DIT4TraM

Distributed Intelligence & Technology for Traffic & Mobility Management

# Generalizability, transferability, and scalability of DIT4TraM solutions

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Distributed Intelligence & Technology for Traffic & Mobility Management

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# Contents

# 1. Introduction

One of the challenges in assessing urban traffic is developing universal tools that apply to different types of urban forms, transportation systems, drivers' habits, etc. In this report, we address the assessment methodology for qualitative and quantitative data-driven analyses which is based on the percolation methodology.

Here, we use the dynamic percolation process of the traffic loads and the static streets-morphology to develop new, assessment tools for different scales of urban environments. We use network percolation analysis (which examines the robustness of the traffic flow network to failure) to identify street clusters that represent functional modules (i.e. continuous areas where traffic flow is fluent), composed of connected roads with traffic load lower than a pre-defined threshold. We define a fixed threshold for the percolation process (see the methodology section for further elaboration) and focus on the clusters themselves rather than on the links that connect the different clusters. Based on the above, we identify spatially embedded clusters and track their dynamics at different temporal scales, ranging from one hour to a week. By doing so, we present the different patterns of urban mobility, its evolution, and dynamics, and develop new tools for assessing the quality and predictability of urban traffic flow. These tools will be later used on the outcomes of the studied cases and the pilot sites with the aim to produce generic outputs

## 1.1. State of the art

Historically, the nature of urban streets and their land uses are in correlation with the volume of the street's traffic flows. These two parameters are interdependent and together with other urban factors (e.g., social, cultural, etc.) create urban variety and dynamics that make the city a complex system (Portugali 2000, 2012, Batty, 2007). Understanding these interdependencies, may shed light on different urban phenomena and could be developed into new, real-time, decision-making tools that can be useful for planners under a new understanding that planning can no longer address long-term plans only, but should keep up with new phenomena and address the urban area as the complex, self-organizing system it is.

We present a new framework, based on complex networks tools and in particular percolation theory. This interdisciplinary complex network field addresses, among other things, spatially embedded transportation networks that control many aspects of modern urban life and thus affect problems such as traffic jams, urban sprawl, epidemiology, etc. (Barthélemy, 2011; Verbavatz and Barthélemy, 2020). However, in these studies, most of the work focused on the network topology where the nodes and the links between them are fixed in time and set top-down (for a comprehensive review on this see Barthélemy, 2011). Some studies on traffic networks defined the networks using fixed nodes with dynamics links (i.e. the links between the nodes vary, and are usually formed due to bottom-up forces) see for example Chowell et al. (2003) or Austwick et al. (2013). The influence of the street-networks topology on traffic volumes has also been studied extensively (Goh et al., 2001; Girvan and Newman, 2002; Ercsey-Ravasz and Toroczkai, 2010; Ercsey-Ravasz et al., 2012; Freeman, 1977; Guimerà et al., 2005; Borgatti, 2006; Serrano et al., 2009; Grady et al., 2012). Yet, here also, most of the work on that subject overlooked the dynamic of the traffic flow and the influence it has on the overall urban system.

Recent work introduced an innovative approach that employs percolation processes to identify urban clusters (Li et al. 2015, Arcaute et al., 2016) and to identify links that act as significant and repetitive temporal bottlenecks in urban traffic networks (Li et al. 2015). They defined the percolation threshold based on the maximal size of the second-largest component and then examined the resulted clusters and focused on the links that were identified as bottlenecks. This methodology (which has been tested on real urban data) not only reveals the blocked links but also presents the resulting decomposing process of the city into spatio-temporal clusters that correspond to different traffic flows at different time scales (daily and weekly). This is based on a description of the city as a collection of local functional traffic–flow clusters connected by temporal bottlenecks. By examining the temporal speed of each link (road segment) and comparing it to a threshold, the researchers were able to classify the different links as blocked or unblocked at each given time and to follow the dynamics of the percolation process of the road network as discrete clusters. We elaborate on this idea and extend it into a set of assessing tools for urban traffic quality and stability (predictability).

# 2. Methodology

In this chapter, we present the methodology for developing the tools to assess urban traffic quality and stability. Our methodology is based on complex network theory and percolation processes and results in simple indices that reflect the traffic quality in near-real-time, and the traffic stability over time. We developed a two-stage methodology to identify functional clusters and use them to evaluate traffic quality and stability. In the following, we present these stages.

## 2.1. Urban Functional Clusters

In the first stage, we transform the road network into a topological network where for each road, $e_{ij}$, the velocity $v_{ij}(t)$ varies during a day according to time-dependent traffic operations. We use speed rather than flow as this data can be easily extracted from the API of different navigation apps and thus, this method can be easily implemented on such datasets. For each road $e_{ij}$, we set the 95th percentile of its measured velocity as its limited maximal velocity and define $r_{ij}(t)$ as the ratio between its current velocity and its limited 95% percentile measured velocity.

