Fig. 6 shows that the number of handover and floating car observations correlate, except for the off-peak daytime, when there are relatively more handovers, likely due to pedestrian movement and increased mobile phone usage. The strong correlation (Pearson-$\rho = 0.86$) is a main motivational aspect to our work, and we found similar correlations between mean travel speed and artificial handover counts in previous studies [37].

3) Mapping FCD to the Mobile Network: In order to enable the use of FCD for validation purposes, we need to map the most likely associated mobile network cell to each FCD data point. Fig. 7 shows an example of the method we used: First, we can easily determine the nearest *Base Station* (BTS) of each location by distance. In the example, that is BTS1 for the first three floating car data points, and BTS2 for the next three. In general, a BTS hosts multiple mobile network cells emitting into different directions, e.g. cell 1, 2 and 3 for BTS1 and cells 4 and 5 for BTS2. From a FCD trajectory we can thus identify a sequence of base stations, i.e. a set of cells potentially covering the vehicle trajectory. Then, in order to identify the single, most likely visited cell sequence, we choose the most frequent cell transition during that day to be the likely cell pair visited. That way, we build a chain of visited cells over the entire trip. In the example above, the most likely cell transition (handover) is $3 \rightarrow 5$, because most handovers are between these two cells. Thus, we pick these two cells as the most likely occurred sequence.

Using this method, we get a one-to-one mapping between each FCD data point and a cell, i.e. the cell that the driver's phone was most likely connected based on the current location. This allows to compute road traffic statistics relative to the connected cell. In the last step, to compute the *Traffic State* variable ν, i.e. the ratio between the actual observed link speeds and their respective speed limits, we perform map-matching of the Floating-Car Data entries to the *OpenStreetMap* (OSM) road network to obtain the speed limit at each entry.

Finally, the resulting merged data set contains the partition number, hour of day, inner and exiting flows ($[i, o]$) and the traffic state (ν).

B. Results

Using the merged data set as described above, we trained our model as described in Section III on the data of Monday, Tuesday and Wednesday, validated it on Thursday and tested it on Friday data.

1) Mobile Network MFD Proxy: The linear regression model resulted in the following parameters:

$$\begin{cases} a = 0.26 \\ b = -0.32 \\ c = 0 \end{cases}$$

Since there is no intercept ($c = 0$), the scale factor is 1 (i.e. $exp(c)$ in Eq. 2). Thus the prediction equations of the

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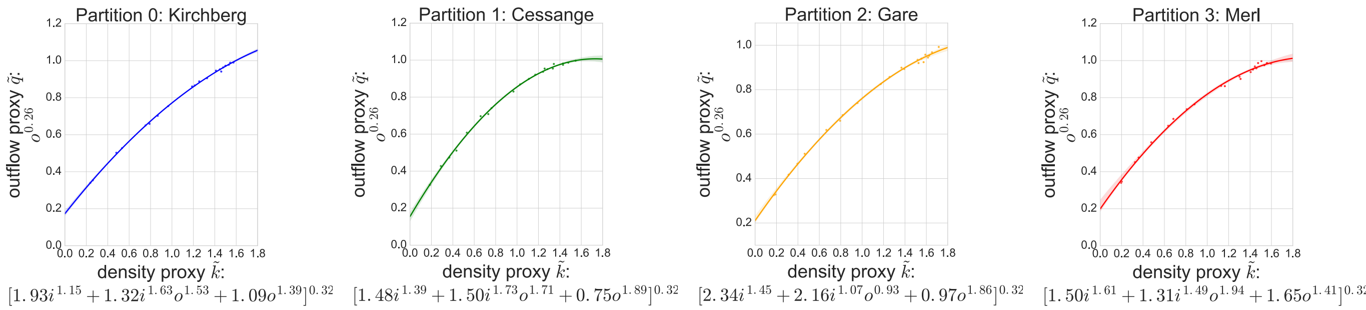

Fig. 8. Real data study: mobile network macroscopic fundamental diagrams: flow-density relationships by partition.

