

On the new era of urban traffic monitoring with massive drone data: The *pNEUMA* large-scale field experiment

Emmanouil Barmounakis, Ph.D. and Nikolas Geroliminis*, Ph.D.
École Polytechnique Fédérale de Lausanne (EPFL),
Station 18, CH-1015, Lausanne

* Corresponding author e-mail: nikolas.geroliminis@epfl.ch

Abstract

The new era of sharing information and “big data” has raised our expectation to make mobility more predictable and controllable through a better utilization of data and existing resources. The realization of these opportunities requires going beyond the existing traditional ways of collecting traffic data that are based either on fixed-location sensors or GPS devices with low spatial coverage or penetration rates and significant measurement errors, especially in congested urban areas. Unmanned Aerial Systems (UAS) or simply “drones” have been proposed as a pioneering tool of the Intelligent Transportation Systems infrastructure due to their unique characteristics, but various challenges have kept these efforts only at small size. This paper describes the system architecture and preliminary results of a first-of-its-kind experiment, nicknamed *pNEUMA*, to create the most complete urban dataset to study congestion. A swarm of 10 drones hovering over the central business district of Athens over multiple days to record traffic streams in a congested area of a 1.3km² area with more than 100 km-lanes of road network, around 100 busy intersections (signalized or not), many bus stops and close to half a million trajectories. The aim of the experiment is to record traffic streams in a multi-modal congested environment over an urban setting using UAS that can allow the deep investigation of critical traffic phenomena. The *pNEUMA* experiment develops a prototype system that offers immense opportunities for researchers that many are beyond the interests and expertise of the authors. This open science initiative creates a unique observatory of traffic congestion, a scale an-order-of-magnitude higher than what was available till now, that researchers from different disciplines around the globe can use to develop and test their own models.

Keywords: unmanned aerial systems, swarm of drones, experiment, traffic monitoring, traffic flow modeling, multimodal systems

1. Introduction

Traffic surveillance and monitoring has been one of the most important tools for transportation managers and engineers. Sensing equipment could be considered of two main types, fixed-and mobile-location sensors. The first type includes the use of cameras for instant view of important parts of an intersection or fixed-location sensors. Loop detectors have been widely used in freeways (e.g. around 39,000 are located in California part of the Caltrans Performance Measurement System – PeMS). Bluetooth or RFID devices are also installed in fixed locations (e.g. toll plazas or major intersections) and can provide travel times between specific locations. Nevertheless, the cost of installation might be high, while measurement errors and malfunctions occur frequently. Lately, collecting traffic data with mobile sensors (GPS or cellphones) has also attracted interest although it can be inefficient for large-scale networks due to reduced coverage and accuracy issues. GPS data are collected either through specific fleet of vehicles (taxis, buses etc.), or through applications via smartphones. While many studies have identified that a penetration rate of 3-5% can be sufficient for space-mean travel times, important traffic phenomena cannot be captured properly with this limited level of information (Bhaskar et al.,

1 2015, 2011; Jenelius and Koutsopoulos, 2013; Liu et al., 2009; Ramezani and Geroliminis,
2 2015).

3 One of the most complete databases for traffic research has been created by the Next Generation
4 SIMulation (NGSIM) initiative almost 15 years ago with an objective the development of
5 algorithms and models for driver behavior at microscopic levels (NGSIM, 2006). Fixed high-
6 resolution cameras were installed at tall buildings (around 100m) in a few locations in major
7 freeways and a collection of real-world vehicle trajectory data was performed. This is still the
8 most detailed and accurate field data collected to date for traffic microsimulation research and
9 development. A significant number of models have been developed and validated with NGSIM
10 for freeways, such as car-following and lane-changing. Even if a few arterial sites were added,
11 they contain small scales of a few intersections and not severe congestion.

12 There is a strong understanding and vast literature of congestion dynamics and spreading in
13 one-dimensional traffic systems with a single mode of traffic, e.g. a single-lane road section
14 with cars. Besides traffic scientists, mathematicians and physicists have also contributed to the
15 field of traffic flow. Because of the numerous publications, we refer the reader to (Helbing,
16 2001; van Wageningen-Kessels et al., 2015) for an overview. Briefly speaking, the main
17 modeling approaches can be classified as follows: Car-following models deal with the non-
18 linear interactions and dynamics of single vehicles (acceleration, relative speed etc.)
19 (Brackstone and McDonald, 1999; Chen et al., 2012a; Gazis et al., 1959; Gipps, 1981; Park et
20 al., 2019; Wilson, 2008). To address computational burden, cellular automata describe the
21 dynamics of vehicles in a coarse-grained way by discretizing space and time, e.g. (Daganzo,
22 1994; Nagel and Schreckenberg, 1992). First-order flow models such as the LWR model
23 (Lighthill and Whitham, 1955; Richards, 1956) are based on a partial differential equation for
24 the density and a fundamental diagram relation. Second-order models contain an additional
25 equation for non-steady state conditions (Papageorgiou, 1983; Whitham, 1975). Network level
26 models through the macroscopic fundamental diagram (MFD) have attracted attention by many
27 research groups, as they can provide an intuitive way to explain various traffic phenomena and
28 be integrated in large-scale traffic management; a few examples are (Haddad and Mirkin, 2017;
29 Loder et al., 2017; Lopez et al., 2017b; Saeedmanesh and Geroliminis, 2016; Sirmatel and
30 Geroliminis, 2018). Nevertheless, traffic instabilities and the spatiotemporal dynamics of
31 congestion for heterogeneous multi-modal multi-lane traffic streams require a more advanced
32 models allowing faster vehicles to pass slower vehicles. The effect of local disturbances at the
33 urban settings (e.g. lane-changes and service-related stops) require a complete understanding
34 of the local environment both over time and space that sparse loop detectors or low penetration
35 GPS sensors are unable to provide. At the same time, observing congestion propagation at the
36 network level is a challenging task not only due to complex interactions, but also due to limited
37 data obtained from existing traffic experiments. We consider that there are important research
38 gaps to be filled with respect to them while their effect at the network level can be significant
39 and cause strong propagation of congestion.

40 Better monitoring of congestion is a crucial step to better understand the causes of the
41 phenomenon and facilitate more efficient strategies, especially for complex multimodal
42 environments. One of the tools that has intruded lately into our lives are the Unmanned Aerial
43 Systems (UAS) or Unmanned Aerial Vehicles (UAV) or more commonly known as “drones”.
44 While drones had started being in the center of attention for warfare reasons, they have drew
45 the attention of several researchers and practitioners from different research fields (Beloiev,
46 2016; Fadzil et al., 2016; Hoffer and Coopmans, 2017; Ventura et al., 2017; Villa et al., 2016).
47 Their distinctive capabilities, which allow them to carry high quality cameras and other
48 technological equipment, could not have left Transportation engineers out of the game as
49 drones have been proposed as a significant tool of the Intelligent Transportation Systems (ITS)
50 infrastructure (Barmounakis et al., 2016a).

51 The idea to utilize a big number of drones to monitor traffic congestion in different parts of a
52 congested city has intrigued many transportation related researchers and practitioners (Garcia-
53 Aunon et al., 2018). For such cases, researchers use the term “swarm of drones” which is a
54 coordinated team of drones flying together without colliding to perform a task. Research around
55 swarms of drones includes many different scenarios, such as simulations over cities in order to

1 tackle issues that may emerge prior to their operation (Das et al., 2018; Hu et al., 2018).
2 However, existing experiments worldwide are at very small scale, usually flying one drone
3 capturing one or two intersections (Barmounakis et al., 2017; Khan et al., 2018) or a specific
4 part of a road arterial (Barmounakis et al., 2018; Niu et al., 2018). When the need emerges to
5 monitor a small sample of the vehicles for large areas researchers turn to other method (e.g.
6 smartphones or GPS devices) (Herrera et al., 2010; Ji et al., 2014; Kanarachos et al., 2018;
7 Saeedmanesh and Geroliminis, 2017; Vlahogianni and Barmounakis, 2017; Wahlström et al.,
8 2015) which, due to reduced coverage of total traffic and accuracy issues, they do not allow the
9 detailed study of certain phenomena (Coifman and Li, 2017; Laval and Leclercq, 2010).
10 Although, a swarm of drones could overcome a significant number of limitations of the
11 abovementioned methods, pragmatizing an actual one for massive data collection in a busy,
12 multimodal urban environment has not been conducted before.

13 This paper presents the design and preliminary results of a first-of-its-kind experiment,
14 nicknamed *pNEUMA* (New Era of Urban traffic Monitoring with Aerial footage), to create the
15 most complete urban dataset to study congestion. A swarm of 10 drones hovering over the
16 central business district of Athens over five days to record traffic streams in a congested area
17 of a 1.3km² area with more than 100 km-lanes of road network, around 100 busy intersections
18 (signalized or not), more than 30 bus stops and close to half a million trajectories. The aim of
19 the experiment is to record traffic streams in a multi-modal congested environment over an
20 urban setting using UAS that can allow the deep investigation of critical traffic phenomena.
21 One of the aims of this work is to reveal a fundamental mechanism of congestion pattern
22 formation for large-scale networks based on a complete dataset collected by a swarm of drones.
23 The design process of the experiment and the various factors (such as drone regulations, number
24 of drones, maximum flight duration etc.) that had to be taken into account and optimized are
25 described. The analysis of the videos from this urban, multimodal, busy environment can allow
26 different kinds of transportation phenomena to be tested in both microscopic and macroscopic
27 scale for different research disciplines. The *pNEUMA* experiment develops data that can offer
28 immense opportunities for answering additional research questions that are beyond our interests
29 and expertise. Thus, an open science initiative will create a unique observatory of traffic
30 congestion that researchers around the globe can use to develop and test their own models.

31 The remainder of the paper is organized as follows. In the next section, a literature review is
32 conducted, where the evolution and the state of the art in monitoring traffic congestion with
33 aerial footage is discussed. Following, in Section 3 the system architecture of the experiment is
34 described and the barriers that had to be overcome before, during and after the experiment are
35 identified. Additionally, some primary results are provided from the extended dataset that
36 introduce the way drones can contribute in the data collection process and the numerous
37 possibilities it gives when studying how congestion changes over time and space. To conclude,
38 the authors' open data initiative is presented and future research steps and challenges are
39 examined.

40 2. Literature Review

41 Several researchers have reviewed the use of UAS for transportation purposes (Barmounakis
42 et al., 2016a; Kanistras et al., 2014; Puri, 2005). Both challenges and opportunities associated
43 with their becoming a valuable part of the ITS infrastructure have been documented thoroughly.
44 These challenges can be summarized to i) security, privacy and legislation safety above the
45 transportation infrastructure, ii) technical limitations, such as flight duration, automated flights
46 and flying during adverse weather conditions and iii) mining critical transportation information
47 either for real-time applications or not.

48 Another detailed study can be found in (Kamga et al., 2017) where drones applications for
49 several transportation related operations, projects from universities and DOTs are presented
50 regarding traffic monitoring, traffic incident management and traffic data collection. Authors
51 conclude that the weather dependence and UAS' short battery life are the main drawbacks of
52 drones while their advantages can be summarized to:

- 53 i) no need of satellites which are quite costly,
- 54 ii) they can be equipped with communication systems to inform commuters in real-time,

1 iii) their great capabilities in data acquisition.

2 In the following section, an update of the literature is conducted including most recent studies
3 joined by different research directions.

4 **2.1 UAS Operations in a ‘Smart City’**

5 A significant part of the reviewed literature deals with the operational topics regarding the
6 deployment of drones over cities as an important component of Internet of Things (IoT). In
7 (Rosenfeld, 2019) the deployment of traffic enforcement drones is discussed and the benefits,
8 concerns and policy considerations are discussed. Authors present the results of a drivers’
9 survey which shows that, while privacy and safety still remain a significant concern, traffic
10 enforcement drones are alleged as more efficient and would act as a better deterrent compared
11 to current aerial traffic enforcement resources.

12 One fundamental area regarding drones is the way they are safely navigate through the airspace
13 in which manned vehicles are already flying and is expected to get more complicated and busier
14 with the deployment of drones. In (Geller et al., 2016) the major concepts, structures and
15 procedures of a UAS Traffic Management (UTM) are discussed and in (Sampigethaya et al.,
16 2018) authors focus on cyber security related issues for UTM. Since communications are major
17 in drones operations, the reader can read the following studies that focus on UAV networks for
18 civil applications revealing more specialized concerns (Hayat et al., 2016; Mkiramweni et al.,
19 2019; Zeng et al., 2016). An interesting study can be found in (Shi et al., 2018) where drones
20 are examined for their valuable features that can enhance vehicular networks’ performance and
21 applications.

22 Finally, as stated in the introduction, putting a swarm of drones from theory to practice would
23 require many supportive tasks. In (Das et al., 2018) an optimization algorithm is proposed for
24 the number of UAVs for tracking multiple mobile targets. The Team Orienting Problem
25 (TOP) is applied to drones in (Panadero et al., 2018), as a range of limitations need to be taken
26 into account when optimizing their operations and management. A methodology to maximize
27 the persistent coverage of a given terrain is described in (Bogdanowicz, 2018) and while it is
28 focused on military applications, the same concept could be applied for transportation purposes.
29 In (Dung and Rohacs, 2018) drone-following models are described for their safe flying when
30 operating simultaneously in the context of a ‘smart-city’.

31 **2.2 Data and Algorithmic Topics**

32 Except for the operational topics that come with the utilization of drones, other researchers are
33 dealing with the data and algorithmic related issues. Three basic categories can be found
34 regarding these issues which relate to i) tracking vehicles, ii) analyzing traffic and iii) allowing
35 or improving real-time operation of the abovementioned tasks.

36 In (Zhang et al., 2017) a deep learning model using convolutional neural networks (CNNs) are
37 used for detecting vehicles in recorded traffic streams from UAS with accuracy being over 90%
38 compared to manual counts. Another UAV-based vehicle detecting and tracking system has
39 been presented in (Wang et al., 2016) with accuracy reaching up to 100%. In (Guido et al.,
40 2016) a vehicle detection system is presented. Authors calculate the speed of the identified
41 vehicle and evaluate their results compared to GPS measurements pointing out the potential of
42 UAVs as a mean of extracting trajectories. Another study evaluates the accuracy of position
43 estimation from aerial images of objects on a planar scene (Babinec and Apeltauer,
44 2016). Authors propose that the findings can be used to not only in traffic monitoring, but in
45 every application where accurate localization or tracking of moving objects may be required.
46 In (Kim et al., 2018) a vehicle detection algorithm is proposed which performs with good
47 classification metrics in congested traffic conditions. In this study, authors conclude that the
48 use of multiple drones could overcome significant issues related to their short flight time.

49 As far as traffic analysis is concerned, also a significant chapter when it comes to drones used
50 for traffic studies. In (Khan et al., 2018) drones are used to analyze different traffic parameters,
51 such as speed, flow, density, shockwaves, signal cycle length, queue lengths, queue dissipation
52 time etc. and capacity by generating origin-destination (OD) matrices in the scenario of urban
53 roundabouts and four-legged intersection. In (Khan et al., 2017) guidelines are provided for an
54 efficient conduction and completion of a drone-based traffic study.

