# Performance of dynamic urban traffic allocation


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## Abstract

We observe that certain cities exhibit strong congestion throughout the network, others don't. However, it remains unclear how the performance of an urban network should be quantified at a macroscopic level including the daily variations and dynamics. Such performance assessment helps to identify areas of concerns and assist investment decisions in infrastructure. Moreover, building links between traffic performance, network topology, traffic control, demand and socio-economic variables is key to understanding and modeling traffic. This paper gives new insights on how to quantify the macroscopic performance of an urban network. In our analysis, we use loop detector data from Bern, London, Madrid and Zurich. In this paper, we present the available datasets, we provide an overview on how the literature discusses temporal and spatial variability of congestion from a macroscopic traffic perspective, and we present preliminary results of our ongoing work.

## Keywords

MFD

# 1 Introduction

It is common that the urban road infrastructure is only used at full capacity during a short period of time. During peak hours, car accumulation increases and subsequently travel times decrease and congestion starts spreading throughout the city. Depending on the urban network, the traffic control, the traffic demand and other traffic related variables, we expect significant differences between different cities at a macroscopic perspective. Traffic control schemes have an impact on how well traffic flows. Same holds true for traffic demand. If traffic demand distributed evenly throughout the day rather than in distinct peaks, we would expect the road network to perform better, exhibiting less congestion. In other words, we observe that certain cities exhibit strong congestion throughout the network, others don't. However, it remains unclear how the performance of an urban network should be quantified at a macroscopic level including the daily variations and dynamics. Such performance assessment helps to identify areas of concerns and assist investment decisions in infrastructure. Moreover, building links between traffic performance, network topology, traffic control, demand and socio-economic variables is key to understanding and modeling traffic. This paper gives new insights on how to quantify the macroscopic performance of an urban network. The next section discusses existing approaches. Then, a new methodology based on the macroscopic fundamental diagram (MFD) is introduced and some results thereof are shown before we give some concluding remark.

# 2 Background

Discussions around the performance of an urban transport system were covered in numerous papers before. Smeed (1968) investigated the performance of urban roads by comparing average speeds in respect to the fraction of road space used for driving. He then defined a lower and upper limit for the number of vehicles that can travel in the city center and related the road space to speeds. Moreover, Smeed modeled in an semi-empirical approach average travel times for journeys in the city center with respect to different modal splits. He finds that the higher number of commuters the more important is public transportation in order to keep travel times within certain boundaries.

Herman and Prigogine (1979) investigated traffic using the two-fluid theory, where some vehicles are split into two states, moving and stopped. One parameter of the model is $n$, a measure of the network resistance to degraded operation with increased demand. Empirically, $n$ varies from 0.8 to 3.0, with a smaller value typically indicating better operating conditions in the network.

Higher values of $n$ indicate networks that degrade faster as demand increases. Mahmassani *et al.* (1987) ran a series of simulation using the two fluid-model to investigate (among others) the flow-density relation at a network level and showed the model's validity. Later, a macroscopic fundamental diagram (MFD) was formally introduced by Daganzo (2007). It relates travel production (or flow) and vehicle accumulation (or density) in an urban traffic environment. It is assumed to be a function of the network topology and the traffic control, and it is also assumed to be relatively invariant to demand changes. Such macroscopic considerations of urban traffic are useful when analyzing relatively homogeneous regions and are elegant tools to reduce the variables necessary to describe complex traffic networks.

Another simplified model that describes the driving behaviour at a bottleneck (i.e., congestion) is Vickrey's model. According to this, drivers reschedule their departure times in order to reduce their scheduled cost of delay. However, this model is not consistent with the physics of traffic Geroliminis and Levinson (2009).

Other static performance measures at large urban scale inculde for example the average duration of congestion, or congestion resistance of an urban network, or the delays. For example, Stathopoulos and Karlaftis (2002) model the duration of urban traffic congestion. They find that the congestion duration for the center of Athens roughly follows a loglogostic form and is likely to end if it has lasted around 12 minutes. This is evidence that in order to investigate congested traffic states, the aggregation interval is critical. In a large field experiment, Çolak *et al.* (2016) concentrate on the demand-side driven effects of road traffic and investigate the urban traffic patterns in five cities around the world. The authors introduce a dimensionless ratio relating road supply to the travel time, which explains the the travel time lost due to congestion. Similar to the two-fluid theory, they use a factor, $\alpha$, which describes how sensitive the traffic network reacts to more travel demand. The underlying assumptions for the capacities of the network were estimated using standard values for different road classes. Bellocchi and Geroliminis (2016) analyze the efficiency of an urban network. Thereby the authors introduce a metric that compares the actual trave time with the best possible travel time (which runs along the shortest path). The study evaluates the efficiency dynamically over time and space of a Chinese city.