For a given threshold q, the road $e_{ij}$ can be classified into either *functional* when $r_{ij} > q$ or *dysfunctional* for $r_{ij} < q$. In other words, whether a road is functional depends on the extent in which traffic can drive at its free or maximum speed. Note that for q = 0, we have the situation where the traffic network is the same as the original road network and q = 1 represents and situation where it becomes (generally) completely fragmented.

For a certain value of q, the hierarchical organization of traffic in different scales emerges, where only clusters of connected roads with $r_{ij}$ higher than q appear. These clusters represent ***functional modules*** composed of connected roads with speed values higher than q.

As q increases, the size of the giant component decreases, and the second-largest cluster reaches a maximum at the critical threshold ($q_c$) separating the fragmented phase from the connected phase of the traffic network.

For example, the giant cluster exists for q=0.19 (see figure 1A). As the value of q increases, this giant cluster is fragmented into smaller clusters and for q = 0.69, only small clusters of connected roads with high velocity emerge. These cannot maintain the global network traffic (figure 1C). For q = 0.38 (Fig. 1B), the size of the second-largest cluster is in its maximal size, which indicates the phase transition point for network connectivity of a functional traffic network (according to percolation theory).

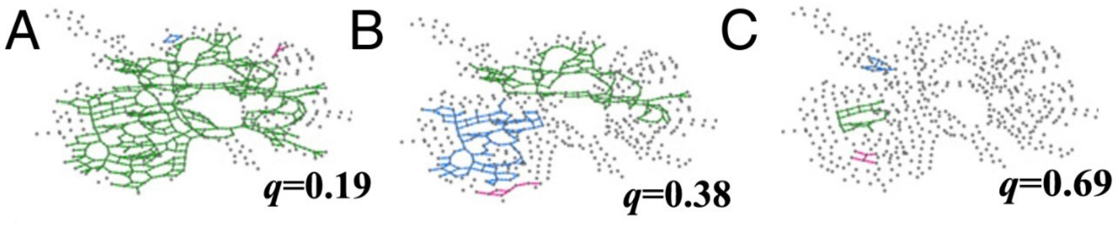


*Figure 1: Percolation of traffic networks for three q values corresponding to different connectivity states. These maps show examples that are based on data obtained during March 2013 for the center of Beijing.*

This percolation process is presented in Fig. 2. As q increases, the size of the giant component decreases, and the second-largest cluster reaches a maximum at the critical threshold ($q_c$) separating the fragmented phase from the connected phase of the traffic network. As an indicator of the robustness characteristics of network connectivity, the critical threshold $q_c$ in this percolation-like process quantifies the global organization efficiency of urban real traffic. In other words, a car can travel most of the city (represented by the giant component of the traffic network) only when its velocity is below $q_c$. Otherwise, it is trapped in small isolated clusters. Thus, $q_c$ measures effectively the maximal relative velocity for the main part of a network, which reflects the global efficiency of traffic in a network view. Thus, the higher is $q_c$ the global traffic is better.

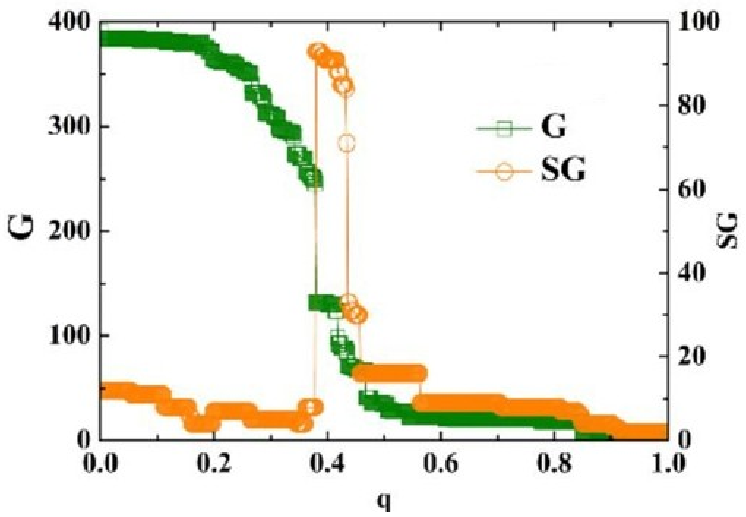

*Figure 2: An example for the size of the largest cluster (G) and the second-largest cluster (SG) of real traffic networks as a function of q at a specific time.*

The bottleneck links of the traffic network are identified by comparing the functional network just below and immediately above the criticality threshold. These links can disintegrate the giant cluster and result in a maximal second-largest cluster as well as smaller clusters.