1 In (Ke and McCormack, 2016) authors propose a framework for estimating traffic flow
2 parameters in real time application. The system was tested in a variety of challenging scenarios
3 such as both congested and uncongested traffic conditions or daytime and nighttime. In (Ke et
4 al., 2017) a real time detection algorithm is used extract bi-directional traffic flow parameters
5 such as speed and flow with accuracy over 85%. A real time algorithm is also proposed in (Ke
6 et al., 2018) using a four-stage framework to extract traffic flow parameters (i.e., speed, density,
7 and volume) from UAV. Different techniques, such as Haar cascade classifiers and
8 convolutional neural networks, are combined to form an ensemble classifier with very good
9 estimation accuracy and real-time processing speed in both free flow and congested traffic
10 scenarios.

11 (Sutheerakul et al., 2017) focus on using UAVs to monitor pedestrian traffic flows and to
12 manage pedestrian demand and supply. Authors conclude that a drone can be an alternative
13 viable technology in monitoring pedestrian traffic characteristics. The use of drones for
14 pedestrian observation appears also in (Park and Ewing, 2018) where authors propose it can be
15 a reliable tool for monitoring various characteristics of non-motorized traffic (e.g. attributes,
16 behaviors, spatial patterns). Drones using aerial thermal infrared images instead of video
17 recordings were used in (Ma et al., 2016) also for pedestrian tracking with promising results.
18 In (Lee et al., 2018) the advantages of using drones to extract kinematic features of cyclists-
19 pedestrians mixed flow and model their interactions are highlighted. In (Freeman et al., 2018)
20 a UAS and photogrammetry software was utilized to capture vehicle spacing while stationary.
21 In (Kaufmann et al., 2018) a methodology for microscopic traffic analysis is proposed. Authors
22 analyze drivers' lane changing behavior and highlight the advantages of UAVs for scientific
23 research compared to GPS vehicle probe data. They focus on the fact that probe vehicles' data
24 resolution of 5-10 seconds combined with the 2-4% coverage of total traffic is not adequate for
25 microscopic data, and this issue can be overcome by taking advantage of videos by UAVs.
26 Additionally, aerial observations are examined to study moving synchronized flow patterns by
27 measuring trajectories for all vehicles.

28 In (Zhang et al., 2016), although no UAVs were used, researchers used manned helicopters and
29 Time-Lapsed Aerial Photography (TLAP) to create a large dataset for monitoring drivers
30 behavior. Using two helicopters equipped with seven cameras in total covered an almost 5
31 square miles grid area. Authors state the parameter of cost in using the specific method, as
32 TLAP surveys cost between \$20-60K just for peak-period highway data acquisition that could
33 increase significantly for larger or more complex areas. Other limitations are related to weather
34 conditions, but in a different way than drones. Specifically, due to the high flight altitude,
35 intervening clouds can abort or postpone a survey in order to have a clear view on the ground
36 surface.

37 As seen several operational challenges need to be overcome before standardizing the utilization
38 of drones. Specifically, UTM systems are necessary in terms of safety and privacy. The
39 automatization regarding various tasks and their further optimization, while may be technically
40 feasible with current drone technology, requires a solid set of rules that will take into account
41 their unique characteristics and their smooth embodiment in the already complex urban
42 environment.

43 Additionally, while it is seen that calculation in real time for several parameters can be achieved
44 with quite good accuracy, there are still issues to be tackled and further tests to be conducted
45 for a fully automated system. Thus, complexity is expected to be increased when real time tasks
46 should be modeled for a swarm of drones rather than an individual drone.

47 Finally, aerial traffic observation can be a viable solution when it comes to multimodal and
48 microscopic oriented studies. It is seen that except for not being as expensive as manned
49 helicopters, they can achieve a great level of detail with high percentages of accuracy, a
50 necessary requirement for microscopic modeling.

1 **3. Experiment Description**

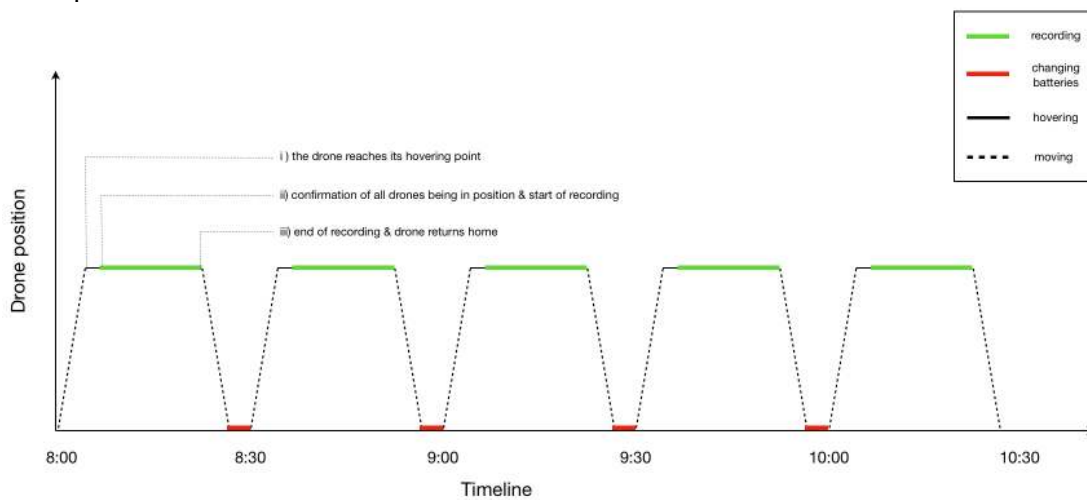
2 **3.1 Designing the experiment**

3 The aim of the experiment was to record traffic streams over an urban setting using UAS and
4 to provide significant insight on how their unique characteristics can overcome existing
5 limitations in traffic monitoring and their potential in becoming a viable part of the ITS
6 infrastructure. For the specific experiment, the central district of the city of Athens, Greece was
7 selected as an urban, multimodal, busy environment that can allow different kinds of
8 transportation phenomena to be examined.

9 First, the survey times and dates were to be selected. Since, evening time would not be an option
10 for conducting the experiment, as it is not allowed according to current regulation, the morning
11 peak (8:00-10:30) was decided to be recorded for each working day of a week. Among others,
12 this “extended” peak hour can allow the analysis of how congestion evolves over time and
13 space until the peak is reached. Due to the peculiarities of the specific experiment, if for any
14 reason flights could not be conducted during a specific day (weather-related issues, strikes,
15 hardware issues etc.) the flight for the specific day would be moved the following week until
16 all days of a week would have been recorded.

17 Second, one of the biggest challenges to overcome was that drones have limited flight time and
18 are not able to record the traffic stream for 2.5 hours continuously. Thus, two options were
19 available. The first one was to swap the drones while on the air so that uninterrupted recording
20 was achieved. In this case, each drone would have a substitute to replace it when its battery
21 would run low. However, this would double the size of the experiment in terms of number of
22 units while making the experiment much more complex in terms of drones’ coordination and
23 flight safety. The second option was to fly the swarm in sequential sessions with ‘blind’ gaps
24 between. Since during these ‘blind’ gaps no data would be available, they should be as short as
25 possible for less data loss. It is expected that having about 10 minutes of no data would cause
26 no significant issues and therefore the second option was chosen. Those gaps would be used
27 for technical tasks, which are to change the batteries of the drones and then send them back in
28 their previous hovering position.

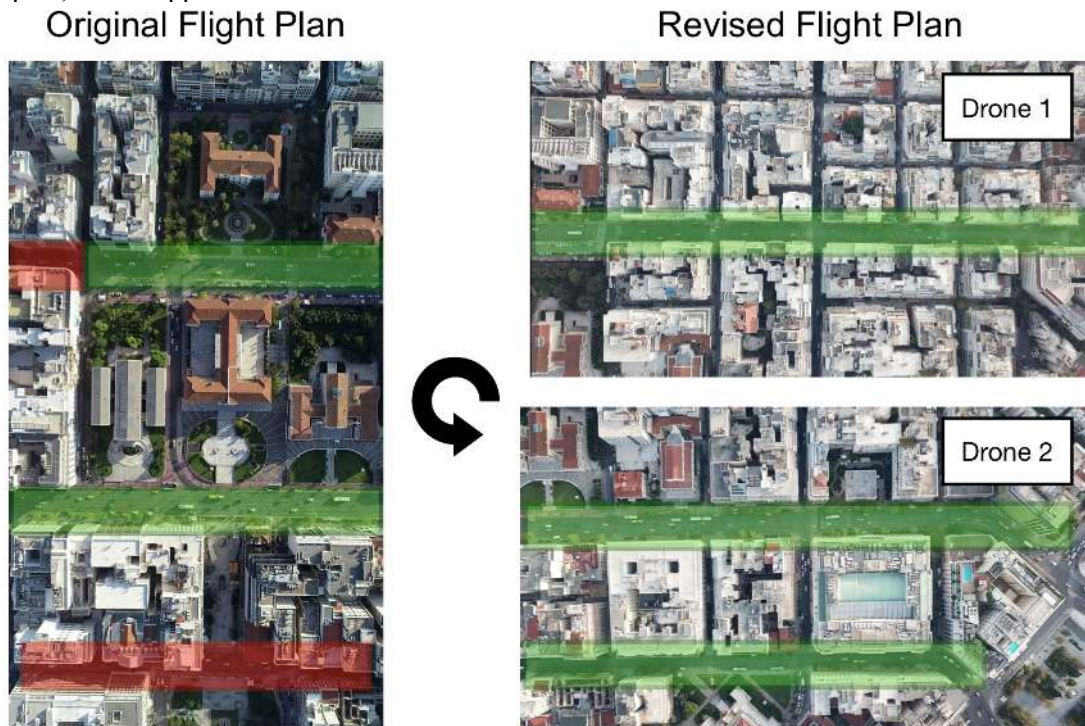
29 The series of actions is illustrated in Figure 1. Specifically, the swarm would take-off at the
30 start of the experiment and each drone would go to its unique hovering point. Then, when all
31 drones were at position, the recording of the traffic stream would start simultaneously and when
32 the battery would run low, they would return to their landing point. Considering that drones
33 could hover up to 25 minutes including take-off, routing and landing times, it was decided that
34 each session would take place every 30 minutes for better coordination and standardization of
35 the experiment.



36
37 **Figure 1: The illustration of the experiment**

38 Third, the locations of the hovering points and the orientation of the drones had to be
39 determined, so to maximize the visibility of the majority of roads in the study area. To
40 accomplish this, a first test flight included the scanning of the study area to test the original

1 flight plan in terms of connectivity, travelling times, etc. and to observe the drones' point of
2 view, while finding the best hovering points to ensure that no hidden points or connectivity
3 issues would appear. This was crucial for the successful outcome of the experimental process,
4 since due to restrictions on regulations and flight permits, there would be no possibility of
5 repeating the experiment the same day. Interestingly enough, one of the problems that was
6 identified during this process concerns the orientation of the drones. Specifically, as shown in
7 Figure 2, the two drones on the right (drones 1 and 2 of the experiment) had a different
8 orientation, rotated 90 degrees compared to what was initially chosen (left part of the figure).
9 Although this did not affect the total size of the area observed, it significantly affected the
10 visibility in the main road arterials, since with the new orientation there were fewer hidden
11 spots, which appear more in the small arterials.



12
13 **Figure 2: Visibility of a main road arterial is restored after the change of the orientation**

14 Another requirement was to have overlapped areas of responsibility for neighboring drones
15 (more information in Section 2.4). This was of top significance for the synchronization of the
16 video footage in terms of space and time and the re-identification of vehicles going from one
17 area to the other. After carefully watching the recorded video, the number of drones and the
18 hovering point for each of the drone were selected to maximize both the area covered and the
19 number of important points of interest.

20 Another challenge was to find safe areas for the take-off and landing of the drones. In terms of
21 maximizing flight duration, these points should be sparse, so that each drone would be close to
22 its hovering point. However, this would add complexity as far as coordination between the
23 pilots and flight safety is concerned. Also, since no similar experiment had been conducted,
24 and in order to address public concerns and private risk, the idea of choosing rooftops for the
25 specific task prevailed. As a consequence, two rooftops located in the city center were provided
26 as take-off and landing areas and two clusters of drones were created; the 'blue' cluster and
27 the 'green' cluster with each one having a leader for better coordination and communication
28 (Figure 3). Having decided for the take-off and landing points, the hovering points, the altitude
29 and the size of the swarm, the flight plans were designed for each drone, including the route to
30 and from the hovering point so that no intercepting routes between the drones were present.

31 Next, the flight plans were tested and the duration of each task was timed as part of the second
32 test flight. Specifically, each drone was following its route to the hovering point, then it would
33 hover for a minute to ensure no connectivity issues would appear and that the area of interest

1 was recorded with no conspicuity issues. It should be noted that Drone 4 was first assigned to
2 the ‘blue’ cluster and Drone 10 to the ‘green’ cluster as being closer to H1 and H2 respectively.
3 However, due to random interference in the connections between the pilots and the drones, the
4 two drones switched clusters to ensure continuous connectivity. Finally, the flight plan was
5 finalized as illustrated in Figure 3. As seen, this led to an intercepting route between Drone 1
6 and Drone 4. However, as this could be avoided in the 3-dimensional airspace with different
7 altitudes, their routes were updated so that the drones would not be at the same altitude when
8 being at the intercepting point.



9
10 **Figure 3: The route for each drone of the swarm and the two clusters formed**

11 **3.2 Flying the swarm**

12 A team of highly experienced, registered drone pilots was hired to conduct the flights, to
13 complete all necessary tasks related both to the ones related with the experiment and to receive
14 all necessary permissions from the Hellenic Civil Aviation Authority (CAA). A briefing took
15 place on the first day of the experiment to ensure the understanding of the requirements of this
16 large-scale experiment, the sequence of events and actions and all other relevant tasks.

17 In order to ensure synchronization of the recorded video and to reduce waste of energy, all
18 drones had to take off at specific pre-defined times based on their distance from their hovering
19 points. When each drone was in position, its pilot would give the signal to the team leader. The
20 two leaders were keeping an open line for every issue that would emerge. When the two team
21 leaders confirmed that every drone is in its position, the recording of the traffic streams would
22 start. Then, the pilots would carefully watch the video coming from the drone’s camera in real
23 time and do any necessary handling for improved stability. Finally, when the battery of the
24 drone would run low, the pilot would bring it safely back for battery swap and then prepare for
25 the next flight session. As stated before, this process was repeated 5 times during the 2.5 hours
26 of monitoring traffic.

