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

Emmanouil Barmpounakis, Nikolas Geroliminis*

École Polytechnique Fédérale de Lausanne (EPFL), Station 18, CH-1015 Lausanne, Switzerland

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ABSTRACT

The new era of sharing information and "big data" has raised our expectations 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 (ITS) infrastructure due to their unique characteristics, but various challenges have kept these efforts only at a 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 1.3 km^2 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 many of which 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.

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 similar 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 is likely to 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 is collected either through specific fleet of vehicles (taxis,

* Corresponding author.
E-mail address: nikolas.geroliminis@epfl.ch (N. Geroliminis).

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

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

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

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

The idea to utilize a big number of drones to monitor traffic congestion in different parts of a congested city has intrigued many transportation related researchers and practitioners (Garcia-Aunon et al., 2018). For such cases, researchers use the term “swarm of drones” which is a coordinated team of drones flying together without colliding to perform a task. Research around swarms of drones includes many different scenarios, such as simulations over cities in order to tackle issues that may emerge prior to their operation (Das et al., 2018; Hu et al., 2018). However, existing experiments worldwide are at very small scale, usually flying one drone capturing one or two intersections (Barmpounakis et al., 2017; Khan et al., 2018) or a specific part of a road arterial (Barmpounakis et al., 2018; Niu et al., 2018). When the need emerges to monitor a small sample of the vehicles for large areas researchers turn to other method (e.g. smartphones or GPS devices) (Herrera et al., 2010; Ji et al., 2014; Kanarachos et al., 2018; Saeedmanesh and Geroliminis, 2017; Vlahogianni and Barmpounakis, 2017; Wahlström et al., 2015) which, due to reduced coverage of total traffic and accuracy issues, they do not allow the detailed study of certain phenomena (Coifman and Li, 2017; Laval and Leclercq, 2010). Although, a swarm of drones could overcome a significant number of limitations of the abovementioned methods, pragmatizing an actual one for massive data collection in a busy, multimodal urban environment had not been conducted before.

This paper presents the design and preliminary results of a first-of-its-kind experiment, nicknamed *pNEUMA* (New Era of Urban traffic Monitoring with Aerial footage), to create the most complete urban dataset to study congestion. A swarm of 10 drones was hovering over the central business district of Athens over five days to record traffic streams in a congested area of a 1.3 km^2 area with more than 100 km-lanes of road network, around 100 busy intersections (signalized or not), more than 30 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. One of the aims of this work is to reveal a fundamental mechanism of congestion pattern formation for large-scale networks based on a complete dataset collected by a swarm of drones. The design process of the experiment and the various factors (such as drone regulations, number of drones, maximum flight duration etc.) that had to be taken into account and optimized are described. The analysis of the videos from this urban, multimodal, busy environment can allow different kinds of transportation phenomena to be tested in both microscopic and macroscopic scale for different research disciplines. The *pNEUMA* experiment develops data that can offer immense opportunities for answering additional research questions that are beyond our interests and expertise. Thus, an open science initiative will create a unique observatory of traffic congestion that researchers around the globe can use to develop and test their own models.

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

2. Literature review

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

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

i) no need of satellites which are quite costly,
ii) they can be equipped with communication systems to inform commuters in real-time,
iii) their great capabilities in data acquisition.

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

2.1. UAS operations in a 'Smart City'

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

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

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

2.2. Data and algorithmic topics

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

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

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

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

(Sutheerakul et al., 2017) focus on using UAVs to monitor pedestrian traffic flows and to manage pedestrian demand and supply. Authors conclude that a drone can be an alternative viable technology in monitoring pedestrian traffic characteristics. The use of drones for pedestrian observation appears also in (Park and Ewing, 2018) where authors propose it can be a reliable tool for monitoring various characteristics of non-motorized traffic (e.g. attributes, behaviors, spatial patterns). Drones using aerial thermal infrared images instead of video recordings were used in (Ma et al., 2016) also for pedestrian tracking with promising results. In (Lee et al., 2018) the advantages of using drones to extract kinematic features of cyclists-pedestrians mixed flow and model their interactions are highlighted. In (Freeman et al., 2018) a UAS and photogrammetry software was utilized to capture vehicle spacing while stationary.

In (Kaufmann et al., 2018) a methodology for microscopic traffic analysis is proposed. Authors analyze drivers' lane changing behavior and highlight the advantages of UAVs for scientific research compared to GPS vehicle probe data. They focus on the fact that probe vehicles' data resolution of 5–10 seconds combined with the 2–4% coverage of total traffic is not adequate for microscopic data, and this issue can be overcome by taking advantage of videos by UAVs. Additionally, aerial observations are examined to study moving synchronized flow patterns by measuring trajectories for all vehicles.

