URBAN HEARTBEATS

(Daily cycle of public transport intensity)

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Abstract

Main focus is put on the daily cycle of public transport intensity. In the city, commuting between places of housing and places of work one of the most important types of recurring organized spatial interactions. This is reflected also on the public transport which has tendency of creating communities as a reaction to demand. This feature of public transport in a city can be clearly identified through network analysis. Network approach recently developed in theoretical physics and related disciplines is still a promising direction of research also in the case of urban transportation studies. We use public transport system in a usual European city, a representative day in Bratislava, to demonstrate that it behaves systematically along the daily cycle in response to changing demand. Even through only basic description of data was calculated, the daytime rhythm, which we call the urban heartbeat, can be clearly recognized in the network structure. Though, the difference between intensity is clearly expressed, only the difference between night and day seems to have bigger statistical difference.

Keywords: public transport, dynamic network analysis, community, Bratislava

INTRODUTION

Each city lives in motion. Households and firms create and abandon connections between them in different roles as economic actors. Some are seemingly random in appearance, others are predictable. Networks of these connections follow surprising orders of their distribution in space and time. Flows of different kinds, as a result of self-organization in city, emerge and die in a rhythm, which we, rather too poetically, give the name urban heartbeats. Time and space merge within and create a spatial-temporal phenomenon crucially important in understanding how cities live.

Movements of people, things, or mere information employ many researchers over generations. Basic aim of their efforts is a functionally better organized city. Public transportation system may serves us as a useful model of spatial interaction, multidimensional complex web of links varying in intensity and regularity over various frequencies, probably most importantly a daily 24-hours long.

One of the prominent types of cyclically organized spatial interactions in the city is commuting between places of housing and places of work. Separation of different functions has been symptomatic over the whole 20th Century urban planning. The notion of order and effective organization of daily life in the city was considered progressive in compare to experienced chaotic mixture of unplanned organic cities. Bratislava is for decades the biggest and the fastest growing city in Slovakia. We assume it has the potential to witness such changes.

Without wanting to go in broad discussion concerning positive and negative sides of modernist urban planning we will remain only concerned with most relevant consequences for urban daily rhythm. Modernist urban plan separating housing from work and services is responsible for creating demand for transportation, increasing and decreasing mostly in synchronicity with daily and weekly economic cycles.

Limiting our attention further it's not really technical details behind commuting behavior modeling, subject of vast economic and technical literature. Cyclical self-organization of spatial interaction networks according to our intentions shall be considered a regularly repeating natural experiment worth attention of researchers.

Each daily cycle in urban life is itself a model of human interaction born and maturing up to morning peak hour, then easing over midday and once again growing before daily peak is reached in the late afternoon. Additionally to changing intensities we also expect asymmetry in speed of variation, probably not independent from further qualities and scale.

The public transport network obviously changes over daily and longer cycles. Connection between different parts of a city is more frequent, possibly also faster in different hours depending on modes of transportation operating. Weekend and nighttime rides can be significantly more difficult, at least requiring more advanced planning for minimizing waiting times.

Besides common observations like these, we try to ask a very simple question, whether topological aspects of complex network of public transportation also significantly change and what kind of change it is. More precisely, we are interested in the specific dynamics of network structure, represented in the categorical variable representing network communities, identified by appropriate technique.

Public transportation network, as described earlier might be decomposed into nodes, geographically located stops, points of departure and arrival of individual vehicles on individual lines, and arcs connecting subsequent stops. In the basic alternative we can use binomial representation for arcs. But network architecture of usual public transportation systems requires the usage of weighted arcs for capturing changing intensity.

We decide to weight the arcs with integer counts of vehicles, connections aggregated over an appropriate interval of time. However, such weighting remains blind to speed of connection. Fast service lines can be significantly preferred to slow lines. Cheap connections can be preferred to expensive. Comfortable connections can be preferred to crowded lines. For the time being we intentionally forget about these complications and only consider frequency of connection indirectly also indicating typical waiting time after arriving at the stop randomly.