27 **3.3 General Information**

28 The specific experiment is first of its kind in scale and for flying a swarm of drones for
29 transportation purposes over a congested city center. As seen in previous sections, while a
30 future monitoring system is expected to require real time operations and communications, such
31 subjects go beyond the scope of this experiment. In order to acquire a high-accuracy detailed
32 dataset, all operations take place off-line. As far as the aerial video footage is concerned, the

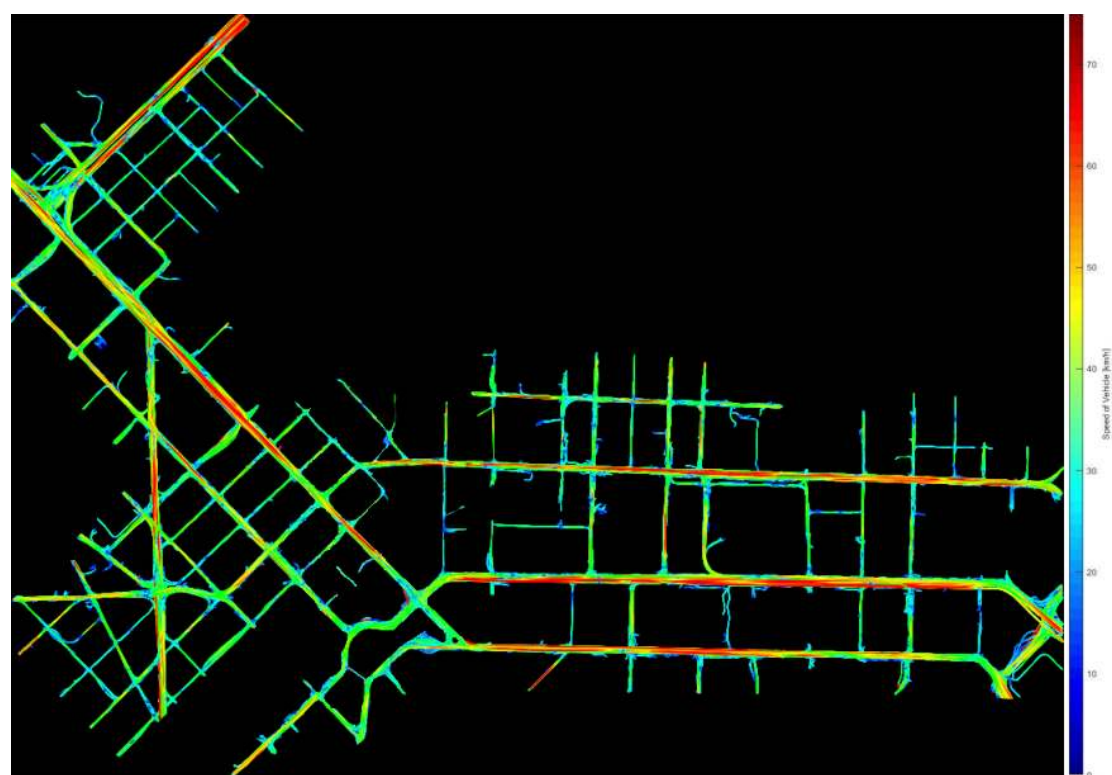
1 videos were recorded in 4K (4096x2160) resolution at 25 frames-per-second (FPS) using
2 consumer quadcopter DJI drones, and specifically the Phantom 4 Advanced. The total duration
3 of the recordings is 59 hours, sizing more than 2 TB. The study area to be analyzed includes:

- 4 i) a total of 1.3 km² area
- 5 ii) a 10 km road network
- 6 iii) low, medium and high-volume arterials
- 7 iv) more than 100 intersections (signalized or not)
- 8 v) more than 30 bus stops

9 It is evident that for such a scale, even for a simple traffic study, one would need more than 100
10 fixed sensors (or humans) to collect data, including all the measurement (or manual) errors.
11 This aerial video footage allows researchers involved to re-watch the videos as many times as
12 they want not only to eliminate errors but for different reasons and in different levels of detail,
13 in order to fulfill the requirements of a variety of studies and different subjects.

14 As seen in Section 2, the vehicle detection and tracking problem is well-defined in the relevant
15 literature. Given the strong advancements in computer vision and the need to guarantee a high
16 level of accuracy, the analysis of the videos was outsourced to ensure increased efficiency,
17 vehicle detectability and detailed accuracy (DataFromSky, 2014). The products of the analysis
18 include detailed trajectories of the vehicles tracked, calibrated in the WGS-84 system. The time
19 frequency is 0.04 seconds as this is the maximum frequency allowed by the videos' frame rate.
20 It should be noted that the detectability of the specific tracking algorithm is over 98.8% while
21 the results have been manually reviewed to eliminate any false positive and false negative
22 identifications.

23



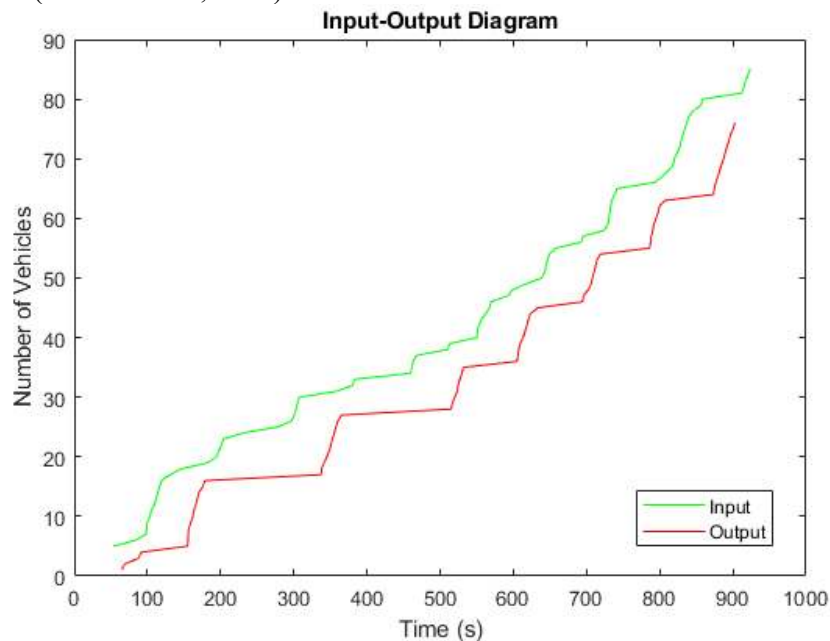
24
25 **Figure 4: Extracted trajectories covering the road network of the study area**

26 Figure 4 represents a speed heat map, produced from all the extracted vehicles from the first
27 flight session (8:00-8:30) of the fourth day of the experiment (Thursday, October 30, 2018).
28 The trajectories are plotted on the map to visualize the road network that is covered during the
29 *pNEUMA* experiment. It can be seen that all major arterials are monitored while there are some
30 parts, mostly in minor roads, that are not covered completely due to visibility issues (refer to
31 the blue area of Figure 5).



1
2 **Figure 5: A minor road between two main arterial that is not visible**

3 However, such cases are not considered a significant issue as the intersections with the main
4 arterials are still visible and allow the entrances/exits of minor roads to be monitored. By
5 placing virtual loop detectors (*gates*) this information can be used to calculate several traffic
6 variables and extract valuable information, for example an input-output diagram (Figure 6),
7 which can be utilized to estimate average density and travel times in the road under
8 consideration (Lawson et al., 2007).



9
10 **Figure 6: Input-Output diagram of a minor road with reduced visibility**

11 Except for the features that can be produced using the position information, for example speed
12 (first derivative of position), acceleration (second derivative of position), distance traveled etc.,
13 the type of each vehicle (car, taxi, motorcycle, bus, heavy vehicle) is also available.
14 Finally, as the speeds and accelerations are produced using the position information, the
15 accuracy of the data is based solely on how well the vehicle is tracked and how well the study
16 area has been geo-registered, a process that includes assigning real-world coordinates to video
17 image coordinates (pixels). More information for the accuracy of the position for the specific
18 algorithms can be found in (Babinec and Apeltauer, 2016). For the *pNEUMA* dataset, at least

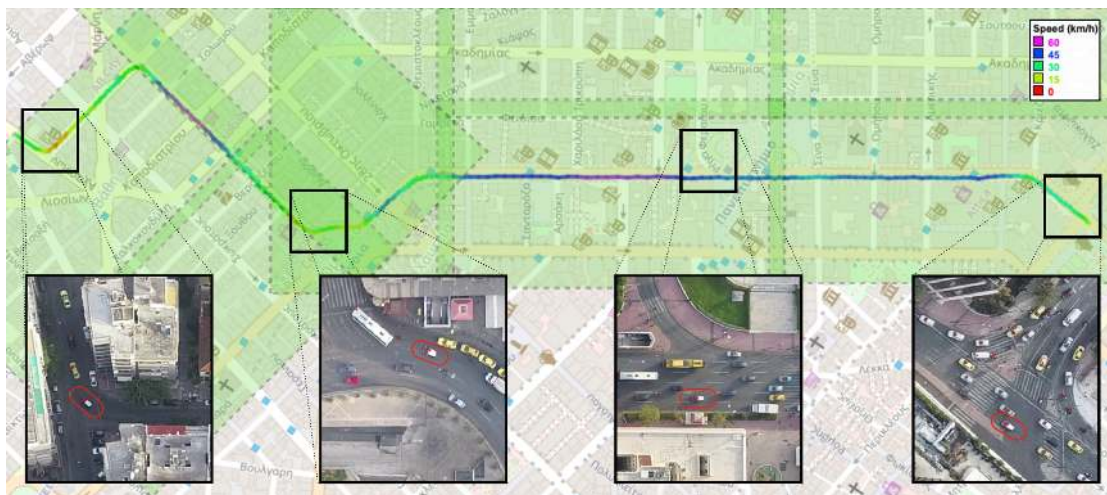
1 10 characteristic points per drone measured with GNSS technology in WGS coordinates with
2 less than 5 mm accuracy were provided. Then, these coordinates were assigned to the
3 corresponding pixels in the stabilized video and the average ground sampling distance is
4 calculated to 16.5 cm/px. As the vehicle positioning may have an error of 2 pixels, the
5 maximum error is equal to 33 cm in every frame. Finally, an advanced Kalman filter that is
6 able to filter out the noise in the measurements up to a level of 3.3 cm is applied, which is
7 equivalent to 2.97 km/h in terms of speed error. While this is the error of a single point speed
8 estimation due to pixel size, if a sequence of multiple points is considered then the error is
9 significantly smaller, as the absolute distance error remains the same, but the time interval is
10 longer (and speed more accurate).

11

12 3.4 Vehicle Reidentification

13 The overlap between the area of visibility of each drone with its neighboring ones, allows us to
14 properly synchronize the videos, automatically re-identify vehicles from one drone to the other
15 based on features such as vehicle type, vehicle color, time information, spatial information etc.
16 and to collect consistent information while it is being tracked throughout the period it remains
17 in the study area.

18



19

20 **Figure 7: The trajectory of a vehicle tracked continuously by different drones throughout**
21 **the study area**

22 In Figure 7 the result of the vehicle reidentification process is illustrated. The transparent green
23 rectangles illustrate the area of recording for each drone. The darker parts correspond to the
24 overlapping areas between neighboring drones. In the lower part of the figure, it can be seen
25 that the vehicle in the red ellipsoid was tracked by 6 different drones in the study area for a total
26 route of 1.8 km. Its trajectory data is visualized as a continuous line with a color scale based
27 the vehicle's speed. Figure 4 contains trajectories of vehicles that have been estimated through
28 this re-identification process.

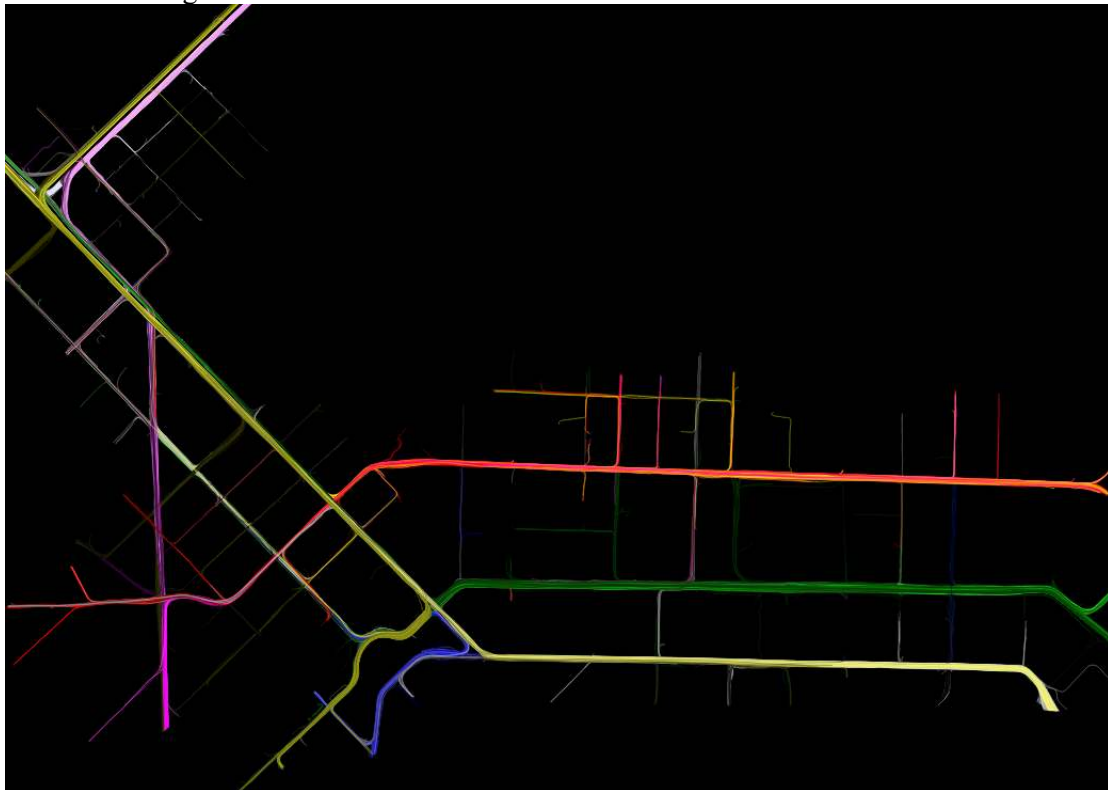
29 4. Primary results and future research possibilities

30 The aim of the experiment is to record traffic streams in a multi-modal congested environment
31 over an urban setting using a swarm of drones that can allow the deep investigation of critical
32 traffic phenomena. The *pNEUMA* experiment develops a prototype system that offers immense
33 opportunities for researchers that many are beyond the interests and expertise of the authors. In
34 this section we provide some preliminary results to highlight a few concrete examples of
35 research domains that *pNEUMA* can facilitate the development of the new era of traffic models.
36 The emphasis of this paper is not on fundamental contributions per se in traffic flow theory, but
37 on the design of an experiment that intends to revolutionize how emerging technologies reshape
38 our understanding of traffic congestion mechanisms, by putting the emphasis on urban
39 networks with disturbances generated by interactions among different types of vehicles. The

1 developed dataset targets to better explain the mechanism of congestion formation and
2 propagation in congested multimodal urban environments through massive data from aerial
3 footage and fundamental research prospective. In this paper, we put effort to ensure that this
4 objective is feasible and that the data is of high quality. We decided to work on breadth more
5 than depth and investigate how well a complete information of the local environment could be
6 extracted by these trajectories. We are able to observe almost every lane-change in all major
7 roads, accurate travel time estimation, interactions between cars, taxis and public transport and
8 many other phenomena that will allow researchers to revisit many fundamental concepts of
9 traffic modeling.

10 **4.1 Origin-Destination Information**

11 An Origin-Destination (OD) matrix has been one of the most critical tools for network loading
12 and traffic assignment. An effective, reliable and handy OD is mainly depended on the quality
13 of the input data, and the number and locations of traffic counting points in the road network
14 (Yang and Zhou, 2002). A detailed review is provided in (Antoniu et al., 2016). It is evident
15 that when all vehicles have been tracked and geotagged information has been extracted, virtual
16 loop detectors can be placed in every part of the recorded area. Additionally, until now, OD
17 information in urban areas was extracted only at intersection level for a big number of vehicles
18 using computer vision techniques that observed the intersections entries and exits. For larger
19 areas, OD information was mainly based on personal interviews or GPS devices that do not
20 allow a large sample to be collected. Thus, the specific experiment allows i) extracting massive
21 OD matrices at a network level, ii) a less costly and time-consuming process, iii) eliminating
22 manual errors and iv) estimating dynamic OD matrices. The results of such a process can be
23 illustrated in Figure 8 where the different OD combinations are illustrated with different colors.