# 3 Data

# 4 Data

In this analysis, we use data from stationary traffic detectors: inductive loop (single and double loops), ultrasonic and passive infrared that measure the flow and the occupancy. Flow is defined as the number of vehicle that pass the detector during a certain period of time, whereas occupancy is the fraction of time a detector is occuppied (i.e. covered) by a vehicle. Occupancy is a proxy for density and can be converted to density Geroliminis and Daganzo (2008). We believe that this data source is most reliable in terms of a cross-comparison of cities for several reasons. First, using a very similar method to collect traffic data reduces the measurement bias. Second, correction methods can be applied to overcome some spatial biases and yield results close to Edie's method (Leclercq *et al.,* 2014, Ambühl *et al.,* 2017). Third, for the probe method, we believe that for a conclusive cross-comparison similar data sources should be used, e.g. only taxis data, navigation devices, or automated vehicle location devices of busses, but neither is this data available to us, nor is it guaranteed that we can measure and control for all important (unobserved) factors such as bus lanes, taxis serving mainly certain routes (between the airport and the CBD), and most importantly probe penetration rates are difficult to estimate accurately and their levels differ between cities. However, we acknowledge that loop detectors also face a sample bias if only a subset of the network is sampled. Nevertheless, research has shown that the MFD can be estimated with reasonable accuracy with only a subset of links in the sample Ortigosa *et al.* (2014), Ambühl and Menendez (2016). It is clear that additionally, there exists a measurement bias since we deal with empirical data affected by noise and potential errors.

We got data in many different ways. For a few cities, the traffic data could be queried via an application programming interface and stored on our computers, whereas for most cities the data was exported from the traffic management computer and provided by employees of the local transport authority. The traffic management software imposed in some cases restrictions on the volume of exportable data, because it was not designed for mass export of traffic data. For example, some software only allows to export the raw data of a single detector for a single day at a time. With limited time, we had to restrict the exported days to just a few. Most cities provided us with already aggregated data, while Frankfurt and Dresden provided measurements for each vehicle passing a loop.

Each city provided us with information on the localization of each detector. Most cities provided us with construction plans of intersections and roads where the position of each detector was indicated. We digitized each detector in a geographic information system. For computing network-wide average flows and densities weighted by the link length $l$, where the length is defined as the distance on the link from major intersection to major intersection for each detector. We define major intersection when two streets intersect with traffic lights, roundabouts, motorway exits, and if a pedestrian traffic light that have an impact on traffic flow.

Since some difficulties occurred when we tried to obtain the desired information (link length, traffic lights, etc) from maps, e.g. open street map, with an automated routine, we decided to draw each link manually in the geographic information system. In addition, the different data formats made it often impossible to automate the identification of driving directions. To accurately determine the link, we used aerial photography and panoramic scenes from the roads. As we draw unique lines for each link (lane), we were able to automatically identify whether multiple loops cover a link. In the final data set, we attribute each loop detector to a single link or lane. The geographic location of the loops is stored in a .shp or .kml file, which includes:

- The identification number of its associated link.
- The length $l$ of its associated link.
- The position $pos$ in meters from the downstream major intersection.
- The road name (from OSM).
- The functional road class as a measure of the road level hierarchy (from OSM); see next paragraph.
- In case we did not receive the data per lane, but per road, we also attributed the number of lanes to each detector. If possible we used the number of lanes given by the data provider, otherwise we inspected the detector location in a panoramic scene from the road.
- In cities, where we identified multiple detectors per lane and link, we flag the detector, that has the largest distance $pos$ to the downstream major intersection as a part of the sample and disregarded the others.

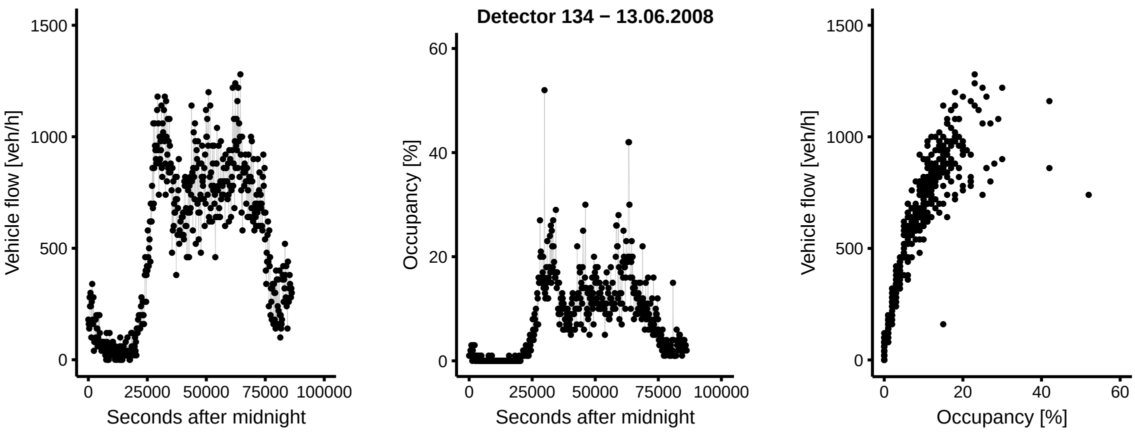
As literature suggests some of our loops tend to show faulty behavior. Moreover, the implemented automatic fault detection routine from some transport authorities did not always yield robust results. Thus, we inspected each detector's scatter and time series plots in order to remove faulty detectors. Figure 2(c) shows scatter plots of two detectors we considered as well operating; they show similarities to a fundamental diagram; while we consider the loop detectors in Figure 2(d) as incorrect because they exhibit a *random* scatter. Other faulty detectors for example showed a constant flow or occupancy measurement.

