Traffic problems in towns - an empirical analysis with macroscopic fundamental diagrams from cities around the world

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ABSTRACT

Travel behavior in urban areas has been widely analyzed from the demand side, while the extent to which the infrastructure imposes constraints on such travel behavior and leads to delays and congestion has almost never been studied. For car-based transportation, the recently developed theory of the macroscopic fundamental diagram (MFD) describes the relationship between the accumulation of vehicles and their trip ending rate as a function of the infrastructure, opening the door to new and meaningful studies that address the gap mentioned above. In this paper, we use empirical traffic data from 12 cities around the world to estimate their MFDs, compare them with respect to their functional behavior and the extent of delays, and explain the observed differences as a function of the network topology, e.g. intersection density, average betweeness. We find that the average betweenness centrality in a network seems to be a very clear indicator for the level of traffic performance. This indicates that it is indeed possible to use some topological features to predict traffic performance at the macroscopic level.

INTRODUCTION

The goal of transportation is to connect people for social and economic interactions *(1)*. Given the rising urbanization levels worldwide, providing and investing in transportation infrastructure, especially in cities, is crucial for economic success *(2–5)*. Despite increasing congestion levels, the car - autonomous or not - will remain among the most important modes of transportation in cities *(6, 7)*. In general, drivers experience either an uncongested or congested traffic state. In the uncongested state, the flows of vehicles are constrained by the travel demand, while in the congested state the flows are constrained by the infrastructure capacity leading to overcrowding, traffic jams, and the resulting delays *(8, 9)*.

Although the understanding of how the infrastructure constraints the flow of vehicles has significant implications on how we build our cities, the focus so far has been almost exclusively on the demand side *(10–15)*. Smeed *(16)* was among the first who raised the question on the relationship between the layout of the road network, the desired travel speeds, and the total capacity. Even though not many followed his path, a few studied the relationship with empirical data *(17–19)* and traffic simulation *(20–23)*. They provided further evidence that delays caused by infrastructure constraints can be described by the design of the road network. The recently introduced theory by Daganzo and Geroliminis *(24)* on the *Macroscopic Fundamental Diagram* (MFD) provides an analytical relationship between the design of the road network and the infrastructure constraints on traffic flow. This analytical relationship holds for homogeneous road networks with similar streets; a condition which might not always hold in complex real urban road networks *(25–27)*. The MFD relates the accumulation of vehicles in a network to the travel production (measured in vehicle kilometers) with a concave and well-defined curve. The MFD is consistent with the physics of congestion and its distinct maximum in travel production has led to new network-wide traffic control schemes and traffic models *(28–30)*. Figure 1 exhibits the MFD for London around St. Pancras station and explains the parameters describing its shape.

Here we use the theory of the MFD to uncover the relationships between the design of the urban road network and the infrastructure constraints this one imposes on the flow of vehicles. The existing analytical method relies on technical information that might be highly variant or not even available. Nevertheless, we can estimate the shape of the MFD from empirical traffic data *(25)*. We compare MFDs and the design of the road network from 12 cities around the world to derive these relationships. We address then two questions: (i) how is the design of the road network linked to the MFD shape? and (ii) how do the structure of the road network affect the macroscopic dynamics of traffic in the MFD?

For each city, we estimate the MFD from inductive loop detectors, measuring traffic flow and an approximation of traffic density within a certain perimeter. For those same areas, we extract the road networks from OpenStreetMaps (OSM) and evaluate the features of each network in terms of their geographic extent and their routing potential. We then approach the first question by combining the MFD's shape parameters (see Figure 1) with the obtained network features. The second question is then addressed by analyzing the temporal variation in the traffic states throughout the day.

The contributions of this study are twofold and follow the lines of the two research questions. From the findings on the first question, urban planners and traffic engineers can derive how the changes to the road network affect the infrastructure constraints and the traffic performance. From the findings on the second question, planners can derive strategies to reduce the duration or severity congestion.