24
25 **Figure 8: Origin Destination illustration for different movements**

26 **4.2 Arterial travel time and congestion propagation**

27 While there is a vast literature in travel time estimation in arterials, there are challenges
28 involved since it requires extensive sensor infrastructure that is less dense than in freeways.
29 Moreover, speed of vehicles at a given time in the network is not a deterministic quantity over
30 space because of different type of vehicles, drivers' behaviors and the queuing effects due to

1 signals (near the stop line vs. further upstream). This creates local speeds that are temporarily
2 different than the widespread average, even for vehicles traveling in the same link during the
3 same cycle length. Reduction in travel time variability is at least as desirable as reduction in
4 mean travel time (Jenelius, 2012), since it decreases commuting stress and uncertainty of
5 decision making. Different indexes of travel time stochasticity-reliability can be found in
6 (Kaparias et al., 2008). The *pNEUMA* database can create unique opportunities for monitoring
7 and modeling travel time variability.

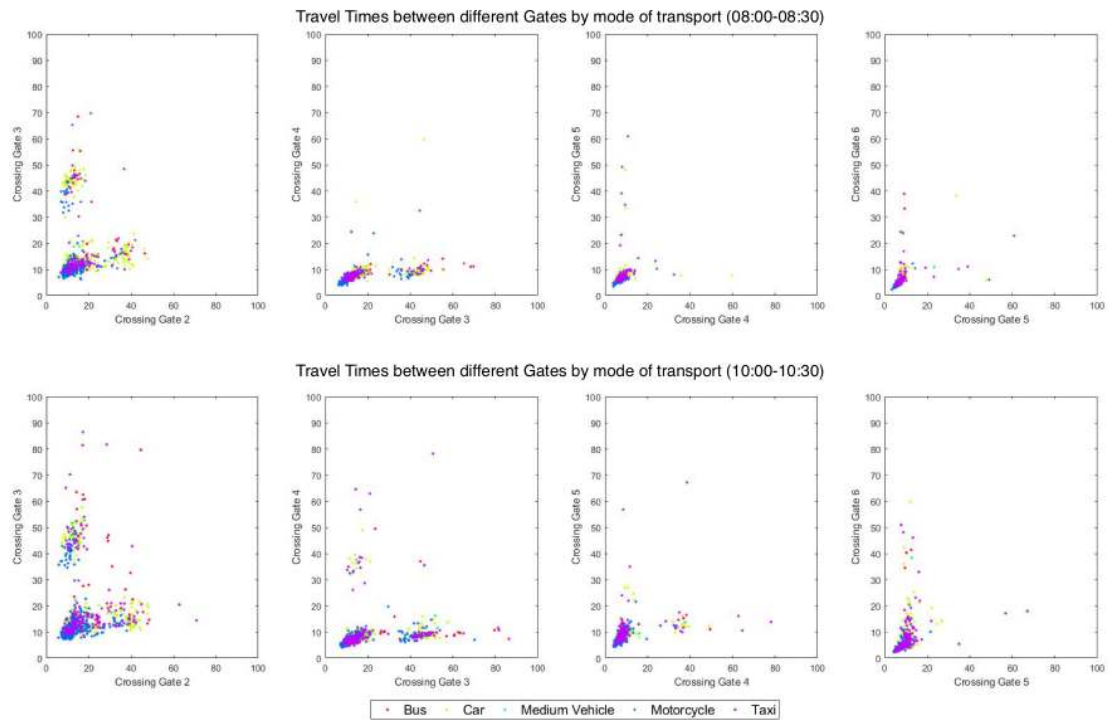
8 When it comes to evaluating traffic network operating characteristics and monitoring
9 congestion, travel time distributions can be a crucial index for both individual travelers and
10 practitioners (Ramezani and Geroliminis, 2012). Here we present an example of the data that
11 can be offered with significant added value for various applications and research directions.

12 Travel time reliability on arterials depends on the efficient progression of vehicles from one
13 traffic signal to another. Various works have considered that spatial correlations and offsets of
14 traffic light phases can influence the variability (e.g. (Chen et al., 2017; Feng et al., 2011; Guo
15 et al., 2013; Herring et al., 2010; Kwong et al., 2009; Ma et al., 2017; Park et al., 2011;
16 Ramezani and Geroliminis, 2012; Zheng et al., 2017). While estimating joint distributions of
17 travel times for successive links, can provide a useful connection with reliability, this time of
18 information is difficult to be collected with loop detectors or low penetration mobile sensors.
19 Building on *pNEUMA* database, using the concept of virtual loop detectors (Figure 9) put at the
20 various intersections of a road section significant information can be extracted regarding travel
21 times.



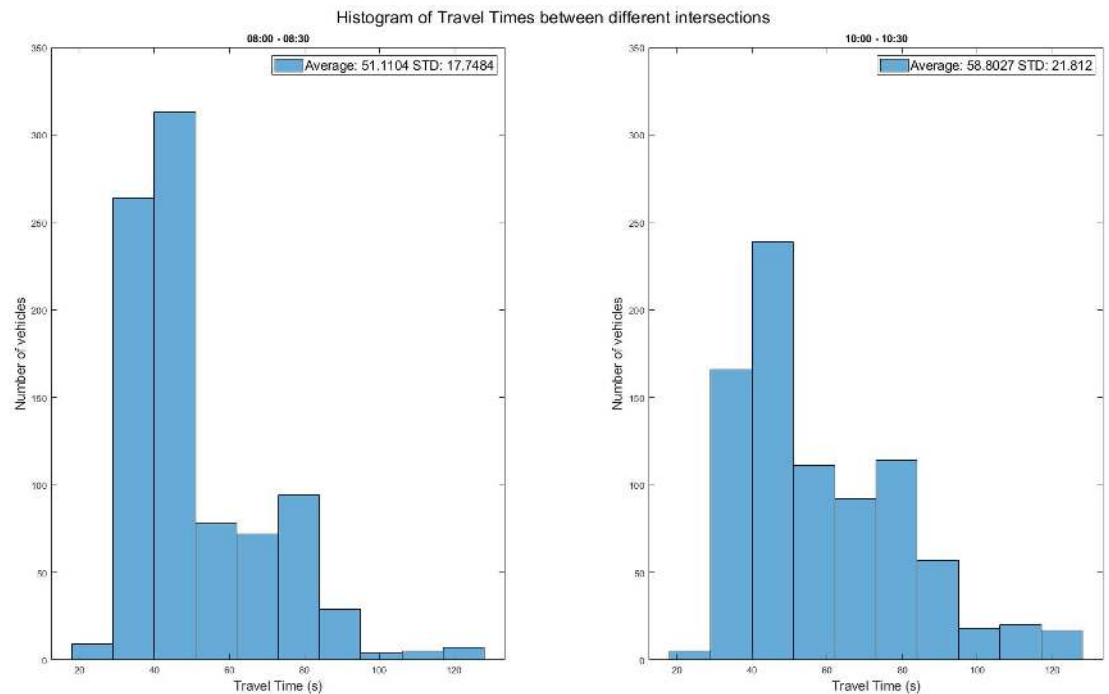
22
23 **Figure 9: A main arterial of the study area with installed virtual loops (gates)**

24 In Figure 10 the results of such a process are presented for one of the most congested routes in
25 the monitored arterials. The figure presents 2D diagrams of joint travel time distributions of
26 successive links, as introduced by (Ramezani and Geroliminis, 2012). Each point represents the
27 actual travel time of a single vehicle in two successive links (link boundaries are two successive
28 gates), for different vehicle types. Looking at the different clusters that are created between the
29 travel times between successive intersections, the effectiveness of the green wave can be
30 evaluated, the variations in travel times by mode and the way congestion propagates or not.
31 Interestingly, taxis and buses experience heavier travel times than normal vehicles, due to
32 service-related stops.



1
2 **Figure 10: Travel times between different gates grouped by transport mode**

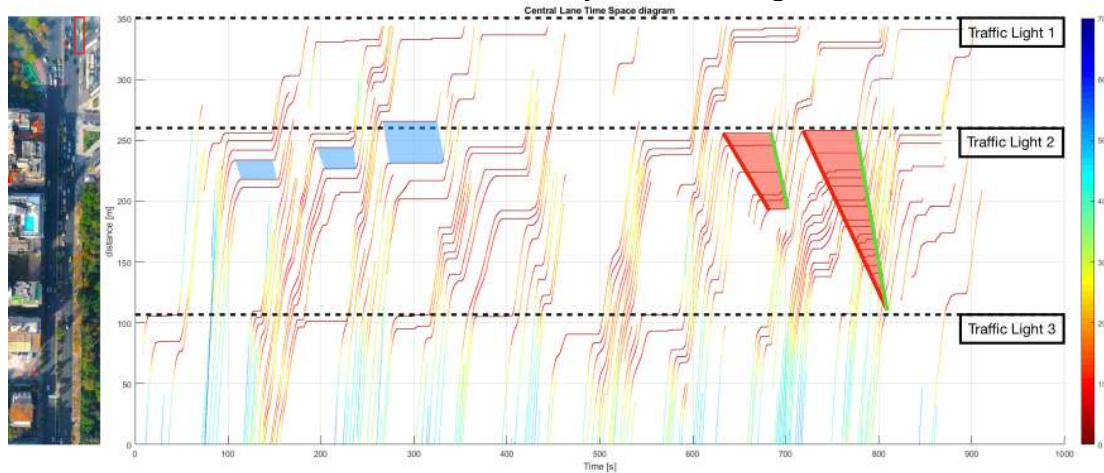
3 In the same context, by plotting the histogram of the data one can have a clearer view on the
4 variations of travel times. For example, in Figure 11 one can see the variations in the
5 distribution of travel times between the onset (left) and the offset (right) of congestion for
6 vehicles that passed from all six gates of Figure 9. Interestingly, the range of this distribution
7 is large as the slower vehicles experienced travel times up 5 times larger than the faster ones.
8



9
10 **Figure 11: Histogram of travel time between an extended arterial during different time**
11 **periods**

12 Additionally, another useful tool to study how traffic moves, to analyze its delays, to coordinate
13 signal timings, to estimate shockwaves and calculate of individual headways and spacings is

1 the time-space (x-t) diagram. Especially when roads become more congested, the time-space
2 diagram can be a significant tool to study and visualize the speed of the shockwaves formed,
3 as well as information about when and where they started forming.



4
5 **Figure 12: x-t diagram of the central lane of a three-lane 450m arterial with sequential**
6 **traffic signals for a 15-minute period (a 4th lane is developed in the downstream end – see**
7 **the red box)**

8 Figure 12 presents x-t diagram for a period of 15 minutes extracted from drone 8, covering
9 450m of the central lane of a major arterial (Alexandras Avenue) and three signalized
10 intersections. The color represents the instantaneous speed (measured in km/hr). Note the
11 significant heterogeneity in driving behavior when vehicles are joining or leaving a queue.
12 Despite this, the queue evolution, shockwaves and spillbacks can be studied at the lane-detail.
13 For example, the maximum wave speed w (as per LWR theory) is almost the same for all cycles
14 and intersections. The speed scale provides a quick overview on the traffic conditions that were
15 present, as the number of stop-and-go due to traffic lights or not. It should be noted that this
16 diagram does not include data from motorcycles, but only from cars, trucks, buses and taxis, as
17 their chaotic trajectories would be illustrated with intercepting points between the different
18 vehicle trajectories and make the diagram less readable. For the same reason, we can distinguish
19 some characteristic issues that appear in this time space diagram compared to traditional ones.
20 Specifically, there is an unexpectedly large headway between the two stopped vehicles,
21 highlighted with light blue color. Such cases were reviewed manually and it was identified that
22 in between there was a motorcycle, whose trajectory does not appear in Figure 12. It should be
23 noted that the motorcycle was properly identified, but Figure 12 focuses on the rest of the
24 vehicles' trajectories as motorcycles can have non-smooth trajectories with multiple lane
25 changes and driving on the border of a lane and between vehicles. The non-continuous lines
26 refer to lane changing phenomena that are discussed in the next section. This figure contains a
27 significant amount of information that is rarely available for arterial networks (e.g. detailed
28 interactions for almost every pair of vehicles moving in a congested urban environment).
29 Clearly, this will allow to revisit and create a new era of microscopic traffic flow models and
30 improve the accuracy, calibration and validation of microsimulation tools.

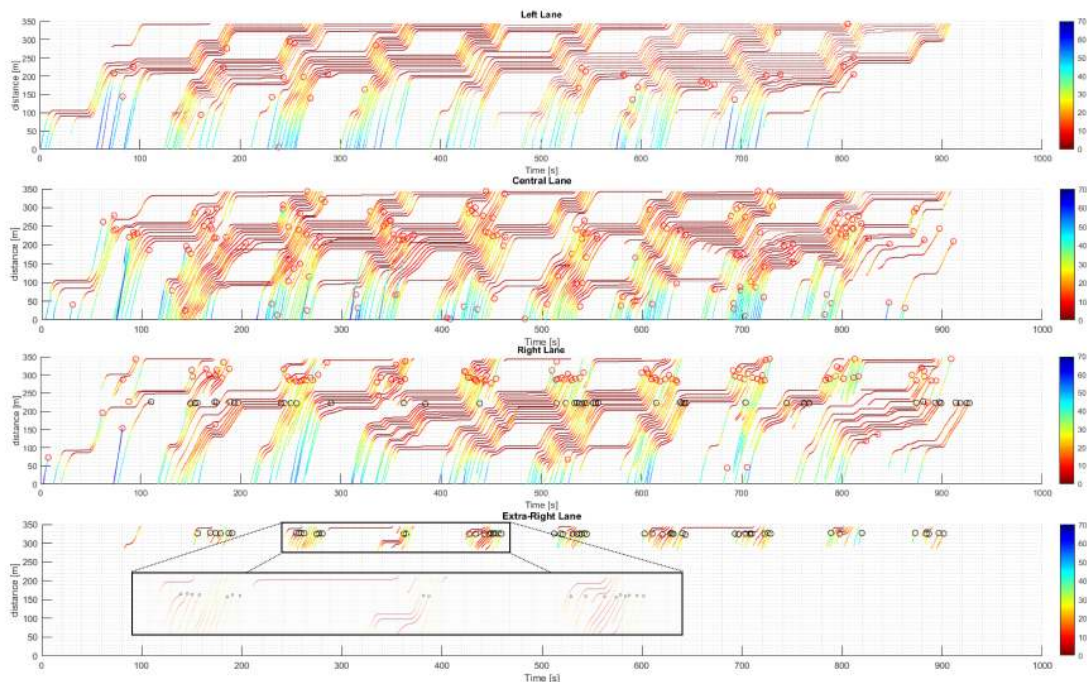
31 **4.3 Lane changing**

32 Lane changing modeling has attracted significant interest, especially for freeway systems
33 (Coifman et al., 2007; Kesting et al., 2007; Laval and Daganzo, 2006; Nagel et al., 1998; Wei
34 et al., 2007). As lane-changing maneuvers often act as initial local disturbances, it is crucial to
35 understand their impact on the capacity, stability and breakdown of traffic flows (Kesting et al.,
36 2007). Most of lane-changing models attempt to identify if an immediate lane change will
37 improve the vehicle's speed given safety constraints (Gipps, 1986). This is typically modeled
38 with gap-acceptance models (Gipps, 1986), (Toledo et al., 2003). One of the most general lane-
39 changing models is described in (Kesting et al., 2007). Authors introduce a utility of a given
40 lane and the risk of a lane change is determined in terms of longitudinal accelerations. This

1 allows the formulation of safety and incentive criteria both for various passing rules. While
 2 these phenomena have been studied in details after the development of NGSIM freeway
 3 database (NGSIM, 2006), their effect in urban settings is unexplored. Reasons for this research
 4 gap is the scarcity of complete trajectory data and the fact that bottleneck locations and the
 5 breakdown mechanism are more difficult to be identified compared to freeways. For measuring
 6 lane changes, conventional cross-sectional data from detectors are not sufficient. Recent
 7 progress in video tracking methods, however, allows for a collection of high-quality trajectory
 8 data from aerial observations (Hoogendoorn et al., 2003; NGSIM, 2006). Data collected from
 9 drones in urban environments can allow a careful study of lane-changing behavior and
 10 investigate the effect of the local phenomenon to network congestion.