TABLE I

REAL DATA STUDY: PEARSON CORRELATION BETWEEN ESTIMATED AND REAL TRAFFIC STATES BY PARTITION

Partition	$Pearson{-}\rho$
0: Kirchberg	0.24
1: Cessange	0.63
2: Gare	0.53
3: Merl	0.58

space-mean traffic state ν proportional to the space-mean velocity v yields the direct ratio of $\tilde{q} \div \tilde{k}$:

$$\nu \sim \frac{o^{0.26}}{k^{0.32}}$$

We plot the MFDs given by $\tilde{q} = o^{0.26}$ and $\tilde{k} = k^{0.32}$ in Fig. 8. Unlike in the simulation study, all the MFDs exhibit very low variance and, as is expected, they all follow a concave shape as the outflow rate saturates at increasing density levels. Partition 1 (green plot) exhibits this behavior clearly.

The lower variance is likely due to the larger training set, as well as the larger number of handovers observed in the real world in comparison to the simulation, reducing the impact of noise. We can also see that there is no severe congestion in the network, caused by possible grid-lock phenomena, that would manifest itself in the descending branch of the MFD diagram. Instead, we only observe saturation of the network.

2) Correlation and Prediction: Table I shows the Pearson correlation coefficient between the model's predictions and the real traffic states observed from the FCD. We observe weak to moderate correlations for all four partitions, highlighting the information content of the mobile network MFDs. The more heterogeneous Partition 0 shows the weakest fit, and the construction of tramway tracks was ongoing during the study period. With a data-driven network partitioning method, the observed results could likely be improved, as presented in works by Ji and Geroliminis [27], Lopez *et al.* [38] and Saeedmanesh and Geroliminis [39]. This point will be further discussed in Sec. VI.

In Fig. 9, we can see the scatter of predicted and true traffic states. We can see that the error appears to be independent from the traffic state, which is likely due to noise in the FCD and the relatively low resolution of our data set. The *Mean Absolute Percentage Error* (MAPE) amounts to 11.12%, which is comparable to other mobile network-based traffic

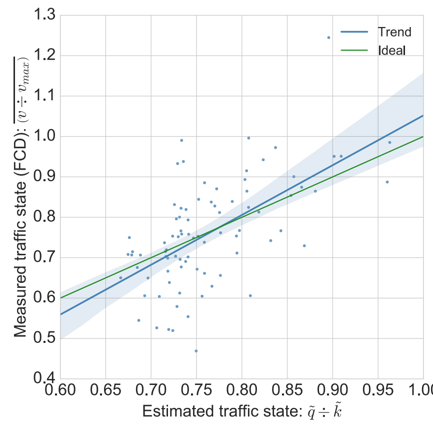

Fig. 9. Real data study: mobile data-based traffic state predictions vs ground-truth floating car data (24 hours of test data for 4 partitions).

state estimation techniques [8], but in an urban setting and with a much more interpretable model.

C. Limitations

The main limitation of our data sets is the temporal aggregation resolution of 1 hour of the mobile network data set. However, we are confident that the results will transfer onto higher temporal resolutions, and will go into some of the specific reasons of this in the following Sec. VI. Another limitation is the low amount of congestion observed in both studies. However, in previous work, we observed that in deliberately congested situations, there is evidence that the mobile network data also reflects low-throughput, high-density situations, i.e. the descending phase of the MFD [19]. In that work, the aim was to deliberately generate grid-lock conditions, while in this study, we opted for realistic demand to be able to compare simulation and real data outcomes. In Sec. VI, we discuss the aspect of congestion further.

The results achieved in this work considering urban areas are much better than previous work using real-world data [20], where we encountered very low correlation in some of the non-highway partitions. Thus, we believe that the polynomial density model introduced in this work is the key to adequately estimating urban MFDs from mobile network signaling data.