The remainder of this paper is organized as follows. The next section describes the available

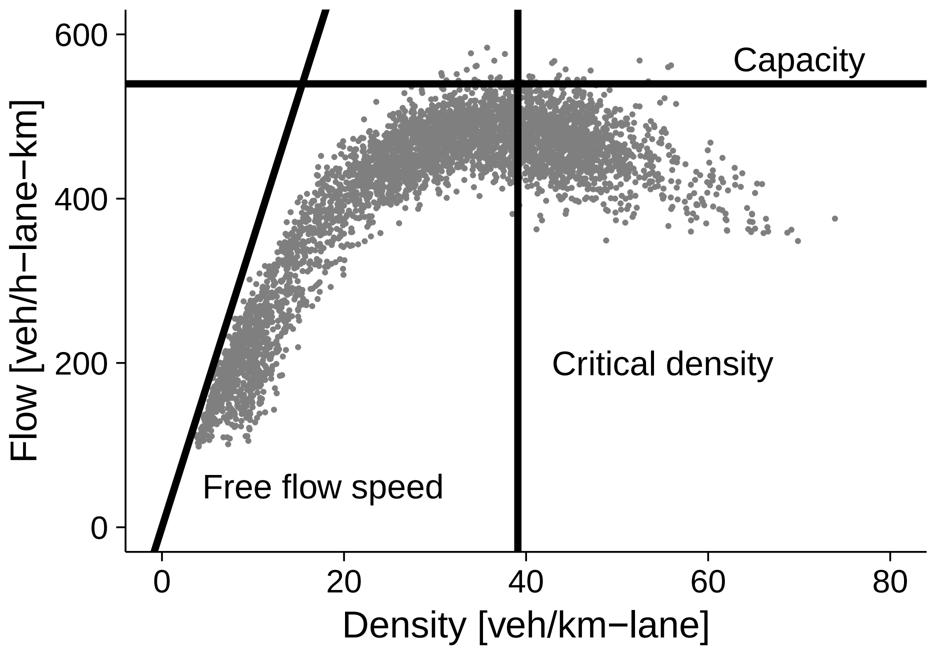


FIGURE 1 MFD estimated for London around the St. Pancras station. Both axes are normalized by the network length in lane-kilometers, such that multiplying them by the network length then leads to the relationship between accumulation and vehicle production. Line 1 marks the capacity of the network, line 2 the critical density, line 3 the free flow speed.

data and the methodology used for the estimation of the MFD and other traffic parameters, as well as the computation of the relevant network features. Thereafter, we present preliminary results on the relationship between road network design and infrastructure constraints described by the MFD. Then, we compare the measures of macroscopic dynamics of traffic across cities and relate them to city size. This paper then closes with some concluding remarks.

DATA AND METHODOLOGY

This sections contains two parts. The first subsection presents the estimation of the MFD, the extraction of the parameters defining its shape, and the indicators we use to measure the traffic dynamics at the macroscopic level. The second subsection describes the preparation of the road network and the extraction of the network features. All data sources are spatially prepared to estimate all parameters and values for the same areas.

Table 1 lists the cities from which we collected data. For most cities, we acquired at least one week of historical data, but less if data export options were a limiting factor.

MFD

All the data used here comes from inductive loop detectors on the road network, and it has been obtained directly either from transport authorities or open data portals. All measurements correspond to single lanes and have been aggregated on 3-5 min intervals. The sensors report the total vehicle count q and the share of time that vehicles occupy the sensor (occupancy) during a time interval. The latter measure is then transformed into traffic density k [vehicles per lane-kilometer] *(31, 32)*.

TABLE 1 List of cities in this analysis paired with the population within municipality borders. The technical details of each data set (number and type of loop detectors, aggregation period, observation period, conversion factor between occupancy and density, distribution of loop detectors across road levels and within the link length, network coverage) are available upon request from the authors.

No	City	Country	Population [1'000]
1	Basel	Switzerland	175
2	Bern	Switzerland	141
3	Bordeaux	France	246
4	Cagliari	Italy	154
5	Constance	Germany	82
6	Darmstadt	Germany	155
7	Frankfurt	Germany	732
8	Graz	Austria	283
9	Lucerne	Switzerland	81
10	Santander	Spain	172
11	Toulouse	France	466
12	Zurich	Switzerland	396

We spatially prepared the data for several purposes: (i) mapping the loop detector locations to the road network to link the traffic performance to the information on the road hierarchy and other topological features *(33)*, (ii) identifying the monitored link length of each detector, and (iii) identifying the distance of the detector to the downstream traffic signal for a potential correction of the density estimation *(25, 27)*. To construct the MFD we then use the length-weighted averages of flow and density across the network *(25, 31)*. The network average flow q in vehicles per hour per lane-kilometer is computed as follows, where l_i represents the length of link i.

$$q = \frac{\sum_i l_i q_i}{\sum_i l_i} \tag{1}$$

The total travel production within the perimeter is then obtained by multiplying the flow q by the total network length. The network average vehicle density is then given by:

$$k = \frac{\sum_i l_i k_i}{\sum_i l_i} \tag{2}$$

The total accumulation of vehicles within the perimeter is then computed by multiplying the density k by the total network length. The average vehicle speed in the network is computed by the fundamental equation of traffic flow $v = q/k$ *(34–36)*.