11 A lane-changing is associated with a discretionary (e.g. improve its position and travel faster
 12 or avoid a stopped vehicle) or compulsory action (e.g. a vehicle turning has to choose the right
 13 lane). Compared to a freeway trip, an arterial one contains a larger number of lane changes that
 14 are associated with events triggering both types above and create a more circuitous route. Lane-
 15 changing creates local disturbances, but the magnitude of congestion formation and
 16 propagation depends on the environment around the involved vehicles, thus a complete
 17 monitoring of the surrounding environment is crucial to properly model these phenomena. A
 18 complete naturalistic dataset can allow for a careful investigation of all the aforementioned
 19 challenges and research gaps.

20 As Figure 12 illustrates the time-space diagram of one lane, the lane-level of detail of the
 21 current dataset allows lane changing phenomena to be illustrated using the time-space diagram,
 22 for multi-lane highways. Figure 13 shows the complete picture for the same 3-lane road arterial
 23 with a x-t diagram for each lane (similar figure developed in Laval and Leclercq, 2010 for a
 24 freeway with NGSIM data). The width of the road in the last 80 meters of the specific arterial
 25 includes an extra fourth lane (note the red box in the aerial photo of Figure 12) and the x-t
 26 diagram of the extra lane can be seen in the bottom part of Figure 13.



27
 28 **Figure 13: Time-Space diagram of a 3-lane arterial illustrating lane-changing phenomena**

29 In Figure 13 all red circles represent lane changes that remained in the study area while the black
 30 circles represent the vehicles that exited the study area from the right lane to adjacent roads of
 31 the network. What is interesting to notice is that many lane changes occur close to the most
 32 downstream traffic light at the end of the road section ($x=340m$), which suggests that some
 33 drivers will conduct a lane change maneuver for a better position in the queue upstream of the
 34 traffic light. It is seen that the use of lane-level x-t diagrams allows the study and modeling of

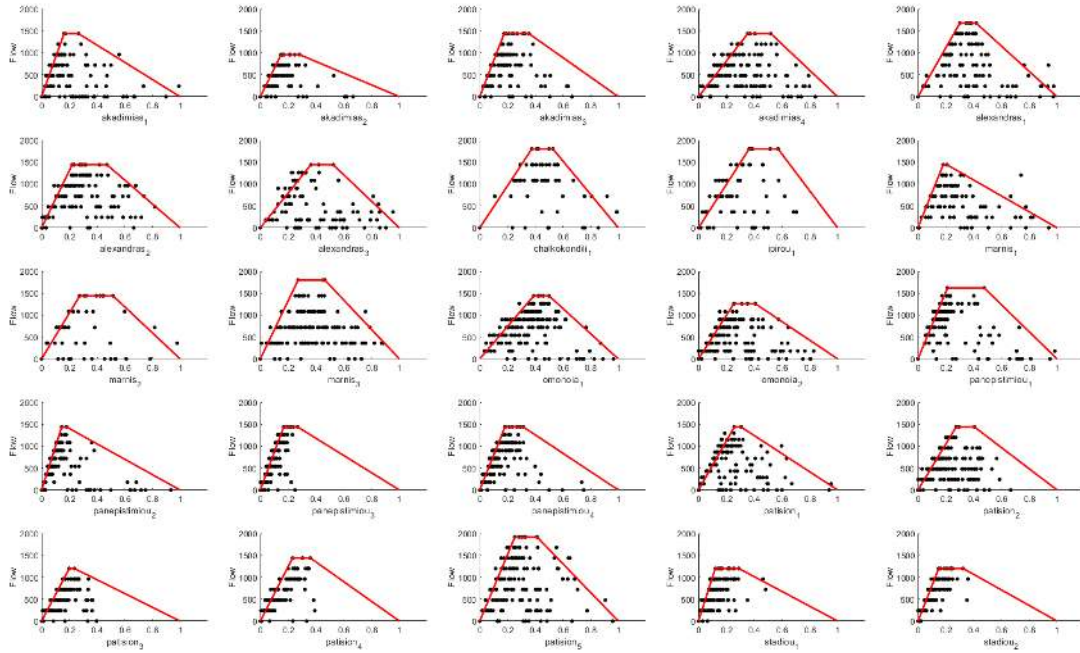
1 queue evolution and spillbacks, phenomena which are directly connected with excessive delays
2 and congested environments. Note for example the spillbacks occurring in the central and right
3 lane at location $x=150\text{m}$, $t=420\text{sec}$. Interestingly, the spillback is active only on the right lane
4 at the next cycle (same x , $t=500\text{sec}$). These phenomena of lane-specific spillbacks have not
5 been studied properly in the traffic community because of lack of available data and
6 microscopic traffic simulators (and models) have never been calibrated at this level of detail.
7 Finally, since the x - t diagrams have not been used massively for multi-lane environment, we
8 expect new ways of illustrating vehicles' trajectories to be proposed that will incorporate the
9 unique cases that occur in dense urban environments.

10 **4.4 Fundamental Diagrams (FD) and Macroscopic Fundamental Diagrams (MFD)**

11
12 The fundamental diagram (FD) is a well-established relationship between flow q and density
13 k at a specific location of a road and it mainly encompasses equilibrium traffic states definition.
14 It is the backbone of various models in traffic flow and it is well-connected with wave structures
15 and congestion propagation. In most cases aggregated data from loop detectors (in time periods
16 30sec to 5min) are utilized to obtain FDs. This aggregation can be problematic because (as
17 stated in various publications, see for example (Duret et al., 2008), various FD states over the
18 aggregation interval occur and the estimated q, k pair is an average state, without proper
19 information for transient states. Lane aggregation is another cause of discrepancy as lane
20 changes and different behavior per lane can influence the results. Methods to determine nearly-
21 stationary situations with cumulative curves (Cassidy, 1998) might fall short in the vicinity of
22 shockwaves (Chiabaut et al., 2009). As stated by (Chiabaut et al., 2009), it is appealing to base
23 FD estimation on spatial measurements, consistent with Edie's definition of equilibrium (Edie,
24 1961). Another alternative is to focus on speed-spacing relationship of individual trajectories,
25 which explains in more details transient states and hysteresis phenomena (Ahn et al., 2013;
26 Chen et al., 2012b; Coifman, 2015; Deng and Zhang, 2015) but mostly for freeway data.

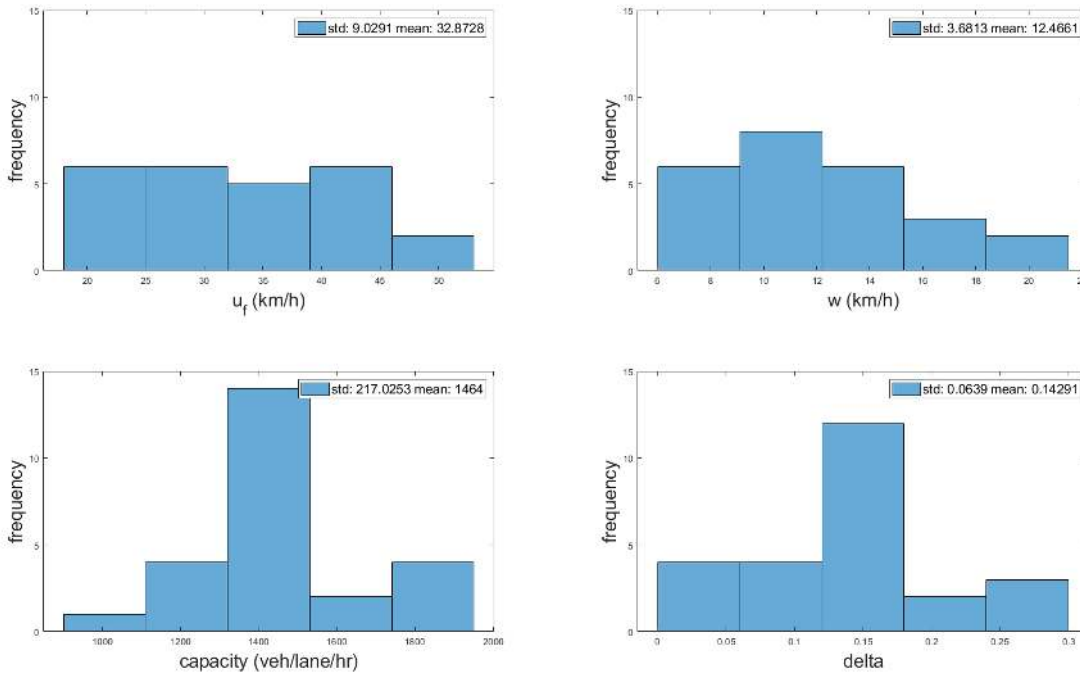
27 We now investigate how the shape of the FD varies, when estimated for various congested
28 locations in the urban network under consideration with detailed trajectory data. The different
29 parameters of fundamental diagrams at various locations are estimated; more specifically free-
30 flow speed (u_f), capacity (c) and maximum shockwave speed (w) and we see how they vary
31 across space. During the empirical analysis, it is seen that most of the locations experience an
32 FD closer to a trapezium shape, so we also estimate a 4th parameter which is the range of
33 occupancy that flow is at capacity. Thus, we chose 25 important intersections in the network
34 and we installed virtual loops a 15m upstream of the stop line that allows us to estimate
35 accurately point flow and occupancy following Edie's definitions. Flow and occupancy are
36 monitored in small time intervals (5sec) and we plot all the various FDs (Figure 14). Then we
37 keep the upper envelope of the constructed FD and the best-fit parameters for the trapezoid FD
38 are estimated, i.e. u_f , w (in km/hr), capacity (in veh/hr/lane) and range of capacity (δ -
39 dimensionless).

40



1
2 **Figure 14: Flow vs Occupancy for various for 25 different locations**

3 Given that virtual loops can be installed in any location of the network, we describe in more
 4 details how point occupancy was estimated. We prefer not to integrate stochasticity due to
 5 vehicle type and length, thus two virtual lines were installed in a fixed distance from each other
 6 (5m in our case) and we estimate as occupancy the time the front of the vehicle occupies the
 7 virtual loop between these two lines (this is the exact definition of Edie for vehicle-hours (VHT)
 8 in a time-space region (with $\Delta t=5\text{sec}$ and $\Delta x=5\text{m}$). In this way, we define a proxy for density,
 9 which is not sensitive to the length of the vehicle. We also tested various Δt ranging from 3sec
 10 to 1min and we considered that 5sec provide the most intuitive results given that higher
 11 resolution had more scatter, while lower resolution was smoothing different states of FD, so
 12 the upper envelope was consistently lower. Figure 15 shows the distributions for the 4
 13 parameters across all the 25 locations.
 14



15
16 **Figure 15: Distribution of the four different FD parameters**

1 An interesting future direction is an automatic procedure to identify shockwaves in the traffic
2 stream and evaluate how well LWR theory can represent various traffic characteristics. More
3 detailed models can also be tested (as for example (Yeo and Skabardonis, 2009) or (Zheng et
4 al., 2011) for freeway data.

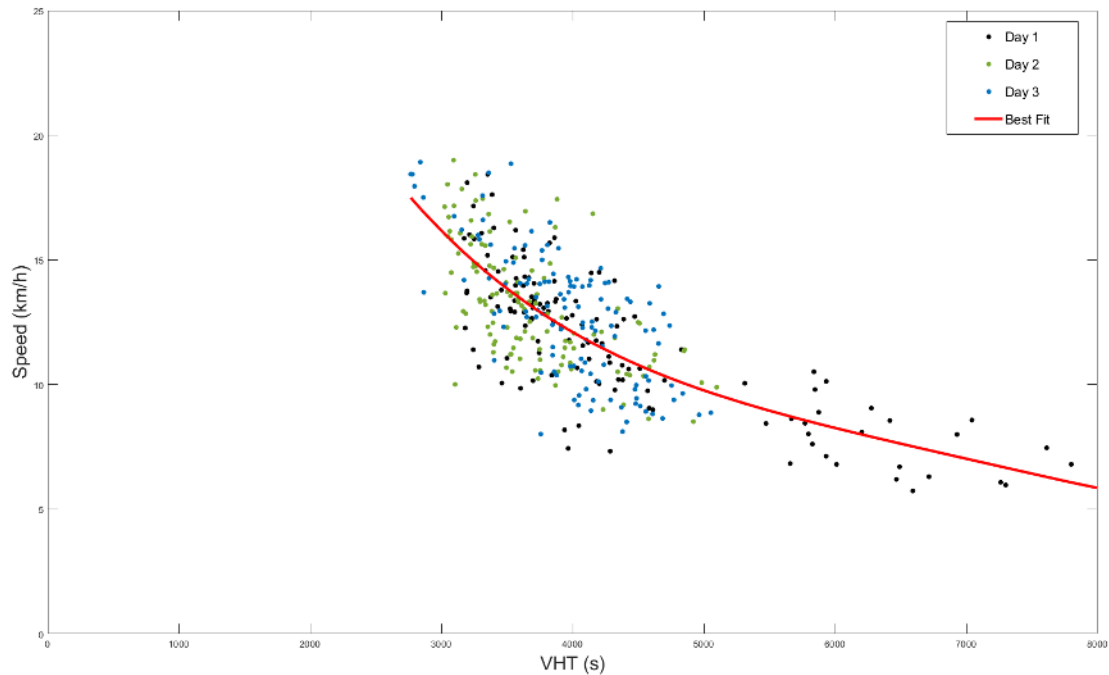
5 **Macroscopic Fundamental Diagrams (MFDs)**

6
7 The existence of a reproducible and well-defined relationship between network-wide space-
8 mean flow, density and speed has been established in the literature known as “Macroscopic
9 Fundamental Diagram” (MFD) or “Network Fundamental Diagram” (NFD) with lower scatter
10 compared to local FDs under some spatial homogeneity in the distribution of congestion
11 (Geroliminis and Sun, 2011).

12 *pNEUMA* provides a unique opportunity to investigate many aspects of MFD modeling with
13 this data. Traffic researchers will be able to test many of the MFD assumptions that have been
14 made in the literature and cannot be verified with existing empirical data due to low
15 penetration rate (from moving vehicles) or local information due to loop detectors. Some
16 examples are distribution of trip lengths, trip based vs. accumulation-based models, the
17 relationship between outflow and production, a 3-D bimodal MFD and other directions. While
18 MFD literature is vast in the last few years, a few examples can be found in (Haddad, 2017;
19 Lamotte and Geroliminis, 2018; Mahmassani et al., 2013; Mariotte et al., 2017).