Figure 1: Available data.

(a) Loop detector coverage at Piccadilly Circus, London[1].

(b) Loop covered network in Stuttgart, Germany. All links covered by a loop are highlighted in black, detector locations are given by black dots. All other roads drawn in gray.

(c) Scatter plots of a loop detectors in Bordeaux, France, considered as well operating.




(d) Scatter plots of a loop detectors in Graz, Austria, with some observations considered as false and, subsequently removed from the sample.

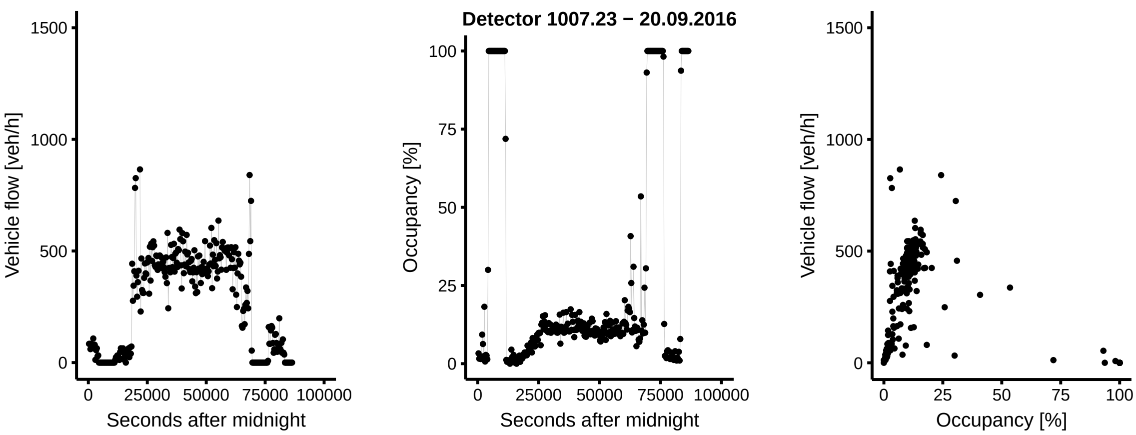


Table 1: Sample overview

| No | City | Country | Population | Detectors | Measurement type | $N_{total}$ | $N_{filter}$[3] | Interval [s] | Observation period |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Amsterdam[2] | Netherlands | 810’938 | From the NDW system | Link | 117 | a | 60 | 20.-26.03.2017 |
| 2 | Basel[1] | Switzerland | 168’620 | | Lane | 83 | a | 300 | 24.-30.10.2016 |
| 3 | Berlin[1] | Germany | 3’469’849 | Traffic counting stations | Link | 740 | a | 300 | a |
| 4 | Bern[1] | Switzerland | 130’015 | | Lane | 1421 | a | 300 | 24.-31.10.2016 |
| 5 | Bordeaux[2] | France | 742’115 | | Lane | 480 | a | 300 | 21.-27.11.2016 |
| 6 | Bremen[1] | Germany | 551’767 | | Lane | a | a | 300 | 19.09.-02.10.2016 |
| 7 | Brisbane[1,b] | Australia | 2’176’799 | SCATS detectors | Lane | 1294 | a | cycle | 01.-03.02.2017 |
| 8 | Cagliari[2] | Italy | 154’019 | | Link | 133 | a | 180 | 30.05.-03.05.2016 |
| 9 | Constance[2] | Germany | 81’692 | Traffic counting stations | Lane | 129 | a | 300 | 13.-19.02.2019 |
| 10 | Darmstadt[1] | Germany | 151’879 | | Lane | 393 | a | 180 | 12.-16.10.2015 |
| 11 | Den Hague / Delft[2] | Netherlands | 602’631 | From the NDW system | Link | 579 | a | 60 | 20.-26.03.2017 |
| 12 | Dortmund | Germany | | not confirmed yet | Link | ~250 | a | | |
| 13 | Dresden[1] | Germany | 536’308 | Traffic counting stations | Lane | 55 | a | 300 | 27.-30.03.2017 |
| 14 | Dusseldorf[1] | Germany | 604’527 | Loops on inbound arterials | Lane | 200 | a | 300 | 06.-09.09.2016 |
| 15 | Eindhoven[2] | Netherlands | 220’920 | From the NDW system | Link | 214 | a | 60 | 20.-26.03.2017 |
| 16 | Essen | Germany | | not confirmed yet | Link | ~50 | a | 300 | |
| 17 | Frankfurt[1] | Germany | 717’624 | | Lane | 530 | a | 300 | 21.12.2016 |
| 18 | Graz[1] | Austria | 269’997 | | Lane | 300 | a | 60 | 04.-08.04. and 19.-23.09.2016 |
| 19 | Hamburg[1] | Germany | 1’762’791 | Traffic counting stations | Lane | 642 | a | 60 | |
| 20 | Kassel[1] | Germany | 194’747 | | Lane | 601 | a | 60 | 28.08.-02.09.2016 |
| 21 | London[2] | United Kingdom | 8’606’201 | SCOOT detectors | Lane | 13787 | a | 300 | 16.-22.05.2016 |