From each estimated MFD we extract the parameters defining its shape and other indicators of traffic dynamics. Table 2 lists all parameters and indicators, including a description. We recover the shape defining parameters free flow speed, u_f, and capacity, q_{cap}, by the 95$^{\text{th}}$ percentile of

TABLE 2 MFD measures. The MFD shape parameters free flow speed, u_f and capacity, q_{cap} are extracted from the 95th percentile of the respective distribution of speed and flow, while the critical density, k_{crit}, is obtained from the mean density of all flow values above the 95th percentile of flow . All other indicators of traffic dynamics are calculated for weekdays between 5:00 and 24:00.

Measure	Description
MFD shape parameters	
Free flow speed	Initial speed, u_f, in the network with only little traffic load. Corresponds to the slope of the MFD at the origin and is measured as the 95th percentile of speed.
Critical density	Number of vehicles, k_{crit}, in the network that maximizes the vehicle flow (the production of vehicle kilometer per hour). The value is obtained where $q(k)$ is maximized.
Capacity	Corresponding vehicle flow, q_{cap}, or travel production at the critical density. The value is obtained where $q(k)$ is maximized.
Indicators of traffic dynamics	
Normalized lowest speed	Ratio of the lowest to highest average network speed. Both values are taken from the distribution of observed speeds.
Daily accumulation	Total accumulation of vehicles during the day. The value is estimated by the integral of accumulation over time. To compare this value across cities, the value is normalized to lane-kilometer.
Daily travel production	Total travel production during the day. The value is estimated by the integral of travel production over time. To compare this value across cities, the value is normalized to lane-kilometer.
Daily weighted delay	Sum of delays multiplied by accumulation per time interval.
Share of congestion	Share of time throughout the day during which the vehicle flow is restricted by the infrastructure.

speed and flow respectively; while the critical density, k_{crit} is estimated from the mean density of all flow values above the 95th percentile of flow, see Figure 1.

Based on the MFD, we introduce in this analysis six additional indicators of the traffic dynamics, all with a very clear physical meaning: (i) normalized lowest speed, (ii) daily accumulation, (iii) daily production, (iv) daily delay, and (v) share of congestion. The normalized lowest speed is calculated as the ratio of the lowest to the highest observed speed (free flow speed). The daily accumulation, production, and delay are all computed from the area under the corresponding graph and give an indication on how heavily loaded the network is during the day. The share of congestion describes the fraction of time when the vehicle flows are constrained by the infrastructure. We estimate these indicators for the time period between 5:00 and 24:00.

Road network features

In his seminal work, Smeed *(16)* explained differences in the speed-flow-relationship of several British cities as a function of the total area dedicated to cars and the area effectively used by cars. Using the macroscopic two-fluid theory of town traffic, the influence of network features such as average link length, number of lanes per link, intersection density, and signal operation characteristics, on the performance of urban speeds have also been analyzed *(17, 18)*. However, given the small sample size, recovering statistical significant relationships has not been fully possible. Using the MFD theory, Knoop et al. *(21)* compared various network designs using traffic simulation and their findings support the theory that the MFD is network-specific, but also that more heterogeneous networks exhibit lower capacity. However, not only the built up environment affects traffic performance, but also the routes chosen by drivers. Evidence suggests that vehicle flows in road networks are reduced with overlapping routes and drivers not changing routes adaptively in case of disturbances *(37–39)* .

Thus, we analyze here road networks not only by their geographic extent and design, but also by their characteristics as a network. A network is defined as a graph consisting of nodes and edges. Network analysis has spread over many disciplines from social sciences to biology, in particular all disciplines that study patterns of connections *(40, 41)*. Intuitively, road networks are represented by roads as edges and intersections as nodes, the so called primal approach *(42, 43)*. Here, we follow such approach and represent all possible origins and destinations also as nodes.