VI. DISCUSSION

The main promising result of this work is that even in complex, realistic networks with heterogeneous zones and

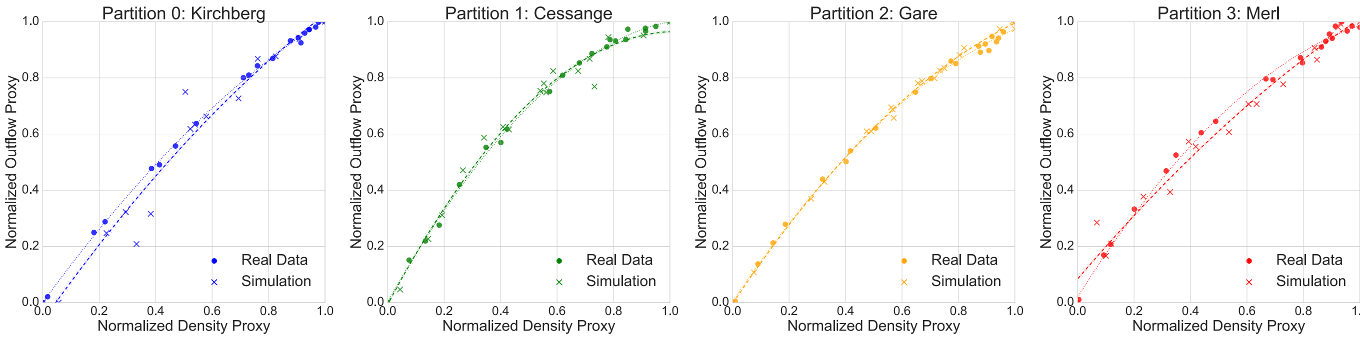

Fig. 10. Comparison of mobile network MFD approximations: Normalized flow-density relationships by partition.

unequally spaced mobile base stations, mobility patterns emerge from mobile phone data. The density proxy functions and MFDs we computed proved to show significant predictive power, leading to a MAPE of 11.12% on real data, which can compete with prior studies on (less complex) highway scenarios [7], [8], [23].

As expected, the real data prediction errors exceed those from the simulation run. This is due to the various limitations and simplified aspects in the simulation, avoiding e.g. stationary users and ping-pong handovers. Generally speaking, the simulated results were surprisingly similar in prediction quality to the real-data ones, which gives rise to a promising direction for future work.

The most important questions that arise from this work are whether complete MFDs can be extracted from mobile network data if there is a significant amount of congestion, and for which spatio-temporal scale this is feasible.

Regarding the first of these questions, we have confirmed the emergence of flow-density proxy relationships similar to MFD in the uncongested and saturated branches, as partially observed in the simulation study and more clearly in the real data study. The fact that our urban study regions do not exhibit heavy congestion and thus do not produce the descending branch of the flow-density diagram is a limitation of this work. However, in previous simulation work involving artificially high congestion, we were able to observe the descending phase of the MFD as traffic enters the congested regime [19]. That study included also the highway ring of Luxembourg city, and 15 partitions overall. The congestion was introduced by lowering the re-routing probability of vehicles in the SUMO simulator to 10%, partially causing gridlock, whereas in this study, we used the setting of 50% on which Codeca *et al.* based their calibration and validation [36]. In this work, using the calibrated demand allowed us to compare real-data and simulation results. Congested traffic conditions ought to be studied further in future work, to allow comparing mobile data-based results with studies on loop detectors by Buisson and Ladier [40] and Geroliminis *et al.* [41]. It is critical to investigate how precisely density can be approximated with mobile networks in low-throughput traffic conditions, to verify whether distinguishing between low and high density situations is possible.

With respect to the second question, i.e. that of spatio-temporal scalability, Geroliminis and Daganzo [10] have indicated 10 km^2 as lower bound on the spatial scale for the emergence of MFD from conventional loop detector signals. Therefore, in this study, we opted for creating 4 partitions with an average area of 12km^2. However, it would be necessary to investigate the impact of partition size on the flow-density approximation and their variance, and to evaluate the temporal scale at which the traffic states can be reasonably estimated from handover counts when using real-world data.