| 22 | Lucerne[1] | Switzerland | 81’057 | | Lane | 160 | a | 60 | 2016 |
| 23 | Madrid[2] | Spain | 3’165’235 | | Link | 3868 | a | 60 | 12.-16.12.2016 |
| 24 | Munich[1] | Germany | 1’429’584 | Traffic counting stations | Lane | 548 | a | 90 | 14.02.2017 |
| 25 | Paris[2,b] | France | 2’229’870 | | Link | 2962 | a | 3600 | Jan. and Feb. 2017 |
| 26 | Rotterdam[2] | Netherlands | 618’357 | From the NDW system | Link | 479 | a | 60 | 20.-26.03.2017 |
| 27 | Santander[2] | Spain | 175’736 | | Link | 220 | a | 60 | 30.11.-02.12.2016 |
| 28 | Singapore[1,b] | Singapore | 5’535’002 | SCATS detectors | Lane | 15295 | a | cycle | a |
| 29 | Speyer[2] | Germany | 49’855 | | Lane | 201 | a | 300 | 19.09.-02.10.2016 |
| 30 | Stuttgart[1] | Germany | 612’441 | Traffic counting stations | Lane | 298 | a | 300 | 3 (5) days in March/July 2016 |
| 31 | Thessaloniki[2,b] | Greece | 315’196 | | Link | 18 | a | 300 | Nov./Dec. 2014 |
| 32 | Toulouse[2] | France | 734’976 | | Link | 484 | | 180 | 7 days in 2008 |
| 33 | Utrecht | Netherlands | | not confirmed yet | Lane | ~500 | | 300 | |
| 34 | Vilnius[2] | Lithuania | 539’707 | | Lane | 1742 | | 90 | 17.03.2015 |
| 35 | Wolfsburg[1] | Germany | 123’027 | | Lane | 406 | a | 300 | 19.09.-02.10.2016 |
| 36 | Zurich[1] | Switzerland | 391’359 | Traffic counting stations | Lane | 1225 | a | 180 | 26.10.-01.11.2015 |

Note
1 http://data.un.org/
2 eurostat
3 Filtering includes removing duplicated loops per link, false loop detector measurements, and detectors in residential areas. For Brisbane, London, Madrid and Singapore we reduced the sample in space to a more manageble size.
a not prepared yet
**b** No (reliable) occupancy / speed measurements

# 5 Methodology

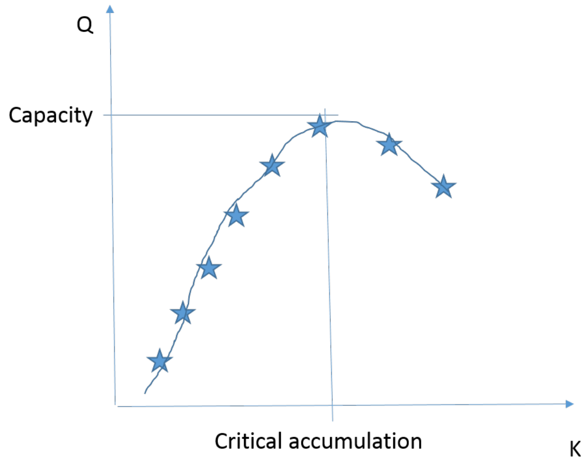
In order to link network features, traffic signal and socio-economic indicators to the performance of dynamic urban traffic we need to firs shed some light on the differences in the traffic performance between different cities. Thus, we must first introduce a methodology that quantifies the performance of urban road networks with data acquired from stationary traffic detectors.

## 5.1 MFD

We use the MFD as a key tool to our analysis. As explained before, the MFD is well defined and reproducible curve that relates the average traffic flow and the average traffic density in an urban region. The averages are computed by weighting the means of the flows and densities with the representative link length. Figure 3 shows a schematic MFD of an urban region. Its uncontested branch is generally characterized through a free flow speed, a critical density and capacity.