Using this simple methodology can identify two significant attributes of urban traffic:

1. A single parameter that identifies the critical point where the global urban traffic is no longer fluent (i.e. $q_c$).
2. The street segments that are responsible for the fragmentation of the traffic flow (i.e. the bottlenecks responsible for the fragmentation of the network).

In the second stage, we present an alternative approach, q is set as 0.5 which represents the maximum flow of vehicles. We demonstrate our methodology for q=0.5, which, based on the canonical Greenshields equation (Greenshields, 1935), represents a maximal flow, which is the maximal number of vehicles per hour, derived from the speed-density relations. However, this threshold can be set based on different transportation models to comply with different situations and data resolution.

We defined clusters as strongly connected components of streets with $r_{ij}(t) > 0.5$ Based on this definition, we identify two types of clusters:

1. Temporal clusters that represent good traffic flow, $r_{ij}(t) > 0.5$, at a given snapshot in time. These were defined as ***Functional Temporary Clusters (FTC)***. As mentioned above, we define a link as functional if its relative velocity (defined here as traffic "availability") is higher than a set threshold. A cluster is thus, a collection of streets where one can drive from each point to all others without facing heavy traffic. To focus on significant clusters we set a minimal size (e.g. number of streets) for a cluster to be identified as a Functional Temporary Cluster (FTC)
2. Overlapping FTCs that represent the change of the traffic flow over time and were integrated into another type of spatiotemporal clusters that is defined as ***Dynamic Spatial Clusters (DSCs)***.

### 2.1.1. Dynamic Spatial Clusters (DSCs)

To follow the dynamics of the traffic flow in specific areas, we develop a method that integrates spatially overlapping FTCs into new clusters: Dynamic Spatial

Clusters (DSC). For that, we defined cores that represent spatial anchors for the FTCs at different times.

The core was defined based on the frequency of the streets that appeared in an FTC during a predefined time frame.  This threshold can be changed in order to control the number of DSCs – increasing it will result in a decrease in the number of the DSCs and decreasing it will enlarge their number. This will allow examining the same urban system at different scales and for different levels of data accuracy.

After a core has been defined for a DSC, we assigned to it all the FTCs that contained the streets of this core (partially or in full). We defined a DSC as a collection of FTCs with a mutual spatial anchor. Finally, after all the DSCs were defined, we identified spatially overlapping DSCs and united them into a single one. If the percentage of overlapping links crosses the threshold, the two DSCs are merged into one. These thresholds are site-specific and based on the characteristics of the examined area and thus are different for each city. They can be used to identify many different DSCs with adjacent cores, or fewer DSCs with distant cores.

# 3. Assessing tools

Here, we describe two indices, based on the functional clusters defined above, that have been developed for traffic quality and traffic stability (predictability) assessment. We start by elaborating on the traffic quality index and then continue to the traffic stability one.

## 3.1. Traffic Quality (TQ) Index

To evaluate the traffic quality and its dynamics, for different streets and areas we developed an index called traffic quality (TQ). We based this index on the assumption that good traffic is represented by a low number of FTCs that cover large areas. In other words – good traffic flow allows fluent mobility in large areas and thus, the best traffic quality is achieved where there is only one FTC that covers the largest area of the surface. The TQ is defined based on:

$$TQ = \sum_{1}^{n} \frac{\sum L_i}{R_i}$$

Where $n$ represents the number of FTCs at the examined time, $\sum L_i$ represents the sum of the lengths of the streets in an FTC ranked $i$, and $R_i$ represents the rank of the FTCs where $R_1 = 1$ indicates the largest area and $R_i = n$ the smallest area. Therefore, TQ is an indicator of the physical area of the DSCs, which represents the area with good traffic flow.

To explore the variation of the area coverage of the TQ in different DSCs, we use their standard deviation (σ). Low $\sigma$ corresponds to steady area coverage at different times while high $\sigma$ indicates large variation in the TQ.

To explore the dynamics of the TQ for each DSC individually we can examine both the dynamics of the TQ over time, as well as their rank-size distribution. The rank-size distribution of each DSC describes the total length of the streets in the different FTCs that compounded it (during the selected time frame). The largest FTC is ranked 1, the second-largest FTC is ranked 2, and so on. This analysis disregards the exact time (hour and day) of the FTCs and focuses on the overall behavior of the DSC in terms of its physical area (described here by the TQ), where high values of TQ indicate better traffic flow and accessibility from the core of the DSC to the rest of the city and vice versa. The decay of the rank-size distribution corresponds to the spatial behavior of the DSCs. DSCs that have good traffic flow from and to their cores, throughout the day and on different days, will result in continuous distributions. On the other hand, DSCs that are connected to the rest of the city during specific hours only and are isolated most of the time from their surroundings, in terms of traffic flow, will result in a "step-function" distribution.

## 3.2. Stability

The second index we developed indicates the level of spatio-temporal stability for each DSC at a given window of time (e.g. hours, minutes, days).

