The MFD and the built environment

A new perspective on traffic problems in towns

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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 42 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 constrains 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 42 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?

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.

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.

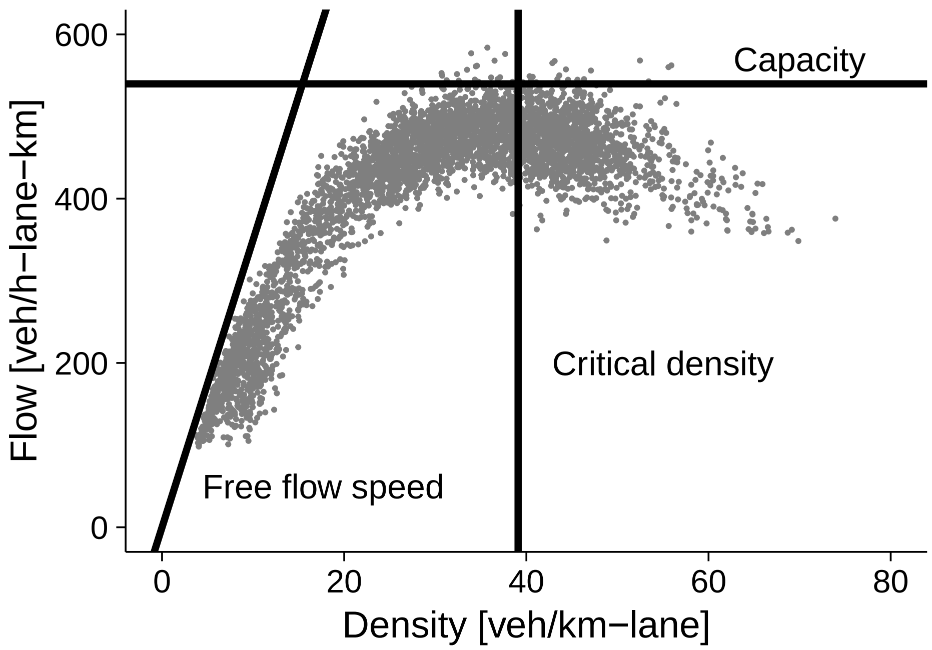

FIGURE 1 MFD estimated for London around the St. Pancras station. Both axes are normalized by the network length in lane-kilometers, such that multiplying them by the network length then leads to the relationship between accumulation and vehicle production. Line 1 marks the capacity of the network, line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

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 comes either directly from transport authorities or open data portals. The vehicle flows q [vehicles/h-lane] are measured by inductive loop detectors and correspond to single lane measurements and have been aggregated on 3-5 min intervals. Traffic density k [vehicles per lane-kilometer] is for most cities derived from detector occupancy (share of time that vehicles occupy the sensor) during the aggregation interval, while for Utrecht we combined detector flow measurements with speed measurements from floating car data *(31, 32)*.

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.

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 speed and flow respectively; while the critical density, k_{crit} is estimated from the mean density of all flow values above the 95$^{\text{th}}$ 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) delay likelihood, (ii) accumulation, (iii) Gini index of density, and (iv) share of congestion. The delay likelihood is defined as the daily average of the differences of free flow speed and actual speed over free flow speed. The accumulation is the integral of $k(t)$. The Gini index of density computes the inequality index for the distribution of density. The lower the value the more evenly is the density distributed over the course of 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.

TABLE 1 List of cities in this analysis paired with the population within municipality borders (Data from Eurostat and UN Data). The Table also provides the free flow speed as obtained from the Google Directions API for the calibration of the MFD as well as the number of available detectors and days of data. Note that in many cases the cities have more detectors installed but we limit our efforts to central areas.

No	City	Country	Population [1000]	Free Flow Speed [km/h]	Detectors	Days
1	Augsburg	Germany	277	26.2	777	20
2	Basel	Switzerland	167	32.2	83	7
3	Bern	Switzerland	129	26.1	769	7
4	Birmingham	United Kingdom	1097	28.2	114	6
5	Bolton	United Kingdom	128	26.3	202	22
6	Bordeaux	France	754	23.0	591	7
7	Bremen	Germany	549	30.3	583	14
8	Cagliari	Italy	154	26.0	133	50
9	Constance	Germany	81	35.6	129	7
10	Darmstadt	Germany	150	30.8	393	5
11	Dresden	Germany	531	35.1	55	4
12	Duisburg	Germany	487	31.6	590	14
13	Essen	Germany	570	35.4	38	36
14	Frankfurt	Germany	701	31.0	112	1
15	Graz	Austria	270	33.4	300	10
16	Groningen	Netherlands	198	29.7	55	6
17	Hamburg	Germany	1746	34.0	419	105
18	Innsbruck	Austria	125	30.1	49	30
19	Kassel	Germany	194	30.9	601	4
20	London	United Kingdom	8478	26.4	5804	22
21	Luzern	Switzerland	81	26.7	159	361
22	Madrid	Spain	3142	36.1	2123	20
23	Manchester	United Kingdom	517	31.2	221	22
24	Marseille	France	1054	23.7	178	32
25	Munich	Germany	1408	31.9	548	1
26	Paris	France	3236	30.7	513	366
27	Rotterdam	Netherlands	618	34.8	277	6
28	Santander	Spain	176	33.8	378	3
29	Speyer	Germany	50	28.9	199	14
30	Stockport	United Kingdom	136	29.5	104	22
31	Strasbourg	France	228	27.2	220	25
32	Stuttgart	Germany	604	31.8	298	8
33	Torino	Italy	902	30.8	787	21
34	Toronto	Canada	2809	27.1	214	61
35	Toulouse	France	747	30.8	910	7
36	Trafford	United Kingdom	210	37.4	181	22
37	Utrecht	Netherlands	328	32.4	1072	4
38	Vienna	Austria	1767	34.8	217	24
39	Vilnius	Lithuania	540	33.3	581	1
40	Wigan	United Kingdom	103	32.1	146	22
41	Wolfsburg	Germany	122	40.9	405	14
42	Zurich	Switzerland	385	24.0	1225	7