Further organization of our paper is typical. We first review an intersection of literatures discussing basic principles of network research in transportation. We are especially interested in papers providing theoretical understanding for the evolving complex network perspective. We also find similar orientation of medical research in mapping of the functional brain topologies. Next we describe a representative daily cycle empirically in the city of Bratislava according to the schedule as of July 09, 2013. Network is separated in eight 3-hours long samples, which are further decomposed into Louvain network communities. Basic counts are provided concerning internal and external flows relative to full network mobility scale, modified between samples. Last section concludes and suggests questions of further interest.

Evolving network perspective in literature

Significant progress on the field of network analysis by Watts and Strogatz (1998), Barabási and Albert (1999) or Albert and Barabási (2002) have contributed to the expansion of network analysis in various scientific fields. Many systems take the form of networks, sets of nodes or vertices joined together in pairs by links or edges (Strogatz, 2001). Examples include social networks (Watts and Strogatz, 1998; Scott, Carrington et al., 2011), technological networks such as the Internet, the World Wide Web (Choi et al., 2006) and power grids (Amaral et al., 2000), and biological networks such as neural networks (Watts and Strogatz, 1998), or metabolic networks (Jeong et al., 2000).

During the past few years many studies have focused on different types of transportation network analyses, especially on airport (Bagler, 2008; Zhang et al., 2010), railway (Seaton and Hackett, 2004) or bus networks (Xu et al., 2007). Also several public transport systems have been investigated using various concepts of complex networks (Latora and Marchiori, 2001, 2002; Von Ferber et al., 2007; Soh et al., 2010).

Most of previous studies have analyzed only specific sub-networks of public transport networks in various urban areas and in different parts of the world. For instance, subway network analysis of Boston by Latora and Marchiori (2000, 2002) who defined measures of local and global network efficiencies. They notably found that the small-world behaviors existed in that system. In another study Sen et al. (2003) found that India's railway network exhibited small-world properties and predicted that railway networks in other countries would also exhibit small world properties. Similar properties were reported by Seaton and Hackett (2004) who calculated the clustering coefficient, path length and average degree vertex of the rail systems in Boston, US and Vienna, Austria.

Also, Musso and Vuchic (1988), Vuchic and Musso (1991) focused on evolution and characteristics of subway networks. Derrible (2012) interested in network centrality of 28 worldwide metro systems, where he studied the emergence of global trends in the evolution of centrality with network size and examine several individual systems in more detail. Sienkiewicz and Holyst (2005) have analyzed the bus and tram networks of Polish cities finding that some systems appeared to show a scale-free behavior, with scaling factors. A very similar analysis was offered by Xu et al. (2007) focusing the complexity of several bus networks in China.

However, as far as the bus, subway, or tram sub-networks are not closed systems, the inclusion of additional sub-networks has significant impact on the overall network properties as has been shown for the subway and bus networks of Boston (Latora and Marchiori, 2001, 2002). Latora and Marchiori (2001) introduced the related concept of efficiency, which measures how easily information is exchanged over the network. They showed that small-world networks are highly efficient. Soh et al. (2010) examined Singapore public transportation system where they focused on the degree, strength, clustering, assortativity and eigenvector centrality characteristics of the transportation networks.

Lu and Shi (2007) analyzed the public transport networks in three Chinese cities and they found that the public transportation networks have the characteristics of complex networks. In addition, the urban transportation network parameters all significantly affect the accessibility, convenience, and terrorist security capability of the urban public transportation network. Von Ferber et al. (2007, 2009) used complex network concepts to analyze the statistical properties of public transport networks of several large cities, looking at all technologies and accounting for the overlapping property of transit systems, notably finding a harness effect. They also attempted to model system based on number of stations and lines.

On the other site we do not register many authors who deal with evolving transport networks, especially public transport networks. Albert and Barabási (2000) brought fundamentals of evolving networks.If new nodes and edges appear while some old ones disappear, we can talk about evolving networks. The Barabási – Albert model was the first model to derive the network topology from the way the network was constructed with nodes and links being added over time. From there they were derived many other evolving network models (Barrat et al., 2004; Yook et al., 2001). Evolution models are often used primarily to study social networks for instance Snijders et al. (2007), Xu and Hero (2013). Nevertheless we register some examples. Zi-You and Ke-Ping (2005) investigated the emergence of scale-free behavior in a traffic system by using the NaSch model to simulate the evolution of traffic flow. Xie and Levinson (2011) describe generally evolving transportation networks. In this publication they tried to understand the process of network growth by identifying and quantifying its determining factors. Zhang and Xu (2012) applied the evolution model on China domestic airline network from the year 1950 to 2010. All of the above works examined the evolution of transportation networks in several decades. But evolution of public transport network in short periods, for instance 24 hours, has not been elaborately described or dealt with in the existing literatures.