20 *pNEUMA* dataset contains some additional challenges with respect to MFD research, but it also
21 creates unique opportunities. Traditionally, MFD plots from real data are based on loop
22 detectors that are located in the major roads of a downtown area. In our case, *pNEUMA* includes
23 also trajectories that are on minor roads, creating higher heterogeneity in the spatial distribution
24 of congestion. Thus, when we tried to plot vehicle-km vs. vehicle-hours (VKT vs. VHT) from
25 all the data, we only observed an uncongested branch and also with more scatter than the other
26 empirical MFD studies. A proposed solution for this is to do a proper clustering to detect
27 directional congestion and partition the networks in different regions with more homogeneous
28 characteristics. (see for example works by (Saeedmanesh and Geroliminis, 2017) or (Lopez et
29 al., 2017a) with the snake algorithm). This is not a straightforward task because this data is not
30 associated yet with a network structure. It is important to create a mapping of the data to the
31 roads of the network by combining detailed street maps with the trajectory data. This is beyond
32 the scope of the current paper, but an important research priority.

33 Given that we also have a strong desire to include some MFD results in this first paper that
34 describes the experiment, we were able to identify one of the drones that monitors a really
35 congested area (around Omonoia square) and clustering is not necessary. Thus, we include a
36 new plot in the paper with a speed vs. VHT for this specific area (Figure 16). Significant
37 congestion is observed with space-mean speeds reaching around 6km/hr. We expect to report
38 further MFD results in the future and more authors can investigate various MFD challenges
39 with the data.



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Figure 16: Speed vs VHT for Omonioa square in three different days

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In Figure 16 the MFDs of the congested area are illustrated for the time window of 2.5 hours for three different days. It can be seen in Figure 16 that the traffic characteristics for Days 2 and 3 are almost identical. However, in Day 1 the effects of a bottleneck can be seen that led to an intense drop in average speed (>50%) as two distribution vehicles parked temporarily on the right lane. Then during the blind spot that the drones were not collecting data the vehicles left and it can be seen how traffic is normalized.

9

4.5 Research on multimodal interactions and specialized urban driving phenomena

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pNEUMA will give the opportunity to also analyze the effect of random service-related stops and maneuvers that are quite frequent in the study area for taxis and buses, and their contributions in congestion. Given the fact that our dataset includes a significant number of taxis, it is possible to estimate their density and stops for different locations for different levels of congestion.

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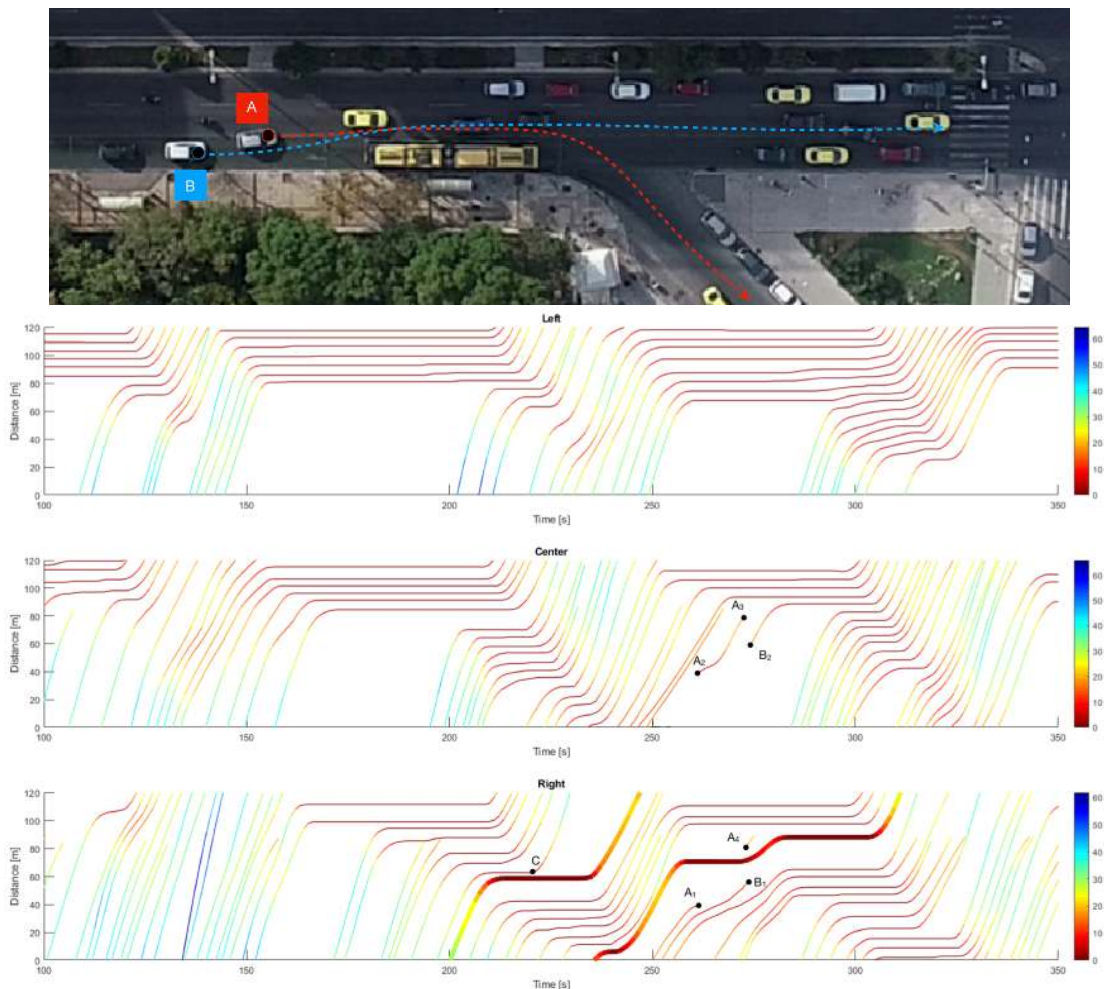
Another significant case of local disturbances to be studied is the way special vehicles of a multimodal environment (e.g. taxis, buses, delivery vehicles) affect the traffic flow characteristics. The increase of ride-hailing and on-demand services for the majority of large cities worldwide can have a significant consequence on the congestion effects for the remaining of traffic. These service-related stops of all relevant modes (taxis, buses, delivery vehicles) create static and moving bottlenecks of different magnitude. Vehicles might queue behind the stopped vehicle creating a local queue that can be analyzed with standard shockwave theory or it might be associated with lane-changing to overpass the service-related stop. Despite the different features of these modes in terms of number of passengers, driving behavior (speeds, acceleration profiles, size), scheduled vs. non-scheduled service, a common characteristic is the following: All of these vehicles when moving to an urban environment make stops related to traffic congestion. For example, buses stop at specific locations for longer durations (30-40sec), while taxis might stop in random locations for shorter durations (5-15sec) to pick up and drop off passengers. The effect of such phenomena in the overall performance of a transportation system still remains a challenge. Nowadays city centers are experiencing high level of congestion and the frequency in time and space of such stops is significantly high. While intuitively we expect the effect of these stops during light demand conditions in the network capacity to be almost negligible, the existing dataset will be enhanced with annotated dataset to study such cases for different traffic conditions (Figure 17).



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Figure 17: The effect of a taxi (red oval) that stopped to pick-up a passenger.

As can be seen in Figure 17 a complex situation may appear when a taxi driver decides to stop in order to pick a passenger (red oval). This affects vehicles that move on the same lane (green oval) and through vehicles in the middle lanes (yellow and blue oval). It is seen during the different time intervals that the green vehicle was waiting behind the red vehicle for more than 10 seconds, and merged to the adjacent lane only after the two yellow vehicles passed. The green merging vehicle found an adequate gap between the yellow and the blue vehicles. The bottlenecks (static and moving) that are created may have a significant impact even on a large 6-lane arterial.



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Figure 18: Time-Space diagram of a 3-lane arterial illustrating the effect of bus stops

Another characteristic example of multimodal interactions is illustrated in Figure 18. The effect of buses stopping for passengers to the rest of traffic is analyzed. The trajectories of two buses are shown with thicker lines in the right lane. The problem is quite complex because there is a traffic light at the downstream end ($x=110m$) that interacts with the bus stop. The traffic signal is red in the time intervals (160, 210) and (250, 300), time units are seconds. Note that the

1 developed queue has almost discharged and vehicle C experiences a short waiting due to the
2 traffic light red phase. Nevertheless, the first bus stops when the traffic light is green at interval
3 (210,235), resulting in a queue of vehicles behind it and a underutilization of green phase. Note
4 that no vehicles are passing the traffic light stopline in the interval (225,245) at the right lane,
5 while the central lane operates at capacity during the same time. Specifically, the queue that is
6 formed in the right lane should start reducing when vehicle C accelerates. However, as the first
7 bus has already stopped at the bus stop, the queue does not reduce until the bus leaves the bus
8 stop. The second bus even if it stops for about the same duration, it does not create any capacity
9 loss and the traffic light operates mostly at capacity at the next cycle.

10 Some lane changes associated with the stopping of the bus occurs. Vehicles A and B were also
11 on the right lane but overtook the second bus during its stop (A1-A2 and B1-B2 respectively).
12 Then Vehicle A conducted a second lane change from the central back to the right lane (B3-
13 B4) to exit the main arterial while Vehicle B stayed in the already formed queue.

14 **4.6 Other future directions**

15 A unique observatory for traffic congestion with data that did not exist before at this resolution
16 and scale has been created from the processing of the videos from the experiment. This massive
17 dataset contains trajectories of *almost every vehicle* in a complex urban environment that can
18 be used to study different phenomena. The preliminary analysis of the dataset exceeded our
19 expectations in terms of quality of extraction and information available and provides unique
20 research opportunities. Some of the potential research challenges that can be investigated with
21 the *pNEUMA* database by researchers in different communities are:

22 i. Develop methodologies to automatically identify lane-changing maneuvers in the
23 complete set of trajectory data. For example, given proper coordinates of the lanes for each
24 road and the direction of travel, events that trigger deviations from a direct straight line will be
25 considered as lane changes. This is one of our current research priorities.

26 ii. Investigate congestion mechanisms and the effect of local disturbances at network
27 level. Local disturbances are associated with stop-and-go situations that involve few or more
28 vehicles. An important challenge is to identify how many vehicles are influenced upstream
29 from a lane-changing event. It is expected that small shockwaves may be developed during the
30 formation that might expand or not in time and space. These observations will allow for the
31 development of proper locally aggregated variables that can explain the congestion mechanism.
32 While the literature of lane-changing mainly models an event by comparing the spacing with
33 the leading vehicle of the same lane and the lead and lag gap of vehicles in the target lane,
34 *pNEUMA* experiments will allow to investigate more advanced models that quantify the effect
35 of the local environment. Even if *pNEUMA* does not have a direct interest on AVs, it can create
36 accurate lane-changing models that AVs can integrate in their design for movements in mixed-
37 usage with conventional cars.

38 iii. Study lane choice, which is another unexplored area for congested arterials. Consider
39 vehicles that have to make a number of turns during their trip, which are associated with
40 compulsory lane changes (see some trajectories in Figure 8, where the coloring represents
41 different origins). A probabilistic framework of lane-choice could be investigated together with
42 decisions of drivers to change lanes as a function of the distance from the turning intersection.
43 While these events might not be interesting under moderate congestion levels, they can create
44 strong capacity loss due to increased friction in case of conflicting movements (similar to a
45 weaving section in a freeway). A better understanding of these phenomena can advance the
46 development of safety features for AVs or advanced traffic management schemes for better
47 utilization of intersections capacity (like prohibiting specific turns or appropriate route
48 guidance information).

49 iv. Investigate lane-changing mechanisms as in points (ii) and (iii) above for multimodal
50 interactions (similar to those of Figure 18) will unhide models of additional complexity, with
51 important consequences for traffic engineering. Data extracted contain the type of vehicle, so
52 the contributions of this task will mainly be in the exploration of dynamic congestion formation
53 and propagation for mixed environments. For example, similar cases apply for motorcycles and

1 Powered Two Wheelers (PTW) in general, which have not been studied in detail until now
2 mostly due to lack of naturalistic datasets (Barmounakis et al., 2016b).

3 v. Study network-level emissions and connect it with local disturbances at the vehicle
4 level. Given the lack of detailed driving cycle data at the network level, the emission footprint
5 of congested city centers is unknown and researchers rely on extracting data from
6 microsimulation. For example, a driver aggressiveness index can be created with *pNEUMA*
7 data based on lane changes, harsh acceleration and harsh braking events and identify
8 distributions of important lane-changing parameters across the population. Given that stop-and-
9 go traffic creates acceleration profiles that are strongly connected with emissions, it is crucial
10 to understand the effect of driver's heterogeneity in the emissions. This analysis can facilitate
11 the development of schemes to penalize aggressive driving or providing incentives for regular
12 drivers and can create significant implications for development of "green" policies.

13 **5. Discussion - Open Dataset Initiative**

14 The new era of sharing information and "big data" has raised our expectation to make mobility
15 more predictable and controllable through a better utilization of data and existing resources.
16 The realization of these opportunities requires going beyond the existing decentralized or
17 simulation-based approaches of modeling and managing mobility. How local disturbances,
18 such as lane changes, service-related stops (of taxis, ride-hailing or buses) influence the
19 network performance and the propagation of congestion especially under congested conditions
20 still requires a careful consideration. While UAS are not yet ready for continuous operation to
21 monitor traffic, the focus of our work is on the potential of a full coverage of a large region that
22 will allow the deep investigation of critical traffic phenomena. The emphasis is on local
23 disturbances that often occur in urban networks and can be associated with a reduced
24 performance at the network level. Observing, understanding, modeling and validating these
25 phenomena for congested urban multimodal settings with an accurate monitoring of almost
26 every vehicle has not been done before at such a scale.

27 With this research, we aim to explain better the mechanism of congestion formation and
28 propagation in congested multimodal urban environments through massive data from aerial
29 footage. The realization of the data opportunities requires going beyond the existing simulation-
30 based approaches of modeling congestion with complex models of many parameters that make
31 their validation questionable. Research community should follow an empirical approach to
32 understand these mechanisms. The first results indicate the tremendous possibilities of the
33 specific dataset that we aim to share with the rest of our community. We believe this can be a
34 benchmark dataset for both existing and future modeling approaches for several disciplines.
35 Thus, an open science initiative is under development.

36 Monitoring mobility movements from the skies emerges nowadays due to the improved
37 technology and advances in vision algorithms. This is a strong alternative to traditional
38 monitoring techniques as data quality can be significantly higher and different modes of
39 transport (private cars, public transport, taxis, motorcycles, bikes or pedestrians) can be
40 observed. It is clear that this unique dataset can offer immense opportunities for answering
41 additional research questions that are beyond our interests and expertise. This open science
42 initiative will create a unique observatory of traffic congestion that researchers around the globe
43 can use to develop and test their own models. The general scope is to provide a unique dataset
44 of almost half a million of naturalistic trajectories that have been collected to estimate
45 congestion models and propose smart mobility solutions. While similar datasets with empirical
46 data have been provided to the transportation society, the need for naturalistic microscopic data
47 still remains. For example, although the NGSIM has become the benchmark dataset for several
48 studies, several limitations may occur due to reduced accuracy or limited sample (Coifman and
49 Li, 2017).