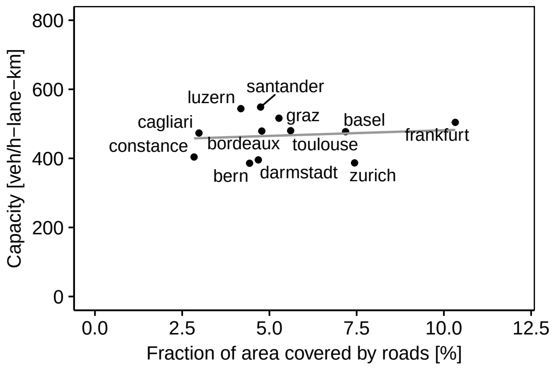
Table 3 summarizes the network features we consider in this preliminary analysis including a description. First, we consider four features that measure the geographic extent of the network: the fraction of area covered by roads, the average link length from intersection to intersection, the average number of lanes per link, and the intersection density. Second, for the graph characteristics of the road network we consider the fraction of one-way streets and the betweenness centrality, which describes how *in between* a node or link is relative to all other nodes and links in the network *(44–46)*. The centrality measure could indicate important edges or nodes, which in turn could indicate bottlenecks in the urban infrastructure. The network average of such a measure then indicates how strongly a network is possibly affected by bottlenecks.

The road networks are queried from OSM. In this analysis, we focus on all main roads and therefore exclude residential and service roads from the network. We chose all perimeter areas so they do not contain any highways. We then process the remaining parts of the network to form an approximate directed graph, where edges stretch from intersection to intersection (traffic signal, roundabout or similar). From the graph representation we compute the network features using the *igraph*-package in R *(47)*.

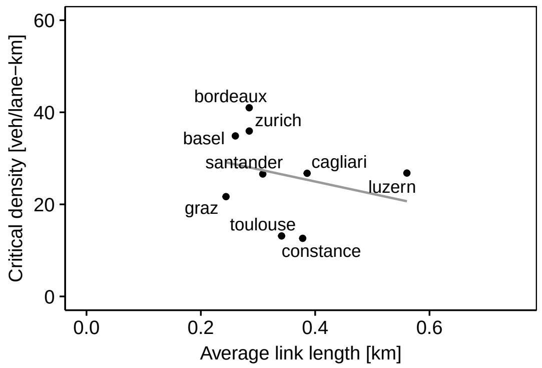
RESULTS

This section shows a selection of preliminary results of our MFD and network analysis. We first describe the results, while we present a comprehensive discussion afterwards. In Figure 2 we compare the parameters critical density, k_{crit}, and the capacity, q_{cap}, with the network features introduced in Table 3. Note that the parameters critical density and capacity are only evaluated for those nine cities where we can identify these values.

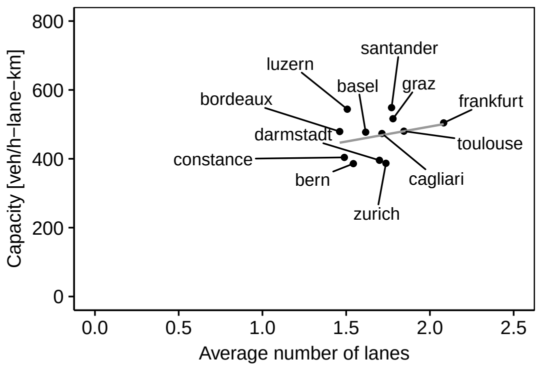
Figure 2(a) shows the relationship between the fraction of area covered by roads versus the capacity of the network. This relationship traces back to Smeed's seminal work on traffic in towns *(16)*. In our sample, we observe a range of values both in the fraction of area as well as in



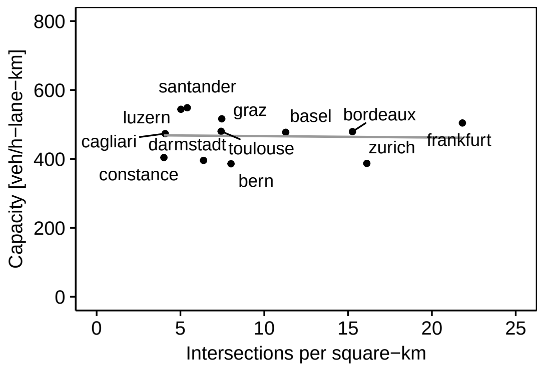
(a) Share of area covered versus capacity.



