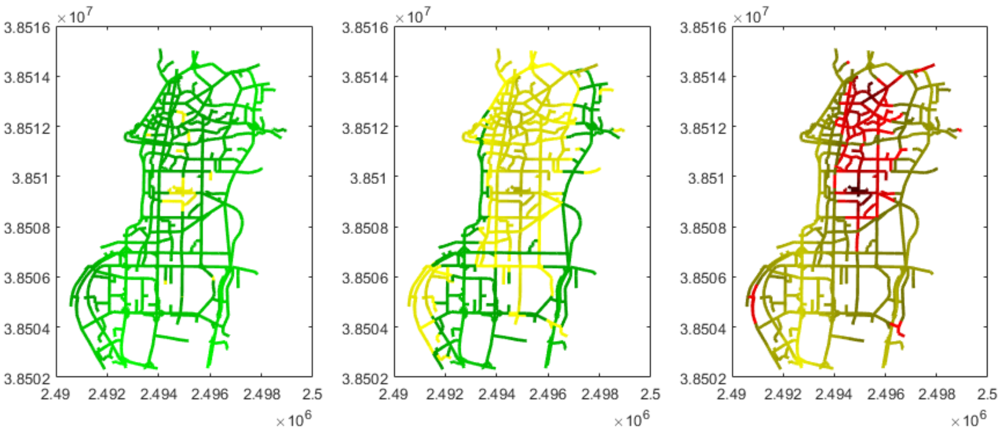

Dynamical efficiency in congested road networks

Leonardo Bellocchi

Nikolas Geroliminis

École Polytechnique Fédérale de Lausanne **May 2016**

STRC | 16th Swiss Transport Research Conference

Monte Verità / Ascona, May 18 – 20, 2016

École Polytechnique Fédérale de Lausanne

Dynamical efficiency in congested road networks

Leonardo Bellocchi
LUTS
École Polytechnique Fédérale de Lausanne
Station 18,1015 - Lausanne
phone: +41 21 69 32486
fax: +41-21-693 24 79
leonardo.bellocchi@epfl.ch

Nikolas Geroliminis
LUTS
École Polytechnique Fédérale de Lausanne
Station 18,1015 - Lausanne
phone: +41-21-693 24 81
fax: +41-21-693 24 79
nikolas.geroliminis@epfl.ch

May 2016

Abstract

The main topological properties of a transportation network can be characterized using different criteria such as structure, the degree distribution of nodes, connectivity and some clustering aspects. *Efficiency* is a property of a network that identifies the easiness for a walker in a graph to reach different nodes in the network given its position (see Latora and Marchiori (2007) for more details). Efficiency, in its static form, has been widely utilized in several spatial networks like communication, social and transportation networks and it is quite established in physical sciences. In this study, we aim to compute the efficiency of the network and track its changes over time by considering average link speed in a city during congestion period. To quantify the time efficiency, we introduce a metric that involves time and not space taking into account the average measured (or estimated) speed for the links during the peak hour. The main idea is to compute the shortest travel times using average link speed that represent traffic condition in the network. For any given node in the network (graph), we compute all (or a part of based, for example, in an OD matrix) shortest travel time starting from that node. Hence, we have a quantitative analysis of the time efficiency for each road. Furthermore, we can divide the city into regions with different levels of efficiency and visualize them.

In this work we show how these new measures of traffic performance at the network level provide a better understanding of congestion evolution compared to state of the art measures and can be utilized to evaluate various management techniques. Results analysis (*i*) of a large number of taxis from a megacity in China and (*ii*) microscopic simulations of an European city with more than 500 lights are presented. Ideas for extensions are also provided.

Keywords

Efficiency, complex networks, shortest time path, urban traffic, congestion propagation.

1 Introduction

Stimulated by the idea to study the congestion phenomenon from a structural point of view, we tried to match some recent findings and measures used in complex network, in particular road networks, with the urban traffic engineering.