Here, we demonstrate this index for hours units, but this, of course, can be modified based on the different time scales of the data availability or the desired analysis.

For that, we calculated the spatial stability of the DSCs for each hour during weekdays only. We based this decision on the results of a previous analysis (presented in the methodology section) that indicated significant differences between weekdays and weekends in terms of traffic flow. The spatial stability (S) for a specific DSC at a specific time is calculated based on:

$$S=\frac{\sum_{1}^{m} l_{FTC}}{m*L_{SCT}}$$

Where $l_{FCT}$ represents the number of links (street segments) in each of the FTCs included in the examined DSC at the examined hour, and $L_{SCT}$ represents the total number of links that appeared at least once in the examined DSC at that hour. $m$ represents the number of days used for the calculation which is 5 in our case (corresponding to working days only). S=1 is at its maximum, when $\sum_{1}^{n} l_{FCT}=m*L_{SCT}$. This indicates that all the FTCs are spatially identical on all the examined days at a specific hour. When $\sum_{1}^{n} l_{FCT}=L_{SCT}$ none of the links appears more than once in the DSC, and its stability is at its minimum. For our calculation this minimum = 0.2. To allow a comparison between different calculations these results are normalized to a range between 0-1. Unlike other methods (e.g. Jaccard index) our method indicates, in one simple number, not only the overlapping that occurs in ***all*** the examined samples (here - days) but also considers overlapping that occurs between only ***some*** of the days. By using this method, we can follow the temporal stability of the spatial behavior of the traffic flows.

Lastly, we focused on the Area-Stability which is the probability of links to be included in a DSC at different times. We analyzed the descending cumulative distribution function (CDF) of the DSCs and its integral, in order to evaluate the DSC in terms of their spatial size as well as the stability of the links they hold at different times. The descending CDF shows the probability of any fraction of links to appear at least x fraction of the time in a DSC. The integral of the CDF indicates, for each DSC, both the number of links it contained throughout the entire examined time frame as well as their stability. In other words, the integral of the descending CDF can be used to evaluate the quality of a DSC in terms of size (represented by the number of streets) and spatio-temporal stability (the appearance of the same links in the DSC at different times). The regression between the values of these integrals provides an overall perspective of the urban traffic and allows a comparison between different DSCs within a city and between different cities.

Each of these analyses provides different insights regarding the overall traffic flow of the DSCs as well as the entire city. They are needed in order to answer different questions, for example: while the area-stability values can be used to prioritize planning and regulation, the stability index can be used for local modifications in public transportation frequencies or traffic-light operation.

# 4. Preliminary Results

In this chapter, we present some preliminary results for the above methodology and indices. As the data from the DIT4TraM partners will be available only at a later stage of the project, we tested this method on data that was available to us from previous projects. The data was collected from Google Direction API for central London and central Tel Aviv. It was collected every 15 minutes for 5 work days in London (Mon-Fri) and in Tel Aviv (Sun-Thur).

We found 19 DSCs in London and 9 DSCs in Tel Aviv (corresponding to the fact that London Center is more than twice as big as Tel Aviv's center). Figure 3 presents the DSCs in London and Tel Aviv.