Interesting element of the basic characteristics in the public transport network is an analysis of communities. The property of community structure appears to be common to many networks. Consider for a moment the case of social networks, for instance networks of friendships or other acquaintances between individuals. It is a matter of common experience that such networks seem to have communities in them: subsets of vertices within which vertex–vertex connections are dense, but between which connections are less dense.

The ability to detect community structure in a network could clearly have practical applications (Girvan and Newman 2002). Communities in a social network might represent real social groupings, perhaps by interest or background; communities in a citation network might represent related papers on a single topic;

communities on the web might represent pages on related topics (Fortunato, 2010). The same can be observed also in public transport networks (Von Ferber et al., 2009).

We do not register any literature that examines in detail communities either in evolving public transport networks or in transport networks generally. It is unexpected, since having the ability to identify communities (in static or dynamic network) could be helpful in more effective understanding and utilizing of these networks.

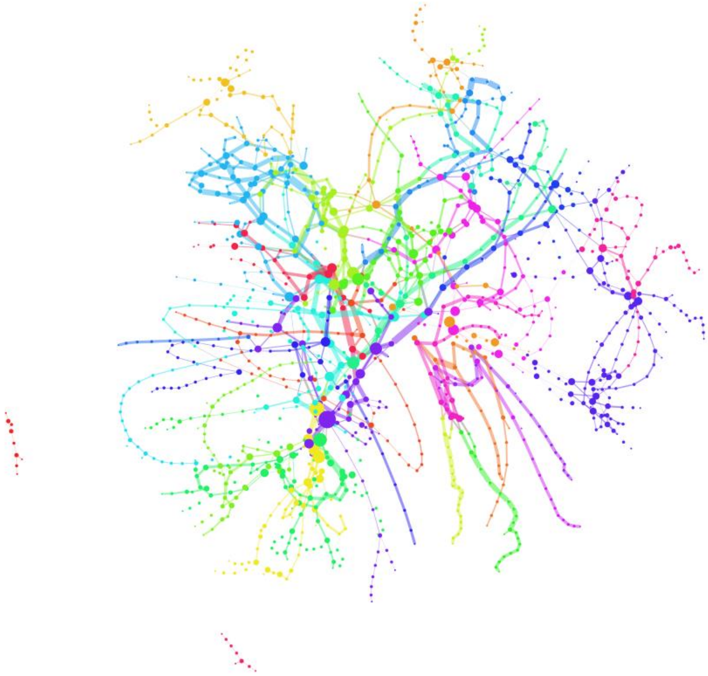

Fig. 1. Louvain network communities identified in pooled 24 hours cycle in Bratislava, space is non-geographic for clarity. Source: July 09, 2013 public transportation schedule by Apptives.

Nowadays has research of communities still mainly significant application in medicine. Communities are widely used in medical science and neuroscience to understanding and examining the processes occurring in the human brain. Zemanová et al. (2008) found that the network of cortical area displays clustered synchronization behavior and the dynamical clusters closely coincide with the topological community structures observed in the anatomical network.

A useful study was elaborated by Wu et al. (2011) and it can be used not only in medicine, but also in public transport analyses. The main objective of this study was to reveal an overlapping community structure of the structural brain network in individuals. They demonstrated that 90 brain regions were organized into 5 overlapping communities associated with several well-known brain systems. The overlapped nodes were mainly attributed to brain regions with higher node degrees and nodal efficiency and played a pivotal role in the flow of information through the structural brain network. Similar overlapped nodes exist in communities of public transport network. Right these nodes (stops) represent the most important places of the public transport network.

There could be also found some parallels between brain network and transportation network research in the recent paper of Crossley et al. (2013) which examines community structure of the human brain. They revealed modifications in network structure of dynamic brain network through changes in communities.

A REPRESENTATIVE DAY IN BRATISLAVA

We have made first analysis of Bratislava public transport network in our previous paper (Ondoš et al., 2013). Since much information remains hidden in a static network representation, we decided to further elaborate research on the role of time. Data analyzed in this paper are more detailed in respect of temporal dimension. Thus, the analysis is based on the dynamics throughout the day. In our assumption, the nature of public transport changes during day, along with changing demand of its users. This is where our research potentially connects with economic literature.