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	
Delay likelihood	The delay likelihood is defined as the daily average of the differences of free flow speed and actual speed over free flow speed.
Accumulation	The accumulation is the integral of $k(t)$.
Gini index of density	The Gini index of density computes the inequality index for the distribution of density. The lower the value the more evenly is the density distributed over the course of the day.
Share of congestion	Share of time throughout the day during which the vehicle flow is restricted by the infrastructure, i.e. $k(t) > k_{crit}$.

CONCLUSIONS AND EXPECTED FINDINGS

s 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 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. As a matter of fact, from the preliminary results, we expect the average betweenness centrality in a network to be an important indicator of the level of performance. This 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.

Importantly, we will also consider traffic signal cycle parameters as well as the influence of public transport networks 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

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.

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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REFERENCES

1. Krugman, P. (1991) *Geography and Trade*, MIT Press, Cambrdige, MA.

2. Schläpfer, M., L. M. a. Bettencourt, S. Grauwin, M. Raschke, R. Claxton, Z. Smoreda, G. B. West and C. Ratti (2014) The scaling of human interactions with city size., *Journal of the Royal Society, Interface / the Royal Society*, **11**, 20130789.

3. Bettencourt, L. M. a. (2013) The origins of scaling in cities., *Science*, **340**, 1438–1441.

4. Venables, A. J. (2007) Evaluating urban transport improvements, *Journal of Transport Economics and Policy*, **41**, 173–188.

5. Venables, A. J. (2017) Breaking into tradables: Urban form and urban function in a developing city, *Journal of Urban Economics*, **98**, 88–97.

6. Buchanan, C. (1964) *Traffic in Towns*, Penguin, Harmondsworth, UK.

7. Mogridge, M. J. H. (1990) *Travel in towns : jam yesterday, jam today and jam tomorrow?*, Macmillan reference books, London [etc.] : Macmillan.

8. Geroliminis, N. and D. M. Levinson (2009) Cordon pricing consistent with the physics of overcrowding, in *Transportation and Traffic Theory 2009: Golden Jubilee*, 219–240.

9. Cascetta, E. (2009) *Transportation systems analysis: models and applications*, 2nd edn., Springer.

10. Ewing, R. and R. Cervero (2010) Travel and the built environment, *Journal of the American Planning Association*, **76**, 265–294.

11. Sun, L., K. W. Axhausen, D.-H. Lee and X. Huang (2013) Understanding metropolitan patterns of daily encounters, *Proceedings of the National Academy of Sciences*, **110** (34) 13774–13779.

12. Anowar, S., N. Eluru and L. F. Miranda-moreno (2014) Transport reviews : A transnational alternative modeling approaches used for examining automobile ownership : A comprehensive review alternative modeling approaches used for examining automobile ownership : A comprehensive review, *Transport Reviews*, **34**, 441–473.

13. Mokhtarian, P. L., I. Salomon and M. E. Singer (2015) What moves us? an interdisciplinary exploration of reasons for traveling, *Transport Reviews*, **35** (3) 250–274.

14. Cao, X. J., P. L. Mokhtarian and S. L. Handy (2009) Examining the impacts of residential self selection on travel behaviour: A focus on empirical findings, *Transport Reviews*, **29**, 359–395.

15. Newman, P. W. G. and J. R. Kenworthy (1989) Gasoline consumption and cities, *Journal of the American Planning Association*, **55** (1) 24–37.

16. Smeed, R. J. (1968) Traffic studies and urban congestion, *Journal of Transport Economics and Policy*, **2** (1) 33–70.

17. Herman, R. and I. Prigogine (1979) A two-fluid approach to town traffic, *Science*, **204**, 148–151.

18. Ardekani, S. A., J. C. Williams and S. Bhat (1992) Influence of urban network features on quality of traffic service, *Transportation Research Record: Journal of the Transportation Research Board*, **1358**, 6–12.

19. Çolak, S., A. Lima and M. C. González (2016) Understanding congested travel in urban areas., *Nature communications*, **7**, 10793.