Following Leclercq *et al.* (2014), four methods exist to estimate an urban area's MFD: (a) analytical method, (b) Edie's method with aggregation of all vehicle trajectories (e.g., using a simulation), (c) loop detector method (Eulerian observations), and (d) probe vehicle method (Lagrangian observations). However, each of these methods faces practical limitations when it comes to empirical applications in cities. Analytical methods are derived for urban corridors, not urban networks, and defining a tight bound for a network's MFD is not trivial, see also Daganzo and Geroliminis (2008). Edie's method with all vehicle trajectories applies only to simulation data, unless all vehicles in a real network are forced to provide trajectories. Loop detectors provide punctual measurements of link traffic states for all vehicles, but not for the entire link. On the other hand, probe vehicles provide information along the entire link, but not for all vehicles. The distribution of the loop detectors' positions affects the estimation of density in the network. Less bias is expected with a uniform distribution of loop detectors within the link length, because loop detectors closer to the traffic signal, typically overestimate traffic density (Leclercq *et al.,* 2014*,* Buisson and Ladier*,* 2009*,* Courbon and Leclercq*,* 2011*,* Ambühl *et al.,* 2017). Thus, Leclercq *et al.* (2014) and Ambühl *et al.* (2017) proposed correction methods to account for this issue. Although probe data alone already provides a familiar relationship between density and flow, see, for example, Ji *et al.* (2014), without exact information on the sampling rate (i.e. the probe penetration rate) and the spatial distribution thereof, these MFDs are rather unreliable and the speed of probe vehicles must be combined with flow measurements from loop detectors, see, for example Tsubota *et al.* (2014). In this paper we use stationary traffic detectors (for more details, see Section 4). Equation 1 shows how flows and occupancies

Figure 3: Multi-Figure2: Long Caption




are used to construct the MFD (instead of density we use the occupancy, which is a proxy for density).

$$\bar{q} = \frac{q_i l_i}{\sum l_i} \qquad \bar{o} = \frac{o_i l_i}{\sum l_i} \tag{1}$$

## 5.2 Performance measures

So far no common macroscopic performance measures, which include dynamic aspects of traffic, exist. We present in the following some approaches based on the MFD.

- Speed drop: $\Upsilon = \frac{p(v, 0.05)}{p(v, 0.95)}$, where $p(v, 0.05)$ and $p(v, 0.95)$ is the 5th and 95th speed percentile respectively. This indicates the drop between the free flow and the lowest speed (5th quantile).
- Daily accumulation of vehicles: $\zeta = \int_{t_1}^{t_2} \bar{k}(t)dt$. This value indicates the accumulation of vehicles per day.
- Fraction of congested times: $\epsilon = \frac{\int_{t_1}^{t_2} I(\bar{k}(t) > k_{crit})dt}{t_2 - t_1}$, where $\bar{k}(t)$ is the average density at time $t$, $\bar{k}_{crit}$ is the critical density. This value indicates the fraction of time during which the network is considered as congested. $I$ is either 1 or 0, depending on the density.

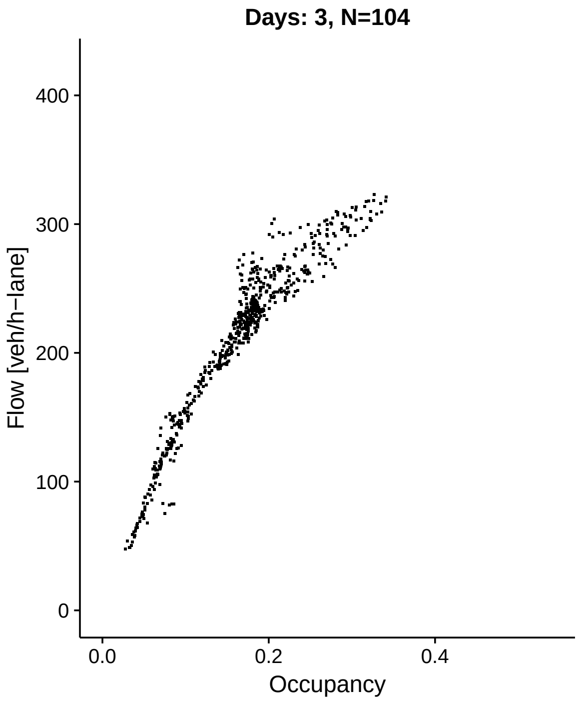
- Total daily delay: $\delta = \int_{t_1}^{t_2} \left( \frac{1}{\bar{v}(t)} - \frac{1}{\bar{v}_0} \right) k(t) dt$. This value indicates the total delay summed over all vehicles for a travel distance of 1 km.
- Delay ratio: $\lambda = \frac{\int_{t_1}^{t_2} \left( \frac{1}{\bar{v}(t)} - \frac{1}{\bar{v}_0} \right) k(t) dt}{\left( \frac{1}{\tilde{v}} - \frac{1}{\bar{v}_0} \right) \tilde{k} \, (t_2 - t_1)}$ The distribution efficiency parameter $\lambda$ compares the experienced total daily travel delay to the case of a constant accumulation of vehicles during the day. If the value is one, no driver would be better off if he reschedules his departure time, however, the larger this value becomes, more drivers travel during peak hours and could improve their travel delays from rescheduling.
- Gini coefficient on traffic distribution: $G_k$ according to **?**gini1997concentration). This value indicates how equally traffic distributes within the region.
- Severity of congestion: $\chi = \frac{\int_{t_1}^{t_2} \bar{k}(t) I(\bar{k} > k_{crit}) dt}{\int_{t_1}^{t_2} \bar{k}(t) dt}$. This value indicates how severe congestion is, by dividing all accumulation above the critical density by the overall accumulation.