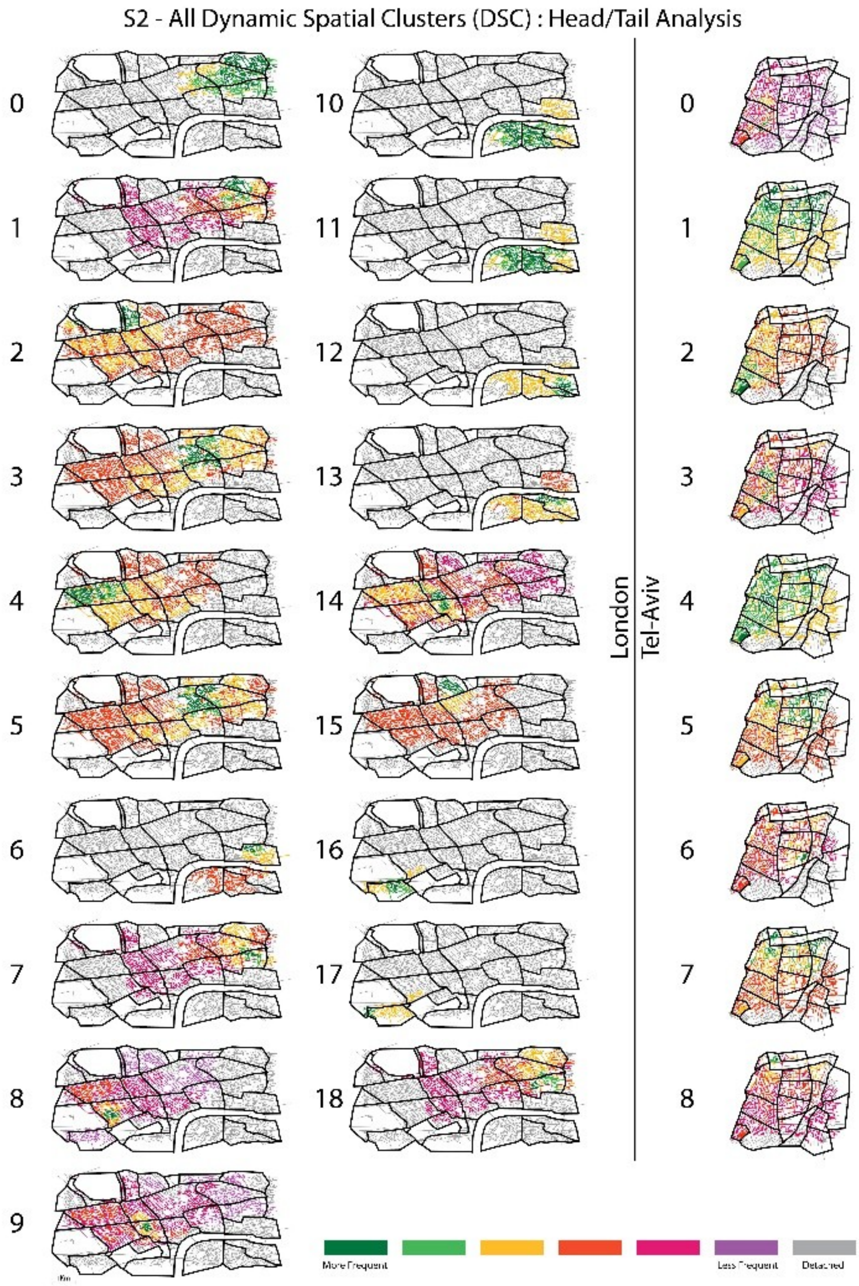


*Figure 3: DSCs in London, and Tel Aviv. The DSCs in London are: 0 - Shoreditch; 1 - Finsbury& Islington; 2 - Regent's Park; 3 – Holborn; 4 – Marylebone; 5 - King's Cross; 6 - City of London; 7 - Barbican; 8 - Mayfair; 9 - Soho; 10 - South Bank East; 11 - Southwark - St. George; 12 - Southwark - London Bridge; 13 - Borough Market; 14 - Fitzrovia; 15 - Somers Town; 16 - Belgravia; 17 - Knightsbridge; 18 - Ferrington. The DSCs in Tel Aviv are: 0 - King George; 1 - Bavli-Bney Dan; 2 - Kerem HaTeymanim; 3 - Ben Gurion; 4 - Ben Gurion - Dizengoff; 5 - Jabotinsky East; 6 - Shikun HaKtsinim; 7 - Rokach West; and 8 - Reading Terminal*

## 4.1. Traffic Quality (TQ) in London and Tel Aviv

We analyzed the TQ of the DSCs in London and in Tel Aviv based on their dynamics at different times during the day, as well as on the rank-size distributions of the total length of the streets they contain (Figure 4). While the σ values of the TQ in Tel Aviv are similar for all the DSCs, in London they increase for DSCs with high TQ. In other words, these results show that the TQ of DSCs in Tel Aviv varies similarly (and significantly) for all sizes, which means that the traffic flow in Tel Aviv is unstable for most of the examined area.

In London, on the other hand, DSCs that cover small areas are more likely to remain small at different times, while DSCs that cover large areas are more likely to change their size at different hours and days.

Thus, these results demonstrate how this index identifies neighborhoods that are well connected to the rest of the city (at different times) and others that are constrained in terms of their traffic flow. It provides an overall insight into the spatial dynamics of the DSCs in each city and thus, can be used as a decision-making tool for planners. Our results also suggest that the dynamics of the DSCs do not follow a universal law and are location-dependent.