We obtain detailed time schedules of public network in Bratislava used for iTransit Android client by Apptives. Reference date for the schedule is July 09, 2013, but it consists of alternative daily schedules for ordinary workday, weekend day, and school vacations workday. We proceed by pooling these different schedules into a representative day not existing in reality, but useful as an analytical generalization.

The network under study consists of 584 stations represented as 1,379 station nodes according to their geographical position and total of 94 routes. Because each station node is operated only in one direction, we used directed graph as representation of network. By connecting stations with all routes regardless of vehicle type, we got 1,536 links served by public network. Only some links are operated throughout the whole day. During 24 hours cycle we record 463,125 one station rides. For a better comparison, we have split the 24-hour day into eight equal-width samples. Ranges of individual intervals are shown in Table 1.

Table 1. Basic statistics and communities of dynamic public transport network. Source: July 09, 2013 public transportation schedule by Apptives.

Sample	1	2	3	4	5	6	7	8
Duration	00:00-02:59	03:00-05:59	06:00-08:59	09:00-11:59	12:00-14:59	15:00-17:59	18:00-20:59	21:00-23:59
Nodes	661	1,206	1,250	1,177	1,246	1,249	1,220	1,150
Arcs	725	1,699	1,684	1,536	1,677	1,666	1,625	1,543
Rides	8,044	30,137	80,098	70,399	75,474	82,339	69,455	47,179
Rides per arc	11.1	17.7	47.6	45.8	45.0	49.4	42.7	30.6
Communities	28	37	32	34	34	31	31	35
Modularity	0.885	0.864	0.866	0.868	0.867	0.863	0.866	0.868
Average number of nodes per community	23.6	32.6	39.1	34.6	36.6	40.3	39.4	32.9
Rides inside communities	7,490	27,250	72,547	63,980	68,609	74,346	63,254	42,999
Between rides	554	2,887	7,551	6,419	6,865	7,993	6,201	4,180
Share of rides inside (%)	93.1	90.4	90.6	90.9	90.9	90.3	91.1	91.1

The physical network described above is transferred to graph in the most typical way, stations to nodes/vertices and links to edges. As Barthélemy (2011) have shown, there are many ways of representing public transport system as a network. For the aim of this paper we have chosen the space-of-stops or so called L-space representation. Each station is represented in graph by a node and an arc (oriented edge) between two nodes indicates that these are consecutive stations of at least one route (Von Ferber et al. 2009).

As the result from previous, neighbors are only those stations that can be reached within single-station trip. As mentioned before, the graph we constructed is directed and thus it better reflects real conditions of selected public transportation network. As weights we used the volume of public traffic between stations for given time.

As expected, there are two modes in the network corresponding with rush hours. The first mode, second and third interval sample, is the sharper one, as during first interval there is only small amount of traffic. Second mode can be detected between 12 and 18 hour. The volume of traffic is then slowly declining when approaching midnight. Both nodes are visible on all statistics, but mostly on the flow.

Rides per arc summarize flow intensities in subsequent samples. Minimum of 11.1 rides is found in the first sample. Network grows fast between first (+60%) and third sample (+168%). First peak is reached over the morning commuting times over 6-9AM period when we observe 47.6 rides per arc. High level of mobility is then preserved with slightly falling trend until afternoon (-4% and -2%). After 3PM the network rises once again (+10%) and reaches 24 hour culmination at 49.4 rides per arc. Last sample is at the level 30.6 rides to which and beyond the network dies relative slowly (-14%, -28%, -64%) in compare to morning rises. Urban heartbeat is regular but not symmetric. Visual representation in graph series in the figure 2 supports this observation.