50 Therefore, it is of our best interest to create an Open Data initiative for a scale an-order-of-
51 magnitude higher than what was available until now and many communities can be benefited
52 for research purposes. Putting together this information and sharing it widely and openly will
53 allow different research communities to test models and hypotheses far beyond our main
54 research interests ranging from modeling microscopic phenomena and vehicle-to-vehicle

1 interactions to network level models and road safety. This dataset can be utilized by the whole
2 research community of transportation science and other disciplines, such as Machine Learning
3 or Artificial Intelligence, to study, model and improve traffic congestion. This dataset can
4 become a benchmark dataset for a new era of traffic models that will be utilized for
5 understanding how people behave and what really causes traffic congestion. The *pNEUMA*
6 database is enhanced continuously and data can be downloaded from traffic.epfl.ch.

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14 **7. References**

- 15 Ahn, S., Vadlamani, S., Laval, J., 2013. A method to account for non-steady state conditions in
16 measuring traffic hysteresis. *Transp. Res. Part C Emerg. Technol.*
17 doi:10.1016/j.trc.2011.05.020
- 18 Antoniou, C., Barceló, J., Breen, M., Bullejos, M., Casas, J., Cipriani, E., Ciuffo, B., Djukic,
19 T., Hoogendoorn, S., Marzano, V., Montero, L., Nigro, M., Perarnau, J., Punzo, V.,
20 Toledo, T., van Lint, H., 2016. Towards a generic benchmarking platform for origin-
21 destination flows estimation/Updating algorithms: Design, demonstration and validation.
22 *Transp. Res. Part C Emerg. Technol.* 66, 79–98. doi:10.1016/j.trc.2015.08.009
- 23 Babinec, A., Apeltauer, J., 2016. On accuracy of position estimation from aerial imagery
24 captured by low-flying UAVs. *Int. J. Transp. Sci. Technol.* 5, 152–166.
25 doi:10.1016/j.ijtst.2017.02.002
- 26 Barmponakis, E.N., Vlahogianni, E.I., Golias, J.C., 2018. Identifying predictable patterns in
27 the unconventional overtaking decisions of PTW for Cooperative ITS. *IEEE Trans. Intell.*
28 *Veh.* 3, 102–111. doi:10.1109/TIV.2017.2788195
- 29 Barmponakis, E.N., Vlahogianni, E.I., Golias, J.C., 2016a. Unmanned Aerial Aircraft Systems
30 for transportation engineering: Current practice and future challenges. *Int. J. Transp. Sci.*
31 *Technol.* 5, 111–122. doi:10.1016/j.ijtst.2017.02.001
- 32 Barmponakis, E.N., Vlahogianni, E.I., Golias, J.C., 2016b. Intelligent Transportation Systems
33 and Powered Two Wheelers Traffic. *IEEE Trans. Intell. Transp. Syst.* 17, 908–916.
34 doi:10.1109/TITS.2015.2497406
- 35 Barmponakis, E.N., Vlahogianni, E.I., Golias, J.C., Babinec, A., 2017. How accurate are small
36 drones for measuring microscopic traffic parameters? *Transp. Lett.* In Press, 1–9.
37 doi:10.1080/19427867.2017.1354433
- 38 Beloev, I.H., 2016. A Review on Current and Emerging Application Possibilities for Unmanned
39 Aerial Vehicles. *Acta Technol. Agric.* 19, 70–76. doi:10.1515/ata-2016-0015
- 40 Bhaskar, A., Chung, E., Dumont, A.G., 2011. Fusing Loop Detector and Probe Vehicle Data to
41 Estimate Travel Time Statistics on Signalized Urban Networks. *Comput. Civ. Infrastruct.*
42 *Eng.* doi:10.1111/j.1467-8667.2010.00697.x
- 43 Bhaskar, A., Qu, M., Chung, E., 2015. Bluetooth vehicle trajectory by fusing bluetooth and
44 loops: Motorway travel time statistics. *IEEE Trans. Intell. Transp. Syst.*
45 doi:10.1109/TITS.2014.2328373
- 46 Bogdanowicz, Z.R., 2018. Optimization of Persistent Land Coverage by Swarm of Drones.
47 *Appl. Math. Sci.* 12, 1219–1237. doi:10.12988/ams.2018.88115
- 48 Brackstone, M., McDonald, M., 1999. Car-following: A historical review. *Transp. Res. Part F*
49 *Traffic Psychol. Behav.* 2, 181–196. doi:10.1016/S1369-8478(00)00005-X
- 50 Cassidy, M.J., 1998. Bivariate relations in nearly stationary highway traffic. *Transp. Res. Part*
51 *B Methodol.* doi:10.1016/S0191-2615(97)00012-X
- 52 Chen, D., Laval, J., Zheng, Z., Ahn, S., 2012a. A behavioral car-following model that captures
53 traffic oscillations. *Transp. Res. Part B Methodol.* doi:10.1016/j.trb.2012.01.009

- 1 Chen, D., Laval, J.A., Ahn, S., Zheng, Z., 2012b. Microscopic traffic hysteresis in traffic
2 oscillations: A behavioral perspective. *Transp. Res. Part B Methodol.*
3 doi:10.1016/j.trb.2012.07.002
- 4 Chen, M., Yu, G., Chen, P., Wang, Y., 2017. A copula-based approach for estimating the travel
5 time reliability of urban arterial. *Transp. Res. Part C Emerg. Technol.* 82, 1–23.
6 doi:10.1016/j.trc.2017.06.007
- 7 Chiabaut, N., Buisson, C., Leclercq, L., 2009. Fundamental diagram estimation through passing
8 rate measurements in congestion. *IEEE Trans. Intell. Transp. Syst.* 10, 355–359.
9 doi:10.1109/TITS.2009.2018963
- 10 Coifman, B., 2015. Empirical flow-density and speed-spacing relationships: Evidence of
11 vehicle length dependency. *Transp. Res. Part B Methodol.* doi:10.1016/j.trb.2015.04.006
- 12 Coifman, B., Krishnamurthy, S., Wang, X., 2007. Lane-Change Maneuvers Consuming
13 Freeway Capacity, in: *Traffic and Granular Flow '03*. doi:10.1007/3-540-28091-x_1
- 14 Coifman, B., Li, L., 2017. A critical evaluation of the Next Generation Simulation (NGSIM)
15 vehicle trajectory dataset. *Transp. Res. Part B Methodol.* 105, 362–377.
16 doi:10.1016/J.TRB.2017.09.018
- 17 Daganzo, C.F., 1994. The cell transmission model: A dynamic representation of highway traffic
18 consistent with the hydrodynamic theory. *Transp. Res. Part B.* doi:10.1016/0191-
19 2615(94)90002-7
- 20 Das, A., Shirazipourazad, S., Hay, D., Sen, A., 2018. Tracking of Multiple Targets using
21 Optimal Number of UAVs. *IEEE Trans. Aerosp. Electron. Syst.* doi:10.1007/978-3-319-
22 12691-3_55
- 23 DataFromSky, 2014. Advanced traffic analysis of aerial video data [WWW Document]. URL
24 <http://datafromsky.com> (accessed 3.30.16).
- 25 Deng, H., Zhang, H.M., 2015. On traffic relaxation, anticipation, and hysteresis. *Transp. Res.*
26 *Rec.* doi:10.3141/2491-10
- 27 Dung, N.D., Rohacs, J., 2018. The drone-following models in smart cities. 2018 IEEE 59th Int.
28 *Sci. Conf. Power Electr. Eng. Riga Tech. Univ.* 1–6.
- 29 Duret, A., Buisson, C., Chiabaut, N., 2008. Estimating individual speed-spacing relationship
30 and assessing ability of newell's car-following model to reproduce trajectories. *Transp.*
31 *Res. Rec.* 188–197. doi:10.3141/2088-20
- 32 Edie, L.C., 1961. Car-Following and Steady-State Theory for Noncongested Traffic. *Oper. Res.*
33 doi:10.1287/opre.9.1.66
- 34 Fadzil, M., Yasin, M., Zaidi, M.A., Nawati, M.N.M., 2016. A review of Small Unmanned
35 Aircraft System (UAS) advantages as a tool in condition survey works. *MATEC Web*
36 *Conf.* 00038.
- 37 Feng, Y., Davis, G., Hourdos, J., 2011. Arterial Travel Time Characterization and Real-time
38 Traffic Condition Identification Using GPS-equipped Probe Vehicles. *Transp. Res. Board*
39 *90th ...*
- 40 Freeman, B.S., Ahmad, J., Matawah, A., Al, M., Gharabaghi, B., Thé, J., 2018. Vehicle
41 stacking estimation at signalized intersections with unmanned aerial systems. *Int. J.*
42 *Transp. Sci. Technol.* In Press. doi:10.1016/j.ijtst.2018.12.002
- 43 Garcia-Aunon, P., Roldán, J.J., Barrientos, A., 2018. Monitoring traffic in future cities with
44 aerial swarms: developing and optimizing a behavior-based surveillance algorithm. *Cogn.*
45 *Syst. Res.* doi:10.1016/j.cogsys.2018.10.031
- 46 Gazis, D.C., Herman, R., Potts, R.B., 1959. Car-Following Theory of Steady-State Traffic
47 *Flow. Oper. Res.* 7, 499–505. doi:10.1287/opre.7.4.499
- 48 Geller, J., Researcher, U., Jiang, T., Ni, D., Collura, J., 2016. Traffic Management for Small
49 Unmanned Aerial Systems (sUAS): Towards the Development of a Concept of
50 Operations and System Architecture 6370, 1–16.
- 51 Geroliminis, N., Sun, J., 2011. Properties of a well-defined macroscopic fundamental diagram
52 for urban traffic. *Transp. Res. Part B Methodol.* doi:10.1016/j.trb.2010.11.004
- 53 Gipps, P.G., 1981. A behavioural car-following model for computer simulation. *Transp. Res.*
54 *Part B.* doi:10.1016/0191-2615(81)90037-0
- 55 Gipps, P.P.G., 1986. A model for the structure of lane-changing decisions. *Transp. Res. Part B*

1 Methodol. 20, 403–414. doi:10.1016/0191-2615(86)90012-3

2 Guido, G., Gallelli, V., Rogano, D., Vitale, A., 2016. Evaluating the accuracy of vehicle
3 tracking data obtained from Unmanned Aerial Vehicles. *Int. J. Transp. Sci. Technol.* 5,
4 136–151. doi:10.1016/j.ijst.2016.12.001

5 Guo, F., Li, Q., Rakha, H., 2013. Multistate Travel Time Reliability Models with Skewed
6 Component Distributions. *Transp. Res. Rec. J. Transp. Res. Board.* doi:10.3141/2315-05

7 Haddad, J., 2017. Optimal perimeter control synthesis for two urban regions with aggregate
8 boundary queue dynamics. *Transp. Res. Part B Methodol.* doi:10.1016/j.trb.2016.10.016

9 Haddad, J., Mirkin, B., 2017. Coordinated distributed adaptive perimeter control for large-scale
10 urban road networks. *Transp. Res. Part C Emerg. Technol.* doi:10.1016/j.trc.2016.12.002

11 Hayat, S., Yanmaz, E., Muzaffar, R., 2016. Survey on Unmanned Aerial Vehicle Networks for
12 Civil Applications: A Communications Viewpoint. *IEEE Commun. Surv. Tutorials* 18,
13 2624–2661. doi:10.1109/COMST.2016.2560343

14 Helbing, D., 2001. Traffic and related self-driven many-particle systems. *Rev. Mod. Phys.*
15 doi:10.1103/RevModPhys.73.1067

16 Herrera, J.C., Work, D.B., Herring, R., Ban, X. (Jeff), Jacobson, Q., Bayen, A.M., 2010.
17 Evaluation of traffic data obtained via GPS-enabled mobile phones: The Mobile Century
18 field experiment. *Transp. Res. Part C Emerg. Technol.* 18, 568–583.
19 doi:10.1016/j.trc.2009.10.006

20 Herring, R., Hofleitner, A., Abbeel, P., Bayen, A., 2010. Estimating arterial traffic conditions
21 using sparse probe data, in: *IEEE Conference on Intelligent Transportation Systems,*
22 *Proceedings, ITSC.* doi:10.1109/ITSC.2010.5624994

23 Hoffer, N. V., Coopmans, C., 2017. Challenges in Bridge Inspection Using Small Unmanned
24 Aerial Systems : Results and Lessons Learned. *Icuas 1722–1730.*

25 Hoogendoorn, S.P., Daamen, W., Piet H.L. Bovy, 2003. Extracting Microscopic Pedestrian
26 Characteristics from Video Data, in: *Transportation Research Board 82nd Annual*
27 *Meeting.* pp. 1–15.

28 Hu, M., Liu, W., Peng, K., Ma, X., Cheng, W., Liu, J., Li, B., 2018. Joint Routing and
29 Scheduling for Vehicle-Assisted Multi-Drone Surveillance. *IEEE Internet Things J.* 4662,
30 1–1. doi:10.1109/JIOT.2018.2878602

31 Jenelius, E., 2012. The value of travel time variability with trip chains, flexible scheduling and
32 correlated travel times. *Transp. Res. Part B Methodol.* doi:10.1016/j.trb.2012.02.003

33 Jenelius, E., Koutsopoulos, H.N., 2013. Travel time estimation for urban road networks using
34 low frequency probe vehicle data. *Transp. Res. Part B Methodol.*
35 doi:10.1016/j.trb.2013.03.008

36 Ji, Y., Luo, J., Geroliminis, N., 2014. Empirical Observations of Congestion Propagation and
37 Dynamic Partitioning with Probe Data for Large-Scale Systems. *Transp. Res. Rec. J.*
38 *Transp. Res. Board* 2422, 1–11. doi:10.3141/2422-01

39 Kamga, C., Sapphire, J., Cui, Y., Moghimidarzi, B., Khryashchev, D., 2017. Exploring
40 Applications for Unmanned Aerial Systems (UAS) and Unmanned Ground Systems
41 (UGS) in Enhanced Incident Management, Bridge Inspection, and Other Transportation-
42 related Operations, Final Report. New York, NY.