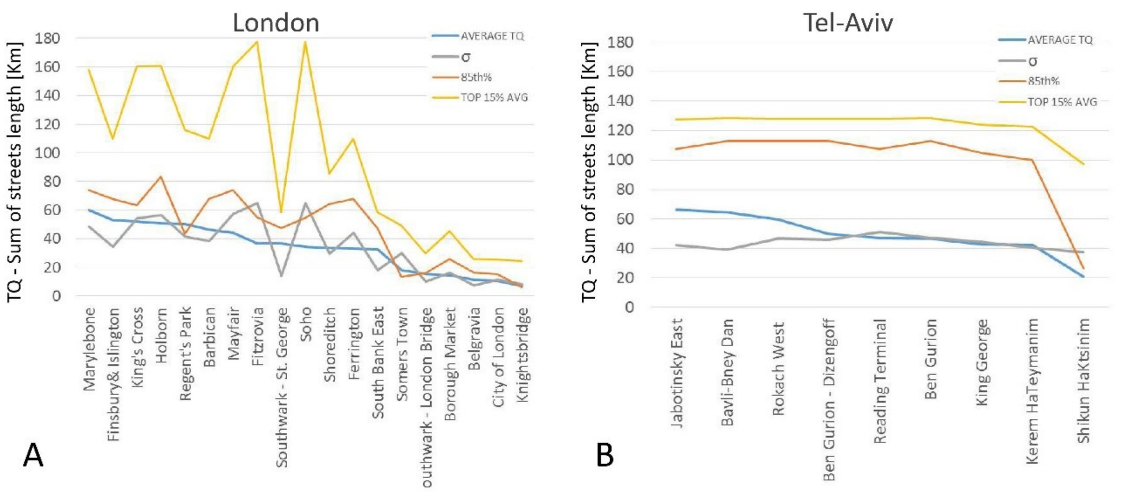


*Figure 4: Average and maximal Traffic Quality (TQ) values and standard deviation (σ) for DSCs in London and Tel Aviv. The maximal values refer to maximal values that appeared in at 85th percentile of the samples and the average of the top 15% values.*

Next, we examined the dynamics of the TQ of these DSCs in London and Tel Aviv at specific times (see figure 5). These dynamics show that the maximal TQ values of the different DSCs are different for London and Tel Aviv. Moreover, the two cities show a major difference in the dynamics of their TQ: in London, high TQ is found in the early morning or late afternoon while in Tel Aviv, high values of TQ occur at different hours on different days. This supports our previous findings and suggests that the dynamics of traffic flow patterns in Tel Aviv are less predictable than those in London.

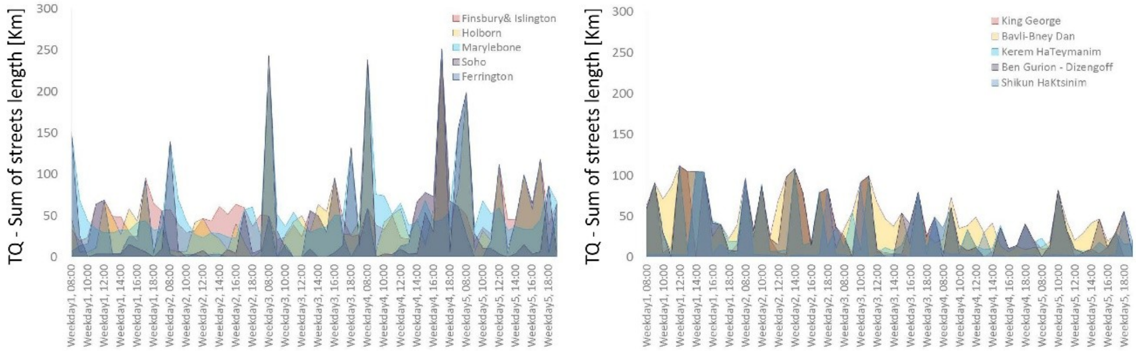


*Figure 5: The dynamics of the Traffic Quality (TQ) of the DSCs in London (left) and Tel Aviv (right).*

## 4.2. Stability in London and Tel Aviv

The Stability index of the DSCs in London and Tel Aviv at different times also presents significant differences (Table 1). The average stability for the DSCs in London is about twice as high as that of Tel Aviv. It can be concluded that most of the DSCs in London are stable in terms of their spatial dynamics. In Tel Aviv, on the other hand, most of the DSCs show low stability values with a few exceptions that are related to two DSCs that cover mainly the immediate surroundings of their cores and are characterized by unique morphologies. Thus, it can be assumed that the high stability index of these DSCs results from the constraints their morphology imposes on their intra and inter-traffic.

This index, as well as the TQ, show that the traffic in London is more stable (though not necessarily better) than that in Tel Aviv.