The aim of this paper is to measure the functional and topological changes that a city has during the day because of congestion or some non-recurrent events (accidents, special events, etc.). We choose to follow the point of view of drivers and then aggregate this at the network level by looking at specific distributions. A driver has to choose the best path to join his destination and we want to be able to find the parts of the city which are "good" and efficient for starting a trip and those parts that because of congestion and spatial allocation result "bad" or non-efficient compared to the best possible scenario (normally the free-flow scenario).

In order to set the typical peak hour scenario for each test city, we need some indicators that involves both spatial properties of the network and online speed data. The remaining presents the structure of the paper and some main results.

In the first section we will talk about definitions of *efficiency* and *betweenness* and the difference between the classical static use and our dynamical measurement. In the second section we show some result of computing this measure for a daily peak hour in an big Chinese city. In the third section we propose some heuristics to decrease the computational cost of our network analysis. In section four we show how to use betweenness to compute a global estimation of network efficiency. In the last section some comments and ongoing works are presented.

2 Efficiency and betweenness

Let $\mathcal{G}(N, V)$ be a graph of N nodes and V links that represents a spatial network. According to the literature (Latora and Porta (2006)) we could define *efficiency* for $\mathcal{G}$ is :

$$E = \frac{1}{N(N-1)} \sum_{i,j=1,\dots,n} \frac{d_{ij}^{euc}}{d_{ij}}$$

where d_{ij}^{euc} is the areal (euclidean) distance between node i and j and d_{ij} is the length of the shortest path between nodes i and j.
The *betweenness* is a network measure for link introduced by a famous social scientist Linton C.

Freeman (see Freeman (1977)) and it describes a centrality of a link in term of transmission of information among all couple of nodes.

We note that for a spatial network this measure involves only the length of the shortest paths and quantifies the straightness of them that for us makes a network more *efficient* in terms of transmission of some signal between all pairs of nodes in the graph.

Our mean idea is to extend this analysis to a dynamical case where the length of links can change or, like in the transportation network, the average speed of links changes in time because of congestion. This is not common in the literature of networks, where the spatio-temporal distance between two nodes is given and fixed when efficiency and betweenness is estimated (see for example Latora and Porta (2006) and Porta *et al.* (2006)).
In order to take into account this effect we define

$$E(t) = \frac{1}{N(N-1)} \sum_{i,j \in N} \frac{\tau_{ij}^{FF}}{\tau_{ij}^{STP}(t)}$$

as *global dynamical efficiency* at time t for link i where τ_{ij}^{FF} is the shortest time path (STP) between nodes i and j under free flow scenario in all network and $\tau_{ij}^{STP}(t)$ is the STP calculated with the experienced speed in the network at time t, that is using the average speed link from available data.
In addition to the global efficiency of the whole network we are also interested in the analysis of the efficiency of each single links in the network. So, we define *local dynamical efficiency* as

$$E(i,t) = \frac{1}{N-1} \sum_{j \neq i \in N} \frac{\tau_{ij}^{FF}}{\tau_{ij}^{STP}(t)}.$$

It could be useful also to see which link has been used more during the computation of all the possible STPs in the network where the speed of links changes in time. That is we are interested in betweenness, that in our case is defined as

$$B(i,t) = n_i(t) / \sum_{k,j \in N} n_{kj} = n_i(t) / \binom{N}{2}$$

where $n_i(t)$ is the number of STPs use link i for a scenario of the network at time t, n_{kj} the number of STP between $k, j \in N$ and in our case it is always 1 for each pair and so we compute the total number of STP n_{kj} equal to the binomial coefficient $\binom{N}{2}$.

3 Analysis and tests

In a static scenario we can compute the network efficiency in a classical way, but our main idea is to use this measure to quantify and analyze traffic conditions in a city whenever we have data of link speeds. In other words, we have to pass from a classical space dimension to a spatio-temporal one to involve speed. This is because we can easily collect data for average speed link from probe vehicles, sensors, and micro-simulations and we can integrate these data to compute the change in efficiency. This probe date are very often not accurate and low frequency. This is an important issue (see for example Bernard *et al.* (2006) and Jenelius and Koutsopoulos (2013)) that with our work we try to overcome as shown later.
We use our analysis also in combination with some clustering algorithms (Saeedmanesh and Geroliminis (2015)) and MFD theory (Geroliminis and Daganzo (2008)) to figure out some macroscopic characteristics of the road network and compute efficiency par homogeneous regions (Kouvelas *et al.* (2015)).