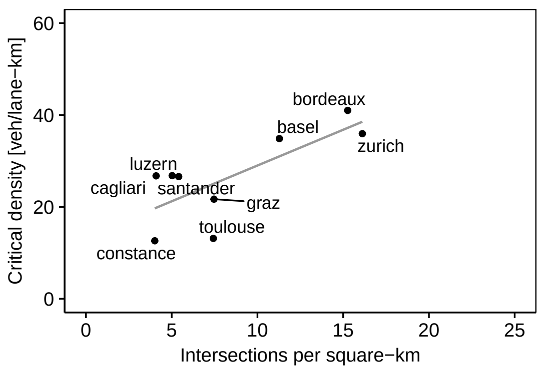
(b) Average link length versus critical density.



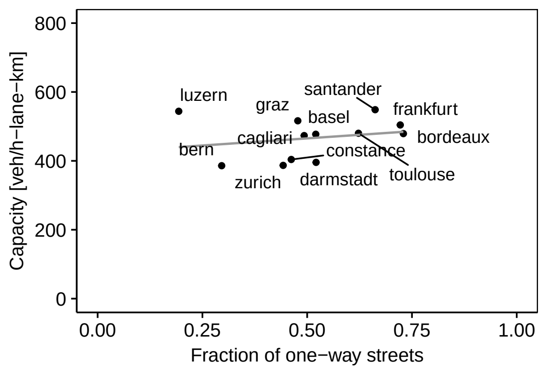
(c) Average number of lanes versus capacity.



(d) Intersections per square kilometer versus capacity.



(e) Intersections per square kilometer versus critical density.



(f) Fraction of one-way streets versus capacity,

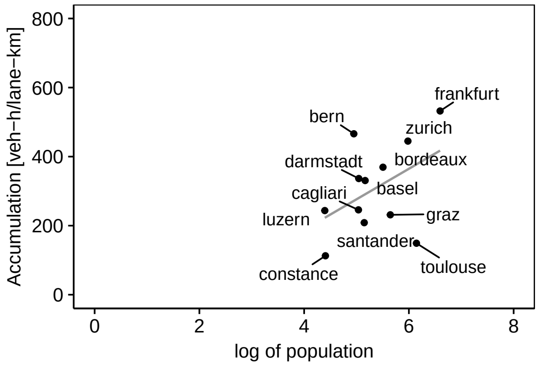
FIGURE 2 Relation between MFD parameters and network features; both are estimated for the same perimeter area and the same road classes (trunk, primary, secondary and tertiary roads following the OSM road classification).

TABLE 3 Network features. All network features are estimated for the same areas as the MFDs. The networks are queried from OpenStreetMap and all residential, service, and unclassified roads are removed. Networks are further processed to result in a graph with edges from major intersection to major intersection. Attributes to the existing layers of OpenStreetMap are added when needed.

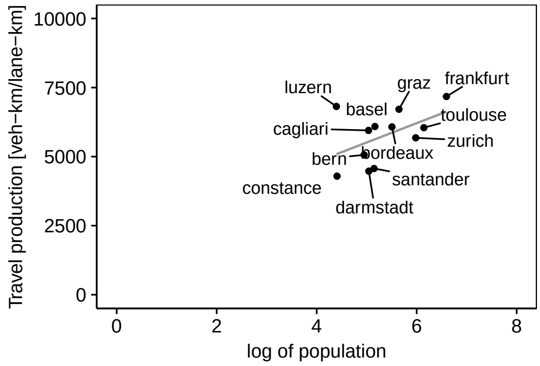
Variable	Description
Share of area covered	Total area of the road network divided by the entire perimeter area. The total area of the road network is calculated by multiplying each link by the number of lanes and 3.5 m of width. In case of a river, we subtracted the river area from the perimeter area.
Average link length	An link is defined as the connection between intersections (nodes). In this computation, we do not consider all links shorter than 40 m as most of these are turning lanes at intersections.
Average number of lanes	Length-weighted average number of lanes per driving direction in the network.
Intersections density	Density of signalized intersections and roundabouts per square kilometer in the analyzed area.
Fraction of one-way streets	Ratio of lane kilometer of one-way streets over the total network length in lane kilometer.
Average betweenness centrality	Betweenness centrality of a node is the fraction of shortest paths passing through that node out of all possible shortest paths. The network average value is obtained by calculating the mean over all nodes.