# 6 Results

## 6.1 MFD

Hereafter we present excerpts of four cities from table 1, Bern, London, Madrid and Zurich. We have created the MFDs for these four cities according to Equation. For each time interval we create the link length weighted mean flow and occupancy. We then apply a local smoothing using a moving mean consisting of the values of two intervals before the actual interval, the value of the actual interval, and the values of two intervals after the actual interval. This allows to remove some noise from the data. Figures 4 - 7 show the MFDs with the corresponding sample region besides. Differences are apparent. Bern, the smallest city in the sample does not show any congested branch, whereas London and Zurich, both, have a well defined congested branch of the MFD. Madrid shows only slight signs of congestions. At the same time we record that the average speeds in these cities do decrease significantly. In London, Madrid and Zurich to around 1/3 of the free flow speeds (these ratios were calculated using $\tilde{v} = q/o$, where $\tilde{v}$ is a proxy for speed, $o$ is the occupancy and serves as proxy for density, $q$ is the flow). It is interesting that the decrease in speeds have different effects on the MFD. Note, these are preliminary results and more research is under-going to verify these results and interpretations.

Figure 4: MFD for the city of Bern, Switzerland. Region used is shown on the right.



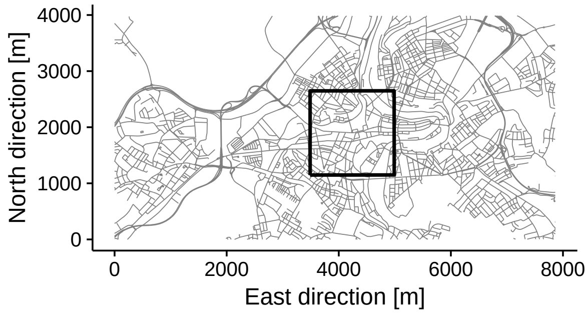
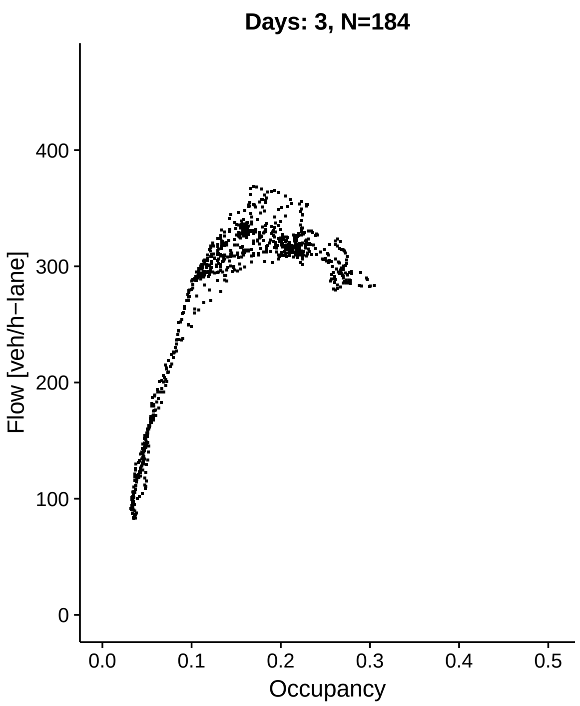




Figure 5: MFD for the city of London, United Kingdom. Region used is shown on the right.



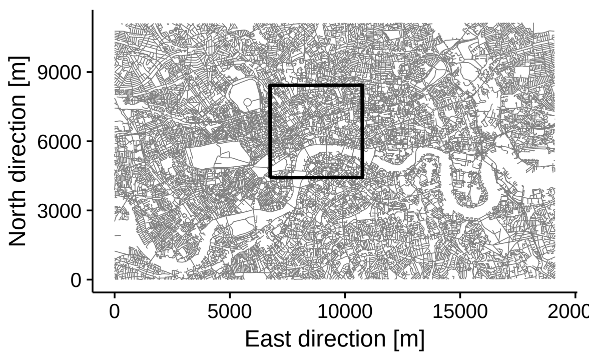



Figure 6: MFD for the city of Madrid, Spain. Region used is shown on the right.