20. Mahmassani, H., J. C. Williams and R. Herman (1987) Performance of urban traffic networks, in N. Gartner and N. H. M. Wilson (eds.) *Proceedings of the 10th International Symposium on Transportation and Traffic Theory*, 1–20.

21. Knoop, V. L., D. de Jong and S. P. Hoogendoorn (2014) The influence of the road layout on the network fundamental diagram, *TRB 93rd Annual Meeting Compendium of Papers*, 1–16.

22. Ortigosa, J. and M. Menendez (2014) Traffic performance on quasi-grid urban structures, *Cities*, **36**, 18–27.

23. Ortigosa, J., V. V. Gayah and M. Menendez (2017) Analysis of one-way and two-way street configurations on urban grid networks, *Transportmetrica B: Transport Dynamics*, 1–21.

24. Daganzo, C. F. and N. Geroliminis (2008) An analytical approximation for the macroscopic fundamental diagram of urban traffic, *Transportation Research Part B: Methodological*, **42** (9) 771–781.

25. Leclercq, L., N. Chiabaut and B. B. Trinquier (2014) Macroscopic Fundamental Diagrams: A cross-comparison of estimation methods, *Transportation Research Part B: Methodological*, **62**, 1–12.

26. Ji, Y. and N. Geroliminis (2012) On the spatial partitioning of urban transportation networks, *Transportation Research Part B: Methodological*, **46** (10) 1639–1656.

27. Ambühl, L., A. Loder, M. Menendez and K. W. Axhausen (2017) Empirical macroscopic fundamental diagrams: New insights from loop detector and floating car data, *Paper presented at the 96th Annual Meeting of the Transportation Research Board, Washington, D.C.*

28. Haddad, J. and N. Geroliminis (2012) On the stability of traffic perimeter control in two-region urban cities, *Transportation Research Part B: Methodological*, **46**, 1159–1176.

29. Schreiber, A., A. Loder and K. W. Axhausen (2016) Urban mode and subscription choice - An application of the three-dimensional MFD, *paper presented at the 16th Swiss Transport Research Conference, Ascona, May 2016*.

30. Aboudolas, K. and N. Geroliminis (2013) Perimeter and boundary flow control in multi-reservoir heterogeneous networks, *Transportation Research Part B: Methodological*, **55**, 265–281.

31. Geroliminis, N. and C. F. Daganzo (2008) Existence of urban-scale macroscopic fundamental diagrams: Some experimental findings, *Transportation Research Part B: Methodological*, **42** (9) 759–770.

32. Coifman, B. (2001) Improved velocity estimation using single loop detectors, *Transportation Research Part A: Policy and Practice*, **35**, 863–880.

33. Buisson, C. and C. Ladier (2009) Exploring the impact of homogeneity of traffic measurements on the existence of macroscopic fundamental diagrams, *Transportation Research Record: Journal of the Transportation Research Board*, **2124**, 127–136.

34. Daganzo, C. (1997) *Fundamentals of transportation and traffic operations*, vol. 30, Pergamon Oxford.

35. Daganzo, C. F. (2007) Urban gridlock: Macroscopic modeling and mitigation approaches, *Transportation Research Part B: Methodological*, **41** (1) 49 – 62, ISSN 0191-2615.

36. Greenshields, B. (1935) A study in highway capacity, *Highway Research Board Proceedings*, **14**, 448–477.

37. Gayah, V. V. and C. F. Daganzo (2011) Clockwise hysteresis loops in the macroscopic fundamental diagram: An effect of network instability, *Transportation Research Part B: Methodological*, **45**, 643–655, ISSN 0191-2615.

38. Daganzo, C. F., V. V. Gayah and E. J. Gonzales (2011) Macroscopic relations of urban traffic variables: Bifurcations, multivaluedness and instability, *Transportation Research Part B: Methodological*, **45** (1) 278–288.

39. Muhlich, N., V. V. Gayah and M. Menendez (2015) An examination of mfd hysteresis patterns for hierarchical urban street networks using micro-simulation, *Transportation Research Record: Journal of the Transportation Research Board*, **2491**, 117–126.

40. Watts, D. J. and S. H. Strogatz (1998) Collective dynamics of /'small-world/' networks, *Nature*, **393** (6684) 440–442.

41. Newman, M. (2010) *Networks: An Introduction*, Oxford University Press, Inc.

42. Porta, S., P. Crucitti and V. Latora (2006) The network analysis of urban streets: A primal approach, *Environment and Planning B: Planning and Design*, **33** (5) 705–725.

43. Porta, S., P. Crucitti and V. Latora (2006) The network analysis of urban streets: A dual approach, *Physica A: Statistical Mechanics and its Applications*, **369** (2) 853–866.

44. Freeman, L. C. (1977) A set of measures of centrality based on betweenness, *Sociometry*, **40** (1) 35–41.

45. Freeman, L. C. (1979) Centrality in social networks, *Social Networks*, **1**, 215–239.

46. Crucitti, P., V. Latora and S. Porta (2006) Centrality in networks of urban streets, *Chaos*, **16** (1) 015113.

47. Csardi, G. and T. Nepusz (2006) The igraph software package for complex network research, *InterJournal, Complex Systems*, **1695** (5) 1–9.