| London | 08:00 | 09:00 | 10:00 | 11:00 | 12:00 | 13:00 | 14:00 | 15:00 | 16:00 | 17:00 | 18:00 | 19:00 | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Somers Town | 0.05 | 0.9 | 0.52 | 0.88 | 0.88 | 0.87 | 0.85 | 0.45 | 0.9 | 0.88 | 0.16 | 0.96 | 0.69 |
| Southwark - London Bridge | 0.56 | 0.46 | 0.65 | 0.76 | 0.82 | 0.67 | 0.61 | 0.95 | 0.46 | 0.16 | 0.39 | 0.9 | 0.62 |
| Regent's Park | 0.12 | 0.67 | 0.77 | 0.82 | 0.82 | 0.72 | 0.79 | 0.65 | 0.8 | 0.11 | 0.27 | 0.2 | 0.56 |
| Belgravia | 0.68 | 0.57 | 0.77 | 0.5 | 0.3 | 0.5 | 0.55 | 0.67 | 0.45 | 0.65 | 0.68 | 0.4 | 0.56 |
| Knightsbridge | 0.68 | 0.48 | 0.84 | 0.69 | 0.24 | 0.84 | 0.23 | 0.24 | 0.46 | 0.68 | 0.48 | 0.73 | 0.55 |
| Marylebone | 0.53 | 0.6 | 0.5 | 0.57 | 0.45 | 0.6 | 0.64 | 0.43 | 0.54 | 0.51 | 0.35 | 0.28 | 0.50 |
| Southwark - St. George | 0.52 | 0.45 | 0.5 | 0.48 | 0.48 | 0.49 | 0.66 | 0.52 | 0.58 | 0.4 | 0.4 | 0.29 | 0.48 |
| South Bank East | 0.44 | 0.15 | 0.47 | 0.33 | 0.37 | 0.52 | 0.62 | 0.54 | 0.58 | 0.36 | 0.32 | 0.24 | 0.41 |
| Borough Market | 0.52 | 0.25 | 0.61 | 0.41 | 0.64 | 0.51 | 0.52 | 0.57 | 0.31 | 0.16 | 0.19 | 0.18 | 0.41 |
| City of London | 0.44 | 0.29 | 0.25 | 0.42 | 0.53 | 0.28 | 0.41 | 0.51 | 0.43 | 0.42 | 0.61 | 0.17 | 0.40 |
| Finsbury& Islington | 0.52 | 0.3 | 0.32 | 0.43 | 0.29 | 0.43 | 0.56 | 0.36 | 0.27 | 0.25 | 0.42 | 0.46 | 0.38 |
| King's Cross | 0.35 | 0.62 | 0.45 | 0.39 | 0.23 | 0.48 | 0.39 | 0.35 | 0.34 | 0.23 | 0.29 | 0.42 | 0.38 |
| Barbican | 0.5 | 0.24 | 0.47 | 0.34 | 0.22 | 0.39 | 0.55 | 0.33 | 0.3 | 0.23 | 0.29 | 0.46 | 0.36 |
| Mayfair | 0.5 | 0.43 | 0.28 | 0.41 | 0.27 | 0.23 | 0.58 | 0.2 | 0.51 | 0.54 | 0.19 | 0.1 | 0.35 |
| Holborn | 0.34 | 0.6 | 0.35 | 0.31 | 0.34 | 0.17 | 0.31 | 0.13 | 0.33 | 0.2 | 0.17 | 0.37 | 0.30 |
| Soho | 0.53 | 0.29 | 0.14 | 0.34 | 0.42 | 0.22 | 0.47 | 0.16 | 0.18 | 0.04 | 0.14 | 0.07 | 0.25 |
| Shoreditch | 0.34 | 0.2 | 0.24 | 0.15 | 0.09 | 0.22 | 0.2 | 0.29 | 0.23 | 0.32 | 0.36 | 0.22 | 0.24 |
| Ferrington | 0.3 | 0 | 0.2 | 0.09 | 0.15 | 0.13 | 0.39 | 0.29 | 0.21 | 0.18 | 0.05 | 0.34 | 0.19 |
| Fitzrovia | 0.53 | 0.31 | 0.23 | 0.16 | 0.25 | 0 | 0 | 0.17 | 0.13 | 0.06 | 0.19 | 0.07 | 0.18 |
| **Tel Aviv** | **08:00** | **09:00** | **10:00** | **11:00** | **12:00** | **13:00** | **14:00** | **15:00** | **16:00** | **17:00** | **18:00** | **19:00** | **Average** |
| Kerem HaTeymanim | 0.23 | 0.31 | 0.24 | 0.17 | 0.12 | 0.63 | 0.19 | 0.2 | 0.3 | 0.31 | 0.41 | 0.32 | 0.29 |
| Bavli-Bney Dan | 0.2 | 0.32 | 0.28 | 0.25 | 0.26 | 0.29 | 0.3 | 0.33 | 0.21 | 0.24 | 0.26 | 0.25 | 0.27 |
| Shikun HaKtsinim | 0.04 | 0.62 | 0.05 | 0.58 | 0.69 | 0.09 | 0.03 | 0.03 | 0.34 | 0.05 | 0.14 | 0.09 | 0.23 |
| Rokach West | 0.07 | 0.14 | 0.18 | 0.24 | 0.23 | 0.22 | 0.21 | 0.32 | 0.21 | 0.19 | 0.2 | 0.03 | 0.19 |
| Ben Gurion - Dizengoff | 0.14 | 0.16 | 0.28 | 0.1 | 0.06 | 0.14 | 0.14 | 0.33 | 0.19 | 0.27 | 0.14 | 0.15 | 0.18 |
| Jabotinsky East | 0.09 | 0.19 | 0.27 | 0.16 | 0.18 | 0.29 | 0.24 | 0.23 | 0.04 | 0.09 | 0.16 | 0.04 | 0.17 |
| Ben Gurion | 0.18 | 0.12 | 0.26 | 0.13 | 0.06 | 0.13 | 0.15 | 0.23 | 0.19 | 0.27 | 0.07 | 0.07 | 0.16 |
| King George | 0.18 | 0.2 | 0.23 | 0.16 | 0.03 | 0.03 | 0.03 | 0.17 | 0.19 | 0.27 | 0.07 | 0.14 | 0.14 |
| Reading Terminal | 0.07 | 0.03 | 0.03 | 0.13 | 0.17 | 0.22 | 0.21 | 0.25 | 0.2 | 0.2 | 0.1 | 0.06 | 0.14 |