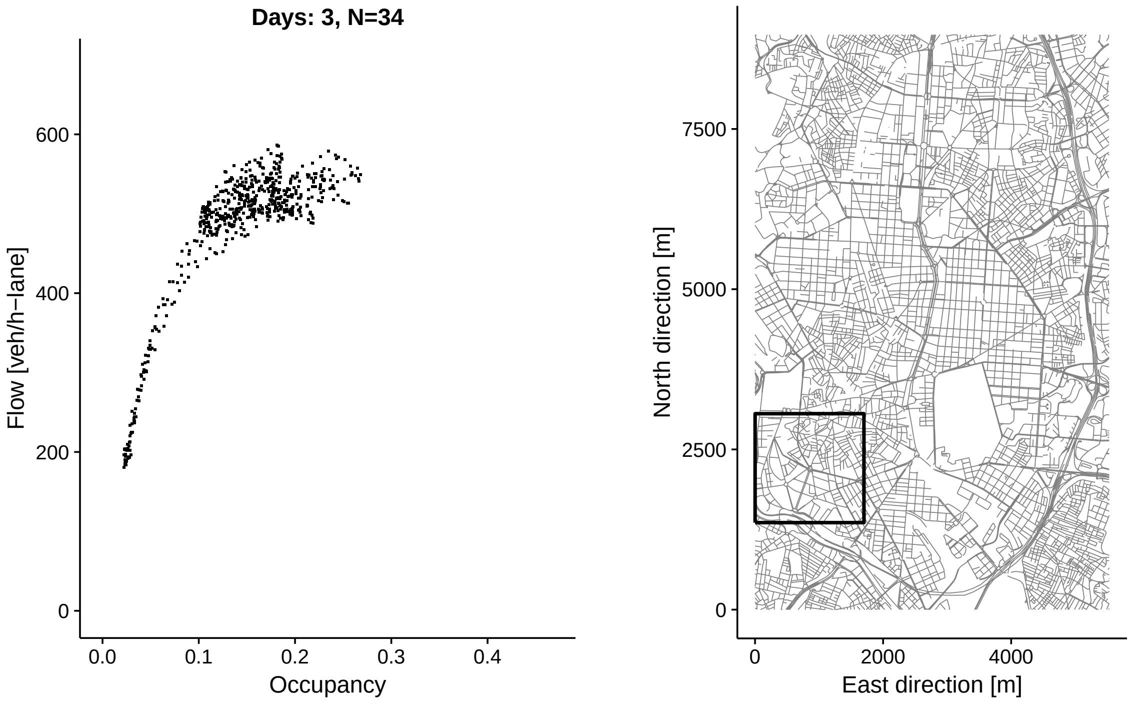



Figure 7: MFD for the city of Zurich, Switzerland. Region used is shown on the right.

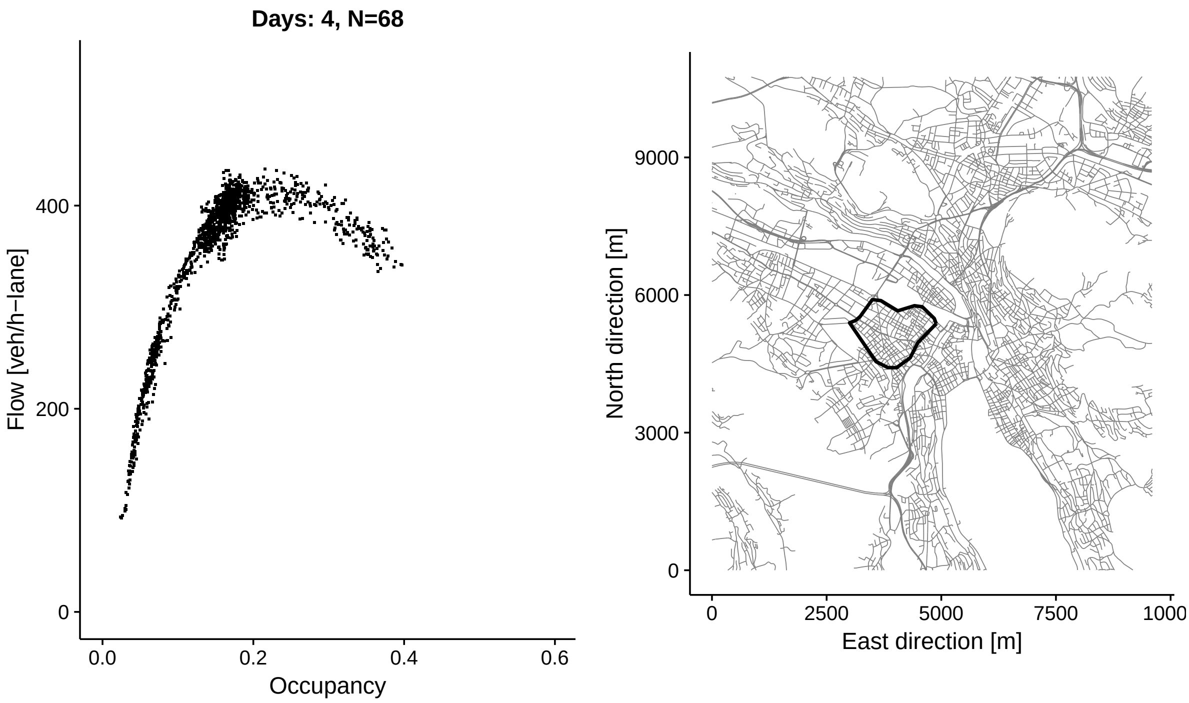


Table 2: Macroscopic performance measures for 4 cities.