43 Kanarachos, S., Christopoulos, S.R.G., Chroneos, A., 2018. Smartphones as an integrated
44 platform for monitoring driver behaviour: The role of sensor fusion and connectivity.
45 *Transp. Res. Part C Emerg. Technol.* 95, 0–1. doi:10.1016/j.trc.2018.03.023

46 Kanistras, K., Martins, G., Rutherford, M.J., Valavanis, K.P., 2014. Survey of Unmanned
47 Aerial Vehicles (UAVs) for Traffic Monitoring, in: *Handbook of Unmanned Aerial*
48 *Vehicles.* Springer, pp. 2643–2666. doi:10.1109/ICUAS.2013.6564694

49 Kaparias, I., Bell, M.G.H., Belzner, H., 2008. A new measure of travel time reliability for in-
50 vehicle navigation systems. *J. Intell. Transp. Syst. Technol. Planning, Oper.*
51 doi:10.1080/15472450802448237

52 Kaufmann, S., Kerner, B.S., Rehborn, H., Koller, M., Klenov, S.L., 2018. Aerial observations
53 of moving synchronized flow patterns in over-saturated city traffic. *Transp. Res. Part C*
54 *Emerg. Technol.* 86, 393–406. doi:10.1016/j.trc.2017.11.024

55 Ke, R., Li, Z., Kim, S., Ash, J., Cui, Z., Wang, Y., 2017. Real-Time Bidirectional Traffic Flow

- 1 Parameter Estimation from Aerial Videos. *IEEE Trans. Intell. Transp. Syst.* 18, 890–901.
2 doi:10.1109/TITS.2016.2595526
- 3 Ke, R., McCormack, E., 2016. A Novel Framework for Real-time Traffic Flow Parameter
4 Estimation from Aerial Videos. University of Washington.
- 5 Ke, R., Member, S., Li, Z., Tang, J., Pan, Z., Wang, Y., 2018. Real-Time Traffic Flow
6 Parameter Estimation From UAV Video Based on Ensemble Classifier and Optical Flow.
7 *IEEE Trans. Intell. Transp. Syst.* 1–11. doi:10.1109/TITS.2018.2797697
- 8 Kesting, A., Treiber, M., Helbing, D., 2007. General Lane-Changing Model MOBIL for Car-
9 Following Models. *Transp. Res. Rec. J. Transp. Res. Board* 1999, 86–94.
10 doi:10.3141/1999-10
- 11 Khan, M.A., Ectors, W., Bellemans, T., Janssens, D., Wets, G., 2018. Unmanned Aerial
12 Vehicle-Based Traffic Analysis : A Case Study for Shockwave Identification and Flow
13 Parameters Estimation at Signalized Intersections. *Remote Sens.* doi:10.3390/rs10030458
- 14 Khan, M.A., Ectors, W., Bellemans, T., Janssens, D., Wets, G., 2017. UAV-Based Traffic
15 Analysis: A Universal Guiding Framework Based on Literature Survey. *Transp. Res.*
16 *Procedia* 22, 541–550. doi:10.1016/j.trpro.2017.03.043
- 17 Kim, E.-J., Park, H.-C., Kho, S.-Y., Kim, D.-K., 2018. Automated framework for vehicle
18 trajectory extraction using Unmanned Aerial Vehicles, in: *Transportation Research Board*
19 *97th Annual Meeting.* pp. 1–12.
- 20 Kwong, K., Kavalier, R., Rajagopal, R., Varaiya, P., 2009. Arterial travel time estimation based
21 on vehicle re-identification using wireless magnetic sensors. *Transp. Res. Part C Emerg.*
22 *Technol.* doi:10.1016/j.trc.2009.04.003
- 23 Lamotte, R., Geroliminis, N., 2018. The morning commute in urban areas with heterogeneous
24 trip lengths. *Transp. Res. Part B Methodol.* doi:10.1016/j.trb.2017.08.023
- 25 Laval, J. a., Daganzo, C.F., 2006. Lane-changing in traffic streams. *Transp. Res. Part B*
26 *Methodol.* 40, 251–264. doi:10.1016/j.trb.2005.04.003
- 27 Laval, J.A., Leclercq, L., 2010. A mechanism to describe the formation and propagation of
28 stop-and-go waves in congested freeway traffic. *Philos. Trans. R. Soc. A Math. Phys.*
29 *Eng. Sci.* 368, 4519–4541. doi:10.1098/rsta.2010.0138
- 30 Lawson, T.W., Lovell, D.J., Daganzo, C.F., 2007. Using Input-Output Diagram To Determine
31 Spatial and Temporal Extents of a Queue Upstream of a Bottleneck. *Transp. Res. Rec. J.*
32 *Transp. Res. Board.* doi:10.3141/1572-17
- 33 Lee, T., Chen, P.-J., Wong, K.I., 2018. Using unmanned aerial vehicle to investigate the
34 kinematic features of cyclist-pedestrian mixed flow on shared paths. *Transp. Res. Board*
35 *97th Annu. Meet.*
- 36 Lighthill, M.J., Whitham, G.B., 1955. On Kinematic Waves. II. A Theory of Traffic Flow on
37 Long Crowded Roads. *Proc. R. Soc. A Math. Phys. Eng. Sci.* 229, 317–345.
38 doi:10.1098/rspa.1955.0089
- 39 Liu, H.X., Wu, X., Ma, W., Hu, H., 2009. Real-time queue length estimation for congested
40 signalized intersections. *Transp. Res. Part C Emerg. Technol.*
41 doi:10.1016/j.trc.2009.02.003
- 42 Loder, A., Ambühl, L., Menendez, M., Axhausen, K.W., 2017. Empirics of multi-modal traffic
43 networks – Using the 3D macroscopic fundamental diagram. *Transp. Res. Part C Emerg.*
44 *Technol.* doi:10.1016/j.trc.2017.06.009
- 45 Lopez, C., Krishnakumari, P., Leclercq, L., Chiabaut, N., van Lint, H., 2017a. Spatiotemporal
46 Partitioning of Transportation Network Using Travel Time Data. *Transp. Res. Rec. J.*
47 *Transp. Res. Board.* doi:10.3141/2623-11
- 48 Lopez, C., Leclercq, L., Krishnakumari, P., Chiabaut, N., Van Lint, H., 2017b. Revealing the
49 day-to-day regularity of urban congestion patterns with 3D speed maps. *Sci. Rep.*
50 doi:10.1038/s41598-017-14237-8
- 51 Ma, Y., Wu, X., Yu, G., Xu, Y., Wang, Y., 2016. Pedestrian Detection and Tracking from Low-
52 Resolution Unmanned Aerial Vehicle Thermal Imagery. *Sensors* 16, 446.
53 doi:10.3390/s16040446
- 54 Ma, Z., Koutsopoulos, H.N., Ferreira, L., Mesbah, M., 2017. Estimation of trip travel time
55 distribution using a generalized Markov chain approach. *Transp. Res. Part C Emerg.*

- 1 Technol. 74, 1–21. doi:10.1016/j.trc.2016.11.008
- 2 Mahmassani, H.S., Saberi, M., Zockaie, A., 2013. Urban network gridlock: Theory,
3 characteristics, and dynamics. *Transp. Res. Part C Emerg. Technol.*
4 doi:10.1016/j.trc.2013.07.002
- 5 Mariotte, G., Leclercq, L., Laval, J.A., 2017. Macroscopic urban dynamics: Analytical and
6 numerical comparisons of existing models. *Transp. Res. Part B Methodol.*
7 doi:10.1016/j.trb.2017.04.002
- 8 Mkiramweni, M.E., Yang, C., Li, J., Zhang, W., 2019. A Survey of Game Theory in Unmanned
9 Aerial Vehicles Communications. *IEEE Commun. Surv. Tutorials PP*, 1–1.
10 doi:10.1109/COMST.2019.2919613
- 11 Nagel, K., Schreckenberg, M., 1992. A cellular automaton model for freeway traffic. *J. Phys. I*
12 *2*, 2221–2229. doi:10.1051/jp1:1992277
- 13 Nagel, K., Wolf, D.E., Wagner, P., Simon, P., 1998. Two-lane traffic rules for cellular
14 automata: A systematic approach. *Phys. Rev. E - Stat. Physics, Plasmas, Fluids, Relat.*
15 *Interdiscip. Top.* doi:10.1103/PhysRevE.58.1425
- 16 NGSIM, 2006. Next generation simulation [WWW Document]. URL
17 <http://ngsim.fhwa.dot.gov/>
- 18 Niu, H., González-Prelcic, N., Heath, R.W., 2018. A UAV-Based Traffic Monitoring System,
19 in: *IEEE Vehicular Technology Conference*. pp. 1–5.
20 doi:10.1109/VTCSpring.2018.8417546
- 21 Panadero, J., Freixes, A., Mozos, J.M., Juan, A.A., 2018. Agile Optimization for Routing
22 Unmanned Aerial Vehicles under Uncertainty, in: *XIII Congreso Español de*
23 *Metaheurísticas, Algoritmos Evolutivos y Bioinspirados (MAEB 2017)*. Granada, pp.
24 635–640.
- 25 Papageorgiou, M., 1983. Applications of automatic control concepts to traffic flow modeling
26 and control.
- 27 Park, K., Ewing, R., 2018. The Usability of Unmanned Aerial Vehicles (UAVs) for Pedestrian
28 Observation. *J. Plan. Educ. Res.* 0739456X1880515. doi:10.1177/0739456X18805154
- 29 Park, M., Kim, Y., Yeo, H., 2019. Development of an Asymmetric Car-Following Model and
30 Simulation Validation. *IEEE Trans. Intell. Transp. Syst.* 1–12.
31 doi:10.1109/tits.2019.2930320
- 32 Park, S., Rakha, H., Guo, F., 2011. Multi-state travel time reliability model: Impact of incidents
33 on travel time reliability, in: *IEEE Conference on Intelligent Transportation Systems,*
34 *Proceedings, ITSC*. doi:10.1109/ITSC.2011.6082874
- 35 Puri, A., 2005. A Survey of Unmanned Aerial Vehicles (UAV) for Traffic Surveillance. *Dep.*
36 *Comput. Sci. Eng. Univ. South Florida* 1–29.
- 37 Ramezani, M., Geroliminis, N., 2015. Queue Profile Estimation in Congested Urban Networks
38 with Probe Data. *Comput. Civ. Infrastruct. Eng.* 30, 414–432. doi:10.1111/mice.12095
- 39 Ramezani, M., Geroliminis, N., 2012. On the estimation of arterial route travel time distribution
40 with Markov chains. *Transp. Res. Part B Methodol.* 46, 1576–1590.
41 doi:10.1016/J.TRB.2012.08.004
- 42 Richards, P.I., 1956. Shock Waves on the Highway. *Oper. Res.* 4, 42–51.
43 doi:10.1287/opre.4.1.42
- 44 Rosenfeld, A., 2019. Are drivers ready for traffic enforcement drones? *Accid. Anal. Prev.* 122,
45 199–206. doi:10.1016/j.aap.2018.10.006
- 46 Saeedmanesh, M., Geroliminis, N., 2017. Dynamic clustering and propagation of congestion
47 in heterogeneously congested urban traffic networks. *Transp. Res. Part B Methodol.* 105,
48 193–211. doi:10.1016/j.trb.2017.08.021
- 49 Saeedmanesh, M., Geroliminis, N., 2016. Clustering of heterogeneous networks with
50 directional flows based on “Snake” similarities. *Transp. Res. Part B Methodol.* 91, 250–
51 269. doi:10.1016/j.trb.2016.05.008
- 52 Sampigethaya, K., Kopardekar, P., Davis, J., 2018. Cyber security of unmanned aircraft system
53 traffic management (UTM). *ICNS 2018 - Integr. Commun. Navig. Surveill. Conf.* 1C11-
54 1C115. doi:10.1109/ICNSURV.2018.8384832
- 55 Shi, W., Zhou, H., Li, J., Xu, W., Zhang, N., Shen, X., 2018. Drone Assisted Vehicular

1 Networks: Architecture, Challenges and Opportunities. *IEEE Netw.* 32, 130–137.
2 doi:10.1109/MNET.2017.1700206

3 Sirmatel, I.I., Geroliminis, N., 2018. Economic Model Predictive Control of Large-Scale Urban
4 Road Networks via Perimeter Control and Regional Route Guidance. *IEEE Trans. Intell.*
5 *Transp. Syst.* doi:10.1109/TITS.2017.2716541

6 Sutherakul, C., Kronprasert, N., Kaewmorachoen, M., Pichayapan, P., 2017. Application of
7 Unmanned Aerial Vehicles to Pedestrian Traffic Monitoring and Management for
8 Shopping Streets. *Transp. Res. Procedia* 25, 1720–1739. doi:10.1016/j.trpro.2017.05.131

9 Toledo, T., Koutsopoulos, H.N., Ben-Akiva, M.E., 2003. Modeling integrated lane-changing
10 behavior. *Transp. Res. Rec.* 1857, 30–38. doi:10.3141/1857-04

11 van Wageningen-Kessels, F., van Lint, H., Vuik, K., Hoogendoorn, S., 2015. Genealogy of
12 traffic flow models. *EURO J. Transp. Logist.* doi:10.1007/s13676-014-0045-5

13 Ventura, D., Bonifazi, A., Gravina, M.F., Ardizzone, G.D., 2017. Unmanned Aerial Systems
14 (UASs) for Environmental Monitoring: A Review with Applications in Coastal Habitats.
15 *Aer. Robot. - Aerodyn. Control Appl.* doi:10.5772/intechopen.69598

16 Villa, T., Gonzalez, F., Miljievic, B., Ristovski, Z., Morawska, L., 2016. An Overview of Small
17 Unmanned Aerial Vehicles for Air Quality Measurements: Present Applications and
18 Future Prospectives. *Sensors* 16, 29. doi:10.3390/s16071072

19 Vlahogianni, E.I., Barmponakis, E.N., 2017. Driving analytics using smartphones:
20 Algorithms, comparisons and challenges. *Transp. Res. Part C Emerg. Technol.* 79, 196–
21 206. doi:10.1016/j.trc.2017.03.014

22 Wahlström, J., Skog, I., Händel, P., 2015. Detection of Dangerous Cornering in GNSS-Data-
23 Driven Insurance Telematics. *IEEE Trans. Intell. Transp. Syst.* 16, 3073–3083.
24 doi:10.1109/TITS.2015.2431293

25 Wang, L., Chen, F., Yin, H., 2016. Detecting and tracking vehicles in traffic by unmanned
26 aerial vehicles. *Autom. Constr.* 72, 294–308. doi:10.1016/j.autcon.2016.05.008

27 Wei, H., Lee, J., Li, Q., Li, C.J., 2007. Observation-Based Lane-Vehicle Assignment
28 Hierarchy: Microscopic Simulation on Urban Street Network. *Transp. Res. Rec. J.*
29 *Transp. Res. Board.* doi:10.3141/1710-11

30 Whitham, G.B., 1975. *Linear and nonlinear waves.* Modern Book Incorporated.

31 Wilson, R.E., 2008. Mechanisms for spatio-temporal pattern formation in highway traffic
32 models. *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.* doi:10.1098/rsta.2008.0018

33 Yang, H., Zhou, J., 2002. Optimal traffic counting locations for origin–destination matrix
34 estimation. *Transp. Res. Part B Methodol.* 32, 109–126. doi:10.1016/s0191-
35 2615(97)00016-7

36 Yeo, H., Skabardonis, A., 2009. Understanding Stop-and-go Traffic in View of Asymmetric
37 Traffic Theory, in: *Transportation and Traffic Theory 2009: Golden Jubilee.*
38 doi:10.1007/978-1-4419-0820-9_6

39 Zeng, Y., Zhang, R., Lim, T.J., 2016. Wireless Communications with Unmanned Aerial
40 Vehicles: Opportunities and Challenges 1–15. doi:10.1109/MCOM.2016.7470933

41 Zhang, J.-S., Cao, J., Mao, B., 2017. Application of deep learning and unmanned aerial vehicle
42 technology in traffic flow monitoring. 2017 *Int. Conf. Mach. Learn. Cybern.* 189–194.
43 doi:10.1109/ICMLC.2017.8107763

44 Zhang, W., Jordan, G., Livshits, V., 2016. Generating a Vehicle Trajectory Database from
45 Time-Lapse Aerial Photography. *Transp. Res. Rec.* 148–158. doi:10.3141/2594-18

46 Zheng, F., Van Zuylen, H., Liu, X., 2017. A methodological framework of travel time
47 distribution estimation for urban signalized arterial roads. *Transp. Sci.* 51, 893–917.
48 doi:10.1287/trsc.2016.0718

49 Zheng, Z., Ahn, S., Chen, D., Laval, J., 2011. Applications of wavelet transform for analysis of
50 freeway traffic: Bottlenecks, transient traffic, and traffic oscillations. *Transp. Res. Part B*
51 *Methodol.* 45, 372–384. doi:10.1016/j.trb.2010.08.002

52