the capacity, but no distinct relationship. Figure 2(b) relates the average link length to the critical density of the networks. The available data shows a slightly downward sloped relationship. This is surprising as it indicates that networks with longer links get congested at a lower average density. Figure 2(c) shows the relationship between average number of lanes and the capacity per lane kilometer. This relationship was first analyzed by Mahmassani et al. using simulation. They found no large differences in the shape of the MFD when varying the number of lanes per link *(20)*. The results from our data also exhibit a similar trend. Figure 2(d) relates the intersection density to the capacity and shows a slightly negative relationship. This is intuitive as an intersection is a very limiting factor in traffic flow, and thus a higher number of intersections should decrease the overall capacity. Regarding the critical density, Figure 2(e) shows a positive relationship between the intersection density and the critical density. This confirms the findings from Figure 2(b). Lastly, the relationship between the fraction of one-way streets and the capacity shows no trend.

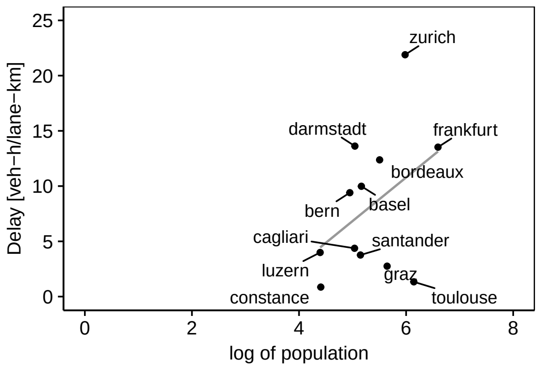
Figure 3 shows the indicators of traffic dynamics as a function of the log of city population (which can be considered as a first approximation of travel demand), and the average betweenness centrality of the network. We take the log of population as we expect a decreasing marginal effect of population on these indicators. The share of congestion is only evaluated for the 9 cities where the critical density can be identified.



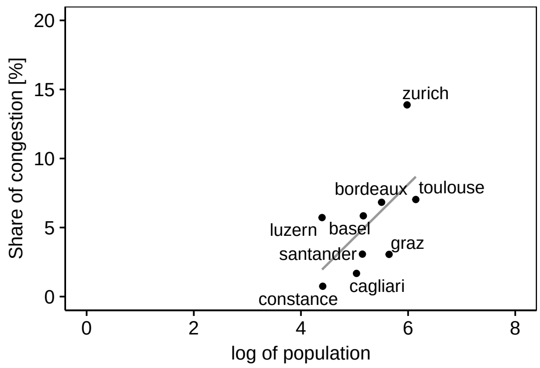
(a) Share of area covered versus capacity.



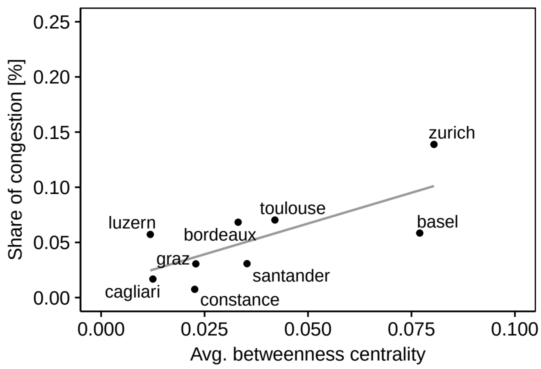
(b) Average link length versus critical density.



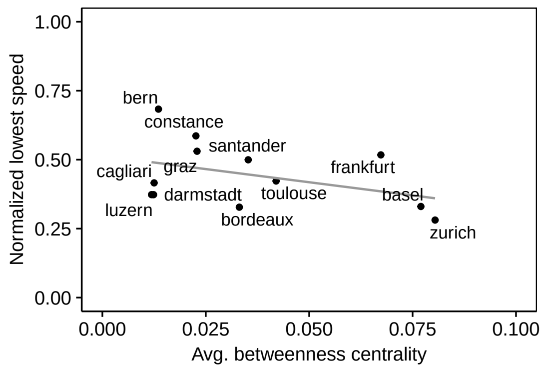
(c) Log of population versus total daily delay.



(d) Log of population versus share of congestion.



(e) Share of congestion versus average betweenness centrality.



(f) Normalized lowest speed versus average betweenness centrality.