| **City** | $\Upsilon$ | $\zeta$ | $\epsilon$ | $\delta$ | $\lambda$ | $G_o$ | $\chi$ | **median** $o$ |
|---|---|---|---|---|---|---|---|---|
| zurich | 0.26 | 15483.42 | 2.78 | 6.61 | 20.72 | 0.26 | 0.09 | 0.157675 |
| madrid | 0.29 | 21802.00 | 1.73 | 9.19 | 1.82 | 0.23 | 0.16 | 0.148858 |
| bern | 0.58 | 16969.94 | 0.00 | 7.29 | 5.34 | 0.23 | 0.00 | 0.172846 |
| london | 0.34 | 20729.64 | 2.96 | 13.56 | 12.53 | 0.28 | 0.12 | 0.155638 |

### 6.2 Performance measures

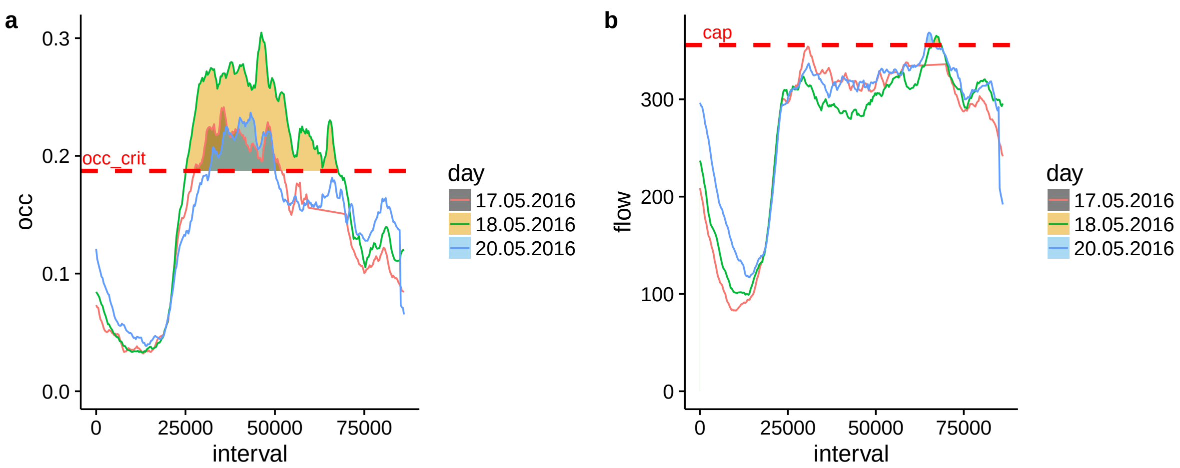
We present in table 2 the results of the different performance measures introduced above. Therefore, only limited interpretation is applicable. Note, these measures are all based on $o$, the occupancy, which serves as a proxy for density. Therefore, $v$, the speed is also only a proxy as well, calculated from $\tilde{v} = \bar{q}/\bar{o}$. It is clear that the interpretation is limited, as the occupancy-density conversion depends on the geometry of the loop detector (which we do not control for in this study). Nevertheless, the values generally follow the expected trends. Zurich and London show higher values for the severity of congestion. The speed drop is similar for all three major cities (Madrid, London, Zurich). Even though Madrid shows only little signs of congestion (see MFD), its speed drops significantly. This indicates that the city deals rather well with higher vehicle densities. We have added the median occupancy,$o$, for all cities. Bern has a significantly higher median occupancy than the other three cities, even though no signs of congestion in the MFD exist. This shows that a careful interpretation of the values in 2 is necessary and a conversion to density is required in order to make a proper assessment.

Figure 8 shows the time series of occupancy and flow for London. The area labeled shows the times at which the occupancy is above the critical occupancy. The critical occupancy was calculated using the mean occupancy for the 95th percentile of flow values.

## 7 Outlook

This is currently on-going work. Thus we present here a brief outlook on how we envisage to further analyze the data. It remains to explain why some cities experience stronger levels of congestion compared to others. Arguably, a first simple approach would try to link population density and availability of alternative modes with the performance measures developed in the previous section. If a city accommodates more people, we expect that more people move.

Figure 8: Time series for average occupancy and flow for the city of London, United Kingdom, in respect to the critical occupancy and capacity.




Depending on the alternatives available (subway, rail, bus network), users can avoid traveling by car, which in turn would reduce delays on the network. Later, we will build upon the above model, by adding more parameters, including network features (average link length, betweenness, etc.), traffic control parameters (average green times, etc.) and more socio-economic factors (wealth, commuting distances, etc.).

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