*Table 1: Stability values for the DSCs in London and Tel Aviv at different hours. Red represents the lowest values and green represents the highest values.*

# 5. Summary

We based our work on the perception that was introduced by Hägerstrand (1970) and has been widely tested since, that the city is a dynamic entity in terms of its spatio-temporal behavior. Thus, we developed an innovative framework for the identification of functional dynamic areas in the city in terms of their traffic flow. Our method is based on a percolation process where links (that represent street segments) are removed if their traffic flow does not meet a threshold of traffic availability. This threshold represents fluent traffic flow and thus this percolation process results in two types of spatio-temporal clusters: the first is the Functional Temporary Clusters - FTC, which represents temporal functional clusters that contain connected streets in terms of fluent traffic. These clusters exist at specific times and change over time during a day. The second type is the Dynamic Spatial Clusters - DSC, which integrates spatially overlapping FTCs into one cluster that represents the change in traffic flows to and from a specific spatial core over time.

Based on these functional clusters, we developed indices for traffic quality and stability. The first index integrates both the number and the size of the FTCs in a unique DSC.

This index also succeeded in singling out areas with unique morphologies that imposed constraints on the traffic flows as well as areas that were well connected to the surroundings over time.

We also analyzed the area-stability values of the DSCs. These values show for every DSC, the fraction of time it contained a fraction of the same links. This unique value provides information on both the overall size of the DSC over time and its spatio-temporal stability. Thus, very stable but small clusters will have lower values than very stable but large ones. However, while these values provide insights into the overall spatio-temporal behavior of the DSCs, it does not offer information on the similarity of the DSC at specific hours (i.e. how similar is the spatial distribution of a DSC at the same hour on different days).

To complete this information, we also developed the Stability index, which ranges between 0-1, where 1 represents a situation where all the FTCs in a specific DSC are spatially identical at a specific time through all the examined days, and 0 indicates that none of the FTCs appears more than once in the DSC. The stability results showed considerably higher stabilities in London than in Tel Aviv. The empirical examination also suggests that DSCs with small areas are often more stable than others that cover larger areas. These results support the understanding that the larger DSCs have a more global behavior while smaller DSCs are usually limited within the boundaries of a neighbourhood.

In particular, we demonstrated how our proposed methodology could be used as a comparative tool to study the spatio-temporal behavior of different cities as well as different neighbourhoods within a city. The proposed percolation framework enables the identification (both in real-time and integrated over time) of the areas in the city, where traffic flows are fluent as well as the identification of the boundaries of these areas. This can be useful for development decisions-making support tools for urban and transportation planners in their long-term planning processes (e.g. land use distribution, infrastructure development and alternation, public transportation routes, etc.) as well as in real-time interventions (e.g. implementing an adaptive traffic light systems that correspond in real-time to traffic jams, changing public transportation frequencies due to dynamic demand, and so on). In fact, these indices can be used to connect static long-term urban planning and the flexible and dynamic urban rhythm and enable planners to keep their role in the formation of better cities.

We demonstrated these indices on two datasets: London and Tel Aviv centers and analyzed the DSCs based on their spatial size (measured as the sum of the length of the streets), and their spatio-temporal stability. Our findings revealed both the differences between the two cities as well as differences and similarities in neighborhoods within each city.

# 6. Outlook

DIT4TraM proposes novel approaches to traffic and mobility management, at different spatial-temporal scales, based on (decentralised) concepts including auctioning, trading schemes, and distributed intelligence.

Next to the more fundamental work packages WP1-5, the concepts will be tested in several pilot studies in different cities. WP8 deals with the assessment of the concepts and their application in the six pilot studies.

Next to the more traditional approach to assessing traffic and mobility management interventions (e.g., using before-after comparison of KPIs), the method presented here will also be deployed to assess the impacts of the interventions. We believe that by employing complex network theory and more specifically percolation processes, we will provide additional, insights into the impact on traffic -network quality. These can be easily implemented in different mobility management systems as they are based on raw data that can be obtained from various platforms and they yield simple indices that can be followed in near-real time.

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