We have tested our algorithm with the data of Shenzhen city during the morning peak hour (6am - 8am) (Figure 1) based on the GPS signal of 20,000 taxis active in this time window (see Ji. *et al.* (2014)). We have applied our analysis of dynamical efficiency and betweenness in some transportation networks and, in particular, in a city which experiences a traffic congestion where evidently the average speeds among links change because of congestion or traffic, and so imply some changes in route choice and in travel time for users.

The cases studied have been Barcelona and Shenzhen (see Kouvelas *et al.* (2015) and Ji. *et al.* (2014) for more details of the network) where we go deeply in the analysis. In the case of Barcelona we are able to show the improvements that the perimeter control presented in Kouvelas *et al.* (2015) has also in terms of efficiency for the whole network and for each region of the city. We will present more detailed analysis in an incoming paper.

This type of analysis is revealed very advantageous for transportation problems for many reasons. Efficiency express how a link is well and easily reachable in the network, in particular respect its neighborhood. This characteristic makes this measure more trustful and with much less noise that come from data and that we can't avoid. Also in the case where we miss the value of speed for some link and for some periods we can have still a good and reasonable analysis because we compute the mean of shortest time path between many different destination links. For similar reason if we plot on the urban map the value of efficiency in a certain time step we realize that this measure is smoothed and grouped in some connected components from which we can easily detected the congested part of the city growing or decreasing over time in a continuous dynamic

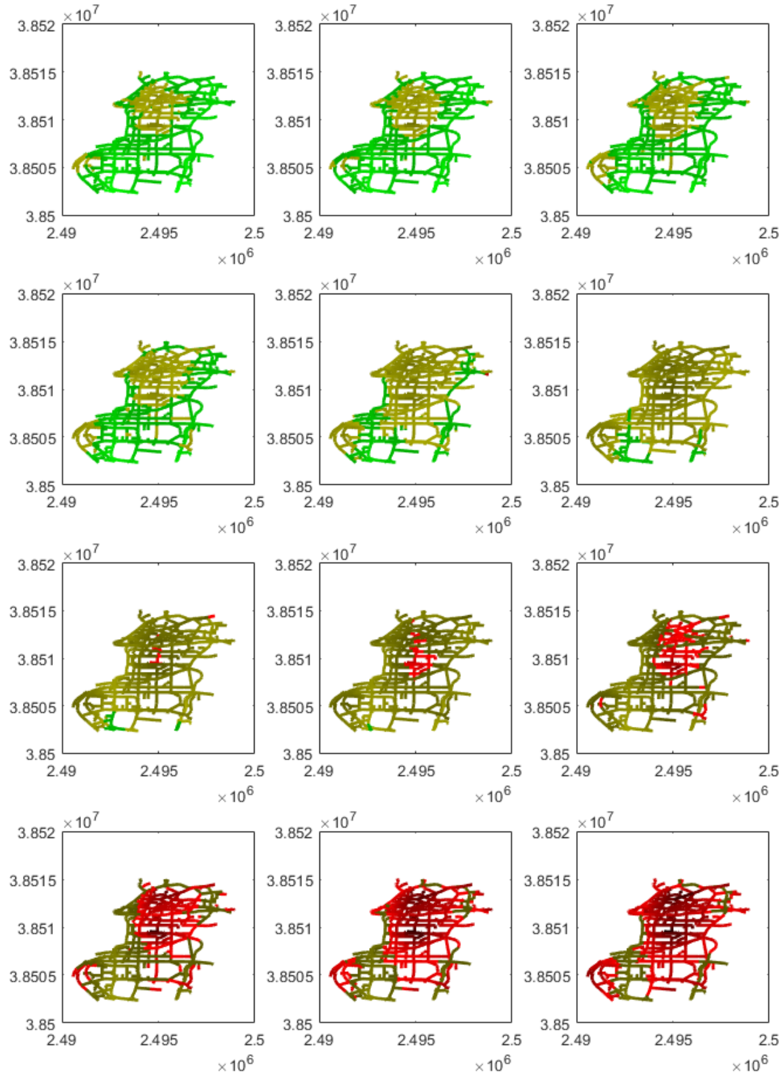

Figure 1: Contour plot of local efficiency for Shenzhen city center during the morning peak hour 6am-8am. The link are colored based on their efficiency in tree equal categories: green (high efficient), yellow (average efficient), red (low efficient). We can associate the red link with the congestion and it easy to follow its propagation during the peak hour (from left to right, from top to bottom.)