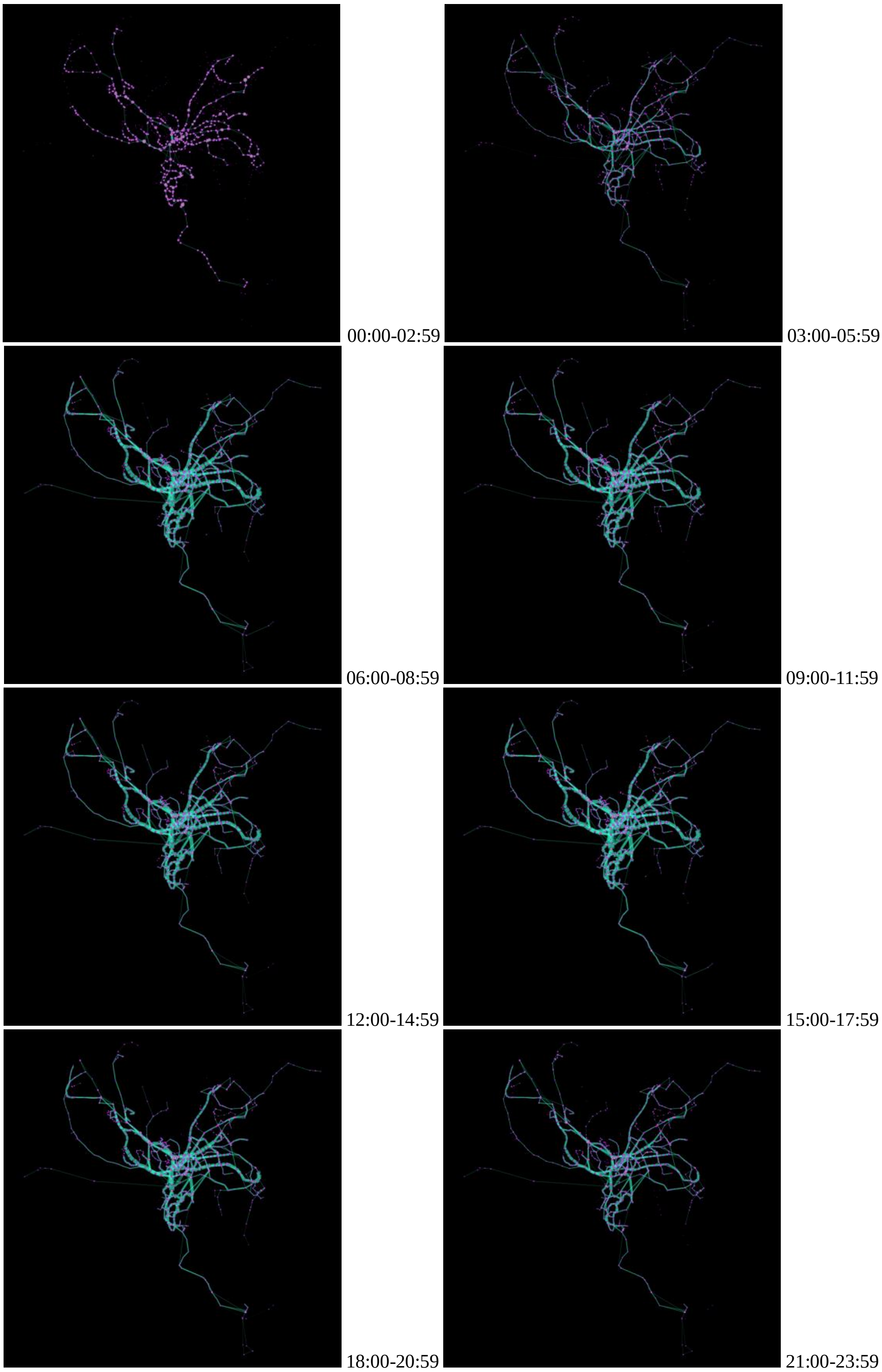

Fig. 2. Eight aggregated samples represent varying degree of connected nodes linked by operating vehicle-count integer weighted links in Bratislava. Source: July 09, 2013 public transportation schedule by Apptives.

Second panel in the Table 1 summarizes few basic statistics for communities identified on described network (Blondel et al., 2008). If we compare statistics with previous we can conclude, that with rising amount of traffic, the network is more concentrated. It is also visible from smaller amount of bigger communities in the rush hours. High modularity levels in all samples suggest that the network under observation is composed of surprisingly well defined structural elements. The individual parts of topology are connected rather inside than between. Links between these play the role of bridges. Only about 9% of rides over 24 hour cycle establish these bridges.