Fig. 10 shows the differences between the MFDs generated from both studies. For this purpose, we scaled all flow and density proxies into the ranges $[0, 1]$ so as to be able to compare both curves. The difference between both studies' results is surprisingly low, as they follow similar, mostly linear trends in partitions 0 and 3, and approaching saturated states in partitions 1 and 2. This indicates that the impact of ping-pong handovers, pedestrians and stationary users is not as high as feared, supporting the utility of handover data for mobility studies. Both studies also yielded comparable space-mean density values $\overline{\rho} \in [0.015, 0.05]$ $\frac{veh.}{m}$. These mean density values also indicate that the observed congestion is not severe or covering the majority of any partition, as can also be seen from the plots in Fig. 10 that reach the saturated but not the descending phase.

While there are some differences between reality and simulation, we could show the predictive power of MFDs in both studies. However, we could also observe the need to partition the network in a more homogeneity-based approach. While in past studies [19], [20], we focused on clustering the mobile network based on handovers and partitioning the road network according to these clusters, we have now identified that going in the opposite direction (road network first) is a more promising method. Different approaches of partitioning road networks into homogeneous partitions have been published and are being used [27], [38], [39]. The methodology in this work would certainly benefit from such improved partitioning, and we are convinced that with higher temporal resolution data and homogeneity-focused spatial partitioning, the correlation between road and mobile networks will even be stronger.

VII. Conclusion and Perspectives

In this work, we have proposed a novel methodology to link mobile network signaling data to the underlying road traffic network. We have shown that it is possible to compute approximations of the road network partitions' *Macroscopic Fundamental Diagrams* (MFDs) using only aggregated mobile phone handover counts. To the best of our knowledge, this is the first work to show that this link exists and that it can be reliable for real-world data in urban areas.

We first evaluated our methodology in a simulation study, which was limited by the absence of pedestrians and the difficulty of adequately simulating the demand in the network, yielding a low *Mean Average Percentage Error* (MAPE) of 10.2% in prediction. As a next step, we generalized our findings using the corresponding real-world data sets. While estimating the traffic states observed in the *Floating Car Data* (FCD) using mobile signaling data from the POST LTE network, we achieved a MAPE 11.12%, which compares well with previous studies (even those focusing on highways only) [7], [8], [23], but with the added advantage of being a simple, easily interpretable model. The interpretability stems from the fact that the model only uses partitions' inner and exiting handovers as aggregate measures, and yields approximate measures for space-mean density, velocity and flows. The approximated MFDs exhibit low variance with respect to a concave flow-density function, which is in line with previous theoretical results on MFDs [41].

We also compared the resulting flow-density relationships of the simulation and real-data studies, and were able to show that they match and that the absence of pedestrians and stationary users from the simulation is of little impact. These results are very encouraging as they show that the presented methodology is able to capture the traffic dynamics independently from the moving-to-stationary user ratio, at least in the low-to-moderate congestion situations given in Luxembourg City. The fact that pedestrian signals do not significantly influence flow-density approximation also lends more credibility to previous results of simulation studies, where we showed that mobile networks can also detect situations of low throughput and high traffic density [19].

Using only two input variables from a set of mobile network base stations, it is possible to express their coverage area's traffic profile and make reasonably precise predictions of its traffic state. In this context, it is noteworthy that the predictive power that was achieved in this work is not its only quality.

One particular strength of this model is its privacy-friendliness, as it uses only aggregated data instead of data on individuals, thus avoiding a common pitfall of using mobility-related data, and mobile network data in particular. Most importantly, this work has shown that the uncongested and saturation density regions of MFDs can be approximated using signaling data. Thus, it is desirable to find out whether highly congested networks exhibiting grid-lock phenomena could be approximated similarly. They cover the full traffic density range of a classical MFD as shown e.g. by Geroliminis and Daganzo on the Yokohama network [10]. Currently, transportation researchers are actively looking for novel ways of obtaining MFDs, because they enable various planning and control measures. In this vein, there are active initiatives looking for novel data sources that show the emergence of MFDs, e.g. the MFD Dataquest [17]. We believe that our work is a first indicator that mobile network signaling data are a potential candidate data source for MFDs, and this line of research should be continued for other, more congested networks to confirm or relativize our findings.

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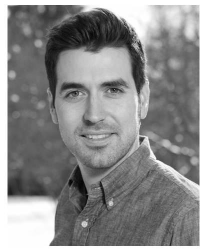

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