(see for example Figure 1). To the efficiency value it is associated also the physical meaning of the *reachability* of a link. This concept is very important in traffic management where it is worth to know the relative condition of a road or zone to estimate its value and convenience in a simulated dynamical routing process.

Then efficiency it is also a immediate and clear measure to quantify and qualify the improvements in some control traffic strategy.

4 Heuristics to reduce computational cost

All our results derived in a simple and immediate way from a unique algorithm that it is the computation of STP for each pair of nodes and for each time step in which we are interested. In same cases, for example in large network or for the computation of efficiency for a long time the computational cost increases exponentially.

To avoid this situation we consider how to exploit the peculiarities of the urban traffic in at least two ways that can still give a good representation of traffic conditions with less computational effort. As first approach we can compute only the STP between all pair of nodes distanced less than a quantity r, for example a value close to the average trip length. It means to compute the STP from each node $i = 1, \ldots, n$ to every node $j \in N_i(r) = \{j \in N : d(i, j) \leq r\}$ in order to guarantee that $N_i(r) \neq \emptyset$ for each $i \in N$ we have to take care that $r > \max_i \min_j d(i, j)$.

The results for this first approach are very encouraging in sense of correlation with the whole network case. We compute the vector for link efficiency $\{E^r(i,t)\}_{i\in N} = \{E(i,t) = \frac{1}{N-1} \sum_{j\neq i\in N} \frac{\tau_{ij}^{FF}}{\tau_{ij}^{SP}(t)}$ such that $d(i, j) \leq r\}_{i\in N}$ the time average of the correlation between $E^r(i,t)$ and $E(i,t)$. The results are showed in Figure 2. As we can see it becomes almost the same very soon. In fact, if we have that the average length trip is L we can compute the STP only for the radius L. A better way is to define an average trip length for some macro regions in the city in order to optimize the ratio between computational cost and consistency of the results.

This max-radius approximation is supported also by some recent papers (for example Carra *et al.* (2016)) that show that the length trip in a city is an exponential distribution ($P(r) = \frac{1}{r^\gamma}$ with $\gamma \approx 3$) and so it makes sense to stop the computation of the STP for a certain radius big enough to assure us to take into account the most part of them.

The second approach that we have mentioned is the so called OD-weighted efficiency. It could be applied if we have some origin-destination matrix information. The main idea is to take into account this data and give a weight in the efficiency formula for each pair of node (i, j). For this purpose we use

$$E_w(i,t) = \frac{1}{\sum_{j\neq i\in N} w_{ij}} \sum_{j\neq i\in N} w_{ij} \frac{\tau_{ij}^{FF}}{\tau_{ij}^{SP}(t)}.$$

The advantages in this approach is that very often the demand between many nodes is zero or negligible. In this case we can avoid to compute the relative STP. The decision to take into account only the OD pair reduces the computational cost and also provides a some peculiar measure of traffic theory. We applied this kind of approximation to some real cases and we show the effective gain in information compared to the all-network efficiency defined at the beginning. In particular we see the improvement that a control strategy based on OD matrix has on the