FIGURE 3 Comparing indicators of the dynamics of macroscopic traffic from Table 2 with population of each city (a)-(d) and average betweenness centrality (e)-(f). The accumulation, production and delay measures are normalized to one lane-kilometer to allow a comparison across cities. All indicators of the dynamics of macroscopic traffic are computed for the time interval from 05:00 to 24:00 on workdays and averaged over all days if applicable.

Figure 3(a) relates the population to the accumulation in the network. We observe a positive trend, indicating that with a larger population more people tend to drive. We observe a similar relationship in Figures 3(b), 3(c), and 3(d) showing the total travel production, delay, and share of congestion during the day, respectively. In terms of delay and share of congestion, the city center of Zurich exhibits the largest values and largest difference with the trend line, indicating that both delay and congestion are over-proportionate with respect to the population. Hence, there might be other aspects (potentially topological) that can be affecting these two metrics. Figure 3(e) shows a positive relationship between the share of congestion and the average betweenness centrality. This is not surprising, as the betweenness centrality can be interpreted as a measure of potential bottlenecks, and the more potential bottlenecks a network has, the higher the level of congestions one should expect. Figure 3(f) shows a negative trend between the normalized lowest speed and the betweenness centrality. Again, this is unsurprising as a higher likelihood of bottlenecks should lead to lower speeds. Note that the last two illustrations do not control for city size nor travel demand.

In summary, the results in Figure 2 do not exhibit clear relationships between all considered MFD parameters and network features, but the findings in Figure 3 show intuitive relationships. As a matter of fact, the average betweenness centrality in a network seems to be a very clear indicator of the level of performance one could expect out of such network. This is very promising, as it indicates that it is indeed possible to use some topological features to predict traffic performance at the macroscopic level. More research, however, is necessary to properly formulate some predictions.

For the graph measures of the road network, we have to mention an important issue. When selecting the area of interest for our analysis, a comparatively small and homogeneous area in terms of traffic is favored in the MFD estimation, while such a small area might neglect attractive routes, e.g. on ring-road or highway, outside the considered perimeter. This might affect the estimation of the betweenness centrality and other related network features.

Even though the traffic data from all cities is recorded from the same sensor type, we cannot entirely rule out differences in the calibration and data processing in the traffic management computers which could influence the recordings. Therefore, we put our efforts into minimizing potential errors in the remaining degrees of freedom in the MFD estimation by (i) paying attention to the precise geometry of the sensors to reduce the error in the density estimation, (ii) examining the recordings of each measurement station to remove all recordings exhibiting any unfamiliar behavior, (iii) doing a precise spatial data preparation to include only recordings from all cities from the same type of roads.

Literature suggests that the data from loop detectors can be paired with floating car data to overcome some drawbacks of loop detector measurements, especially the effect of the loop detector placement on the density estimation *(31, 25, 27)*. Arguably, in such a comparative study, floating car data should come from a similar type of source, e.g. GPS trajectories, in all cities to reduce potential errors. However, the access to such kind of data is limited, but if available we could expand the sample to cities using SCATS traffic control systems, e.g. Dublin, Singapore and Melbourne.

CONCLUSIONS

This paper presents the first empirical comparison of infrastructure constraints on vehicle flow in various cities around the world. This study has been made possible by the idea of the MFD *(31)*, and the increased availability of large-scale traffic data. We propose to use the estimated MFDs for two seminal analyses: (i) link the shape of the MFD and thus the infrastructure constraints to design of complex real urban road networks, and (ii) identify factors that influence the duration of congestion, i.e. the duration of the binding of infrastructure constraints. This study contributes to the understanding on how the design of a city (networks, population, space, etc.) affects congestion and delays, and could have thus several important implications on how we build our cities.

Ongoing efforts are devoted to extend the analysis to include data from twenty to thirty additional cities, e.g. Madrid, London, Munich. With a larger dataset, it will then be possible to study more graph-based network features for a better understanding of the routing effects. Importantly, we will also consider traffic signal cycle parameters to further infer the shape of the MFD. Last but not least, we will also carry out a sensitivity analysis with respect to the MFD parameter estimation method, the chosen area and the influence of inhomogeneity.

Regarding the indicators of traffic dynamics, we aim at explaining the variation across cities with factors such as population density, degree of urban sprawl, provision of public transport, and the value of time as a measure of wealth. We expect the results will then show what level of congestion is unavoidable (in light of the Downs-Thomson paradox) given a certain city size, and to what extent measures as public transport can mitigate it.

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