We further pay attention to the number of nodes per community as one of possible evaluation criteria. Naturally, nodes have varying position in the network captured by different centrality measures, including the basic degree distribution. But still we may see from the figure 3 that we consistently observe about one large community having above 100 departure points. Average number of nodes per community varies between minimum of 24 in the first sample and maximum of 40 in the evening peak sample. The average lies at 35 nodes, which describes a standard network community in Bratislava daily cycle. Larger composition units appear during morning peak 6-9AM and afternoon/evening 12AM-9PM.

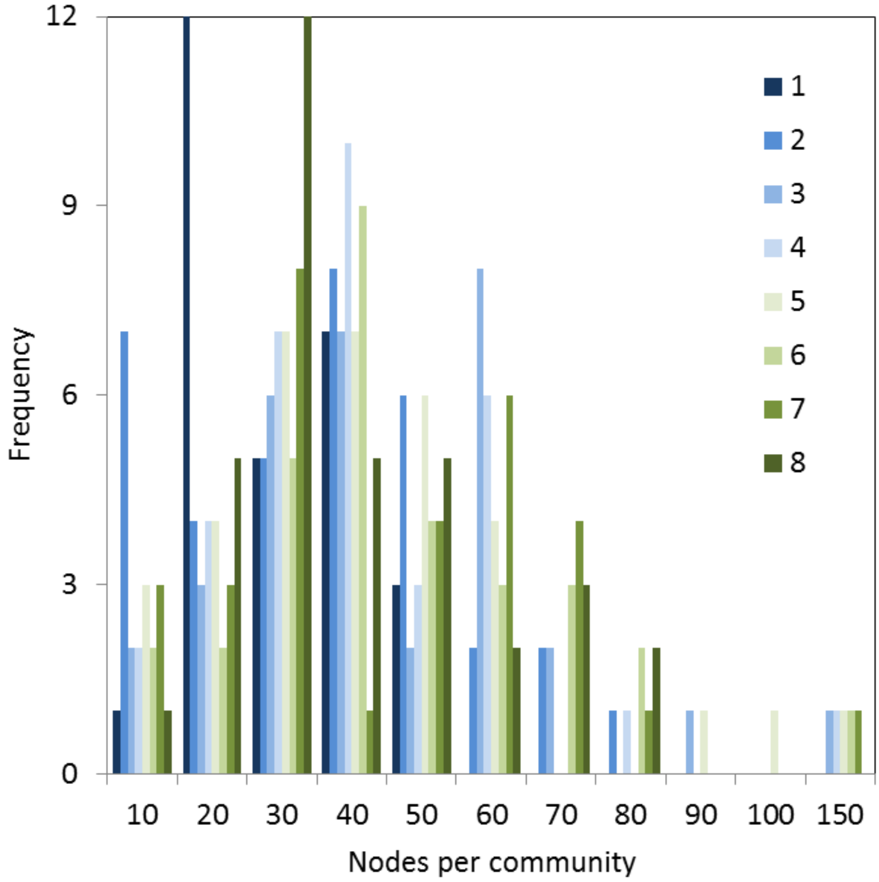

Fig. 3. Size distribution of network communities identified in eight time samples (1-8).
Source: July 09, 2013 public transportation schedule by Apptives.

CONCLUSIONS

Network approach recently developed in theoretical physics and related disciplines continuously proves to be a promising direction of research also in case of urban transportation studies. We use public transport system in a usual European city to demonstrate that it behaves systematically along the daily cycle in response to changing demand from inhabitants and firms in roles of economic actors. Not only overall scale of this network is modified but also structural composition of network topology.

Even the most basic description of data available from schedule demonstrates that daytime rythm, which we call urban heartbeat, is present in network structure very clearly. Network consists of smaller communities in times of lowest intensities of interaction supplied by public service lines and largest communities in times of highest intensities of interaction over peak hours. Mobility system therefore integrates with scale increase and disintegrates with scale decrease. This finding might be trivial, but it has interesting implications hypothetically beyond the lines of transportation research.

This paper did not even touch details of the subject of precise topology composition. Public transport stops are members of the same community consistently with others, on average, exactly 34 partners, but not over the whole day. From hour to hour de-facto barriers within the urban fabric are crossed by the same or different network bridges. Knowing where these are located and possibly explained why exactly there and not in a different place is a suggestion for further developments in this research.

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