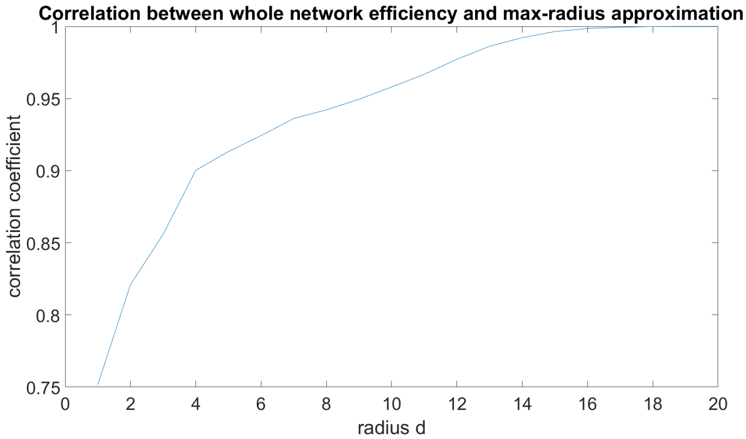

Figure 2: Correlation (in Shenzhen data in Ji. *et al.* (2014)) between the efficiency measure given by computing all the STP in the network and the measure obtained by considering only the trip with a length less or equal a distance $d \in [\max_i \min_j d(i,j), \max_{(i,j)\in N\times N} d(i,j)]$. For each radius d, this value it is the average in time (6am -8am) of the correlation coefficient with the whole network efficiency.

Figure 3: Comparison between the global efficiency weighted (on the right) and non-weighted (on the left) for Barcelona in a perimeter Control scenario (red line) compared to a No-Control scenario (blue line). We notice that the weighted efficient, in this case, catches better the improvement of the perimeter control that it was designed for a particular OD matrix. These results come from a microsimulation with AIMSUM Kouvelas *et al.* (2015).

network as expressed by these performance measures.

5 On-line VS classical shortest path route guidance

Another way to use our algorithm and, in particular, the betweenness for each link at each time step is the following.
For each time step t we compute the shortest time path $STP_{ij}(t)$ between each pair of nodes i and j in the network. This means that all sets of the union $\{STP_{ij}(t)\}_{i,j\in N, i\neq j}$ are topologically equivalent for all t; for every time t they link every pair of nodes but generally through different paths because of congestion. In other words, for each time step t we can achieve all trips that go from each node to any other node in the network, following maybe different paths, based on the dynamical STP algorithm.

As an example, we show in Figure 4 the case of Shenzhen. We compare here the difference of the sum overall all paths of the travel time that follow the STPs and the shortest paths during the period from 6am to 8am. It is clear that the STP (blue line) calculated considering the traffic condition has the minumum value but it is interesting how much time is lost if all drivers follow the shortest path (red line). We want to highlighter that we obtained these measures as direct consequence of the only STP algorithm that we use for all our analysis.
We show that the sum over all commodities of the gain in time at each time step from 6am

to 8am that a driver, because of the congestion, could have following the shortest time path (provided by our algorithm) rather than the shortest path.
We called this value Ghost Total Travel Time (GTTT), because it might be the time that a "ghost driver" who wants go from each node to any other node should spend in the network. It is defined by the following formula

$$GTTT(t) = \sum_{i \in N} \frac{betweenness(i,t) * length(i)}{speed(i,t)}$$

while to compute the time that this "ghost driver" should spend if he follows the shortest path we use

$$GTTTSP(t) = \sum_{i \in N} \frac{betweenness(i) * length(i)}{speed(i,t)}$$

where $betweenness(i)$ is the betweenness of link i computed along all the shortest path on the network. In Figure 4 we can see this value, during the morning peak hour.

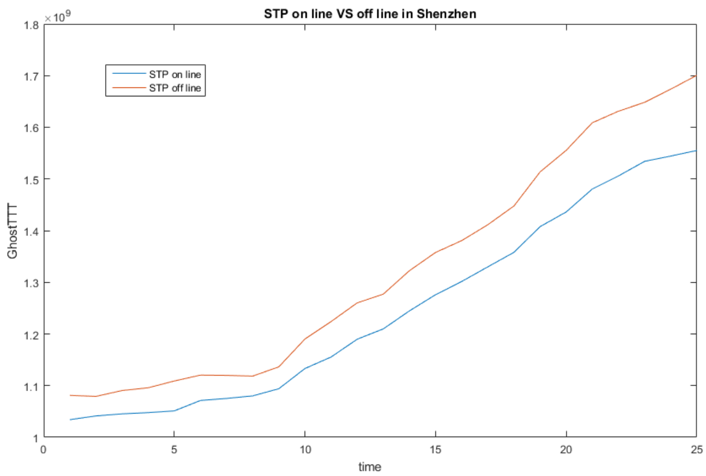

Figure 4: The graphs represent the total amount of time spent to go from each origin node to every destination in the network following the shortest path (red line) or the STP (blue line).

6 Ongoing works

We extend this analysis to other data sets from different cities and see the difference in the distribution of efficiency among links and also its evolution in time, for example during the peak hour. We believe that this kind of analysis could give us a better understanding of the traffic and congestion propagation in the city and how and why some cities are more *efficient* than others. Recently we have access to many different traffic data (for example Uber, microsimulators,

traffic sensors, taxis, etc..) that we can use to compute efficiency.
In fact, it is important also because it involves at the same time some structural properties of the network in terms of paths and route alternatives and also the speed distribution at certain time that generally describes the congestion formation which decreases, in an obvious sense, the global efficiency.
Because of its generality and wide and simple application in road network this measure could be a valid and meaningful indicator also to see the accuracy of traffic models.

We believe that models based on some few, but reasonable, criteria who want predict and simulate traffic and congestion propagation could find in efficiency a more trustful feedback because speed data (as flow and accumulation data) usually have a bigger variance (which depends on weather, accident, route choice, demand, etc.) than efficiency. In fact sensor detectors or GPS signals are, for their own nature, strictly space-depended while *efficiency* is network dependent, or at least neighbor dependent. It means that also if we miss some data or there is some error or strange fluctuation on data, the *efficiency* is much more 'stable' and it catches the general feature of the network part by part that, at the end, it is the most important information for civil engineers to intervene with some solutions.
In this sense it could be useful also for the calibration part for a traffic model because the validation part it would be based in some more stable value (efficiency) that local speed or accumulation and it will avoid a big computational effort in parameter calibration.

For this purpose we have tested and compare dynamical efficiency of the simulation of a congestion model based on the reaction-diffusion system and the real dynamical efficiency for Shenzhen city obtaining good result and useful estimation for the calibration of some parameters. This model estimates the average link speed based on a given sparse OD matrix and the diffusion term which simulate the observable influence that a congested link has on its neighbors. The results will be presented in a incoming paper (Bellocchi and Geroliminis (2016)).
Moreover, if some peculiar distribution of the efficiency has been detected from data then any valid traffic model has to reproduce it to catch the efficiency distribution over all links. It is, at the end, a property of *reachability* that describes how each link is "good" in relation to the whole network.

7 References

Bellocchi, L. and N. Geroliminis (2016) Reaction-diffusion model for traffic propagation, *in preparation*.

Bernard, M., J. Hackney and K. Axhausen (2006) Correlation of link travel speeds, *6th Swiss Transport Research Conference*.

Carra, G., I. Mulalic, M. Fosgerau and M. Barthelemy (2016) Modeling the relation between income and commuting distance, *arXiv preprint arXiv:1602.01578*.

Freeman, L. C. (1977) *Sociometry*, vol. 40.

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

Jenelius, E. and H. Koutsopoulos (2013) Travel time estimation for urban road networks using low frequency probe vehicle data., *Transportation Research Part B: Methodological*, **53**, 64–81.

Ji., Y., J. Luo and N. Geroliminis (2014) Empirical observations of congestion propagation and dynamical partitioning with probe data for large-scale systems, *Transportation Research Record*, 1–11.

Kouvelas, A., M. Saeedmanesh and N. Geroliminis (2015) Feedback perimeter control for heterogeneous urban networks using adaptive optimization, *18th IEEE International Conference on Intelligent Transportation Systems*, 882–887.

Latora, P. C. V. and S. Porta (2006) Centrality measures in spatial networks of urban streets, *Physical Review E*, **73**.

Latora, V. and M. Marchiori (2007) *A measure of centrality based on network efficiency*, vol. 12.

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

Saeedmanesh, M. and N. Geroliminis (2015) Optimization-based clustering of traffic networks using distinct local components, *18th IEEE International Conference on Intelligent Transportation Systems*, 2135–2140.