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

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

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

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

3. Experiment description

3.1. Designing the experiment

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

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

Second, one of the biggest challenges to overcome was that drones have limited flight time and are not able to record the traffic stream for 2.5 h continuously. Thus, two options were available. The first one was to swap the drones while on the air so that uninterrupted

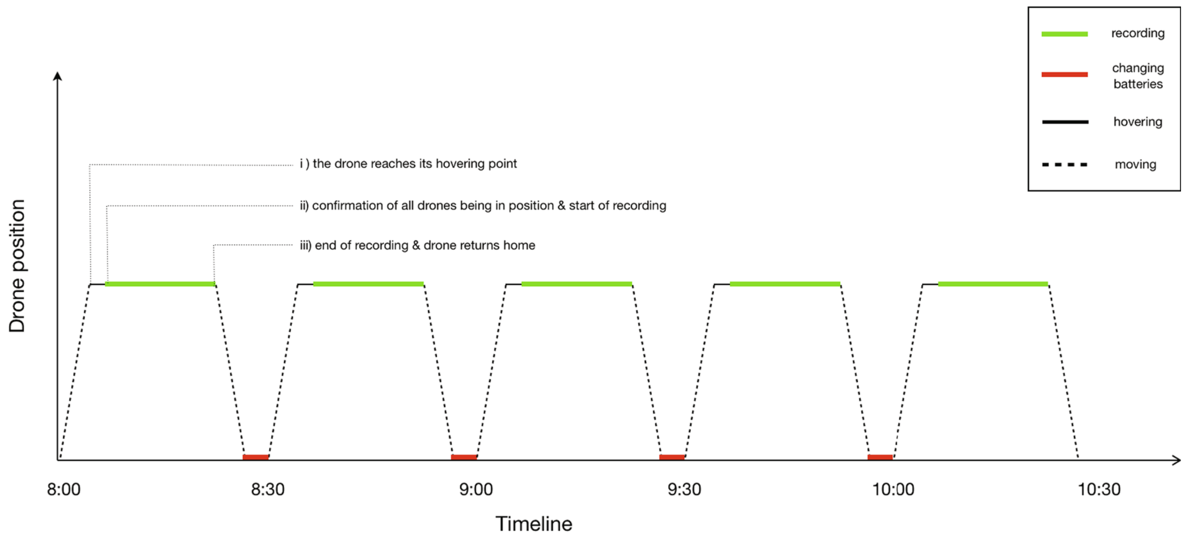

Fig. 1. The illustration of the experiment.

recording was achieved. In this case, each drone would have a substitute to replace it when its battery would run low. However, this would double the size of the experiment in terms of number of units while making the experiment much more complex in terms of drones' coordination and flight safety. The second option was to fly the swarm in sequential sessions with 'blind' gaps between. Since during these 'blind' gaps no data would be available, they should be as short as possible for less data loss. It is expected that having about 10 min of no data would cause no significant issues and therefore the second option was chosen. Those gaps would be used for technical tasks, which are to change the batteries of the drones and then send them back in their previous hovering position.

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

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

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

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

Next, the flight plans were tested and the duration of each task was timed as part of the second test flight. Specifically, each drone was following its route to the hovering point, then it would hover for a minute to ensure no connectivity issues would appear and that the area of interest was recorded with no conspicuity issues. It should be noted that Drone 4 was first assigned to the 'blue' cluster and Drone 10 to the 'green' cluster as being closer to H1 and H2 respectively. However, due to random interference in the connections between the pilots and the drones, the two drones switched clusters to ensure continuous connectivity. Finally, the flight plan was finalized as illustrated in Fig. 3. As seen, this led to an intercepting route between Drone 1 and Drone 4. However, as this could be

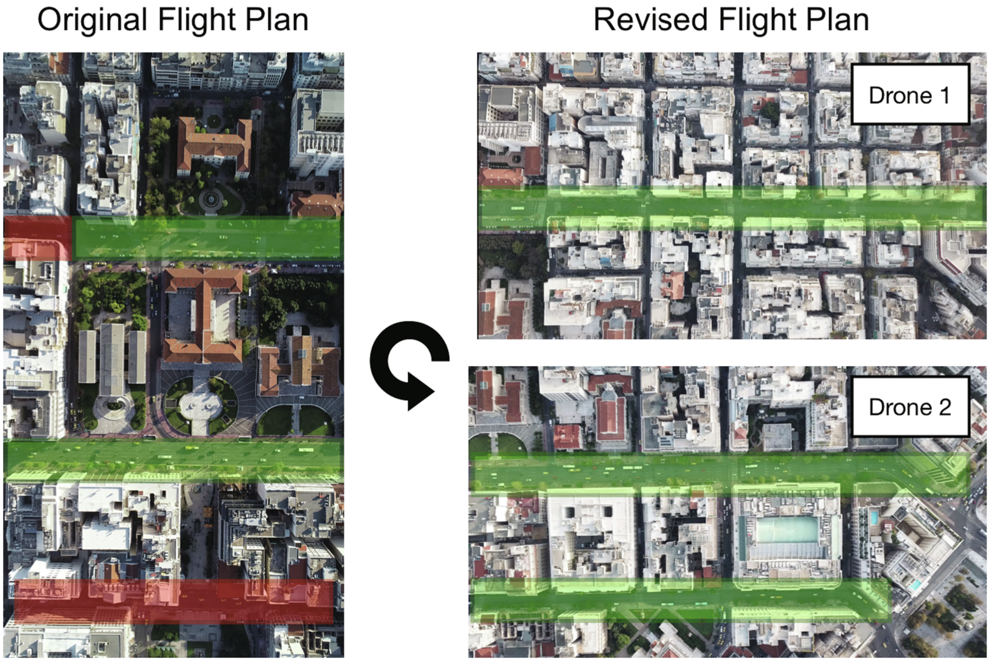

Fig. 2. Visibility of a main road arterial is restored after the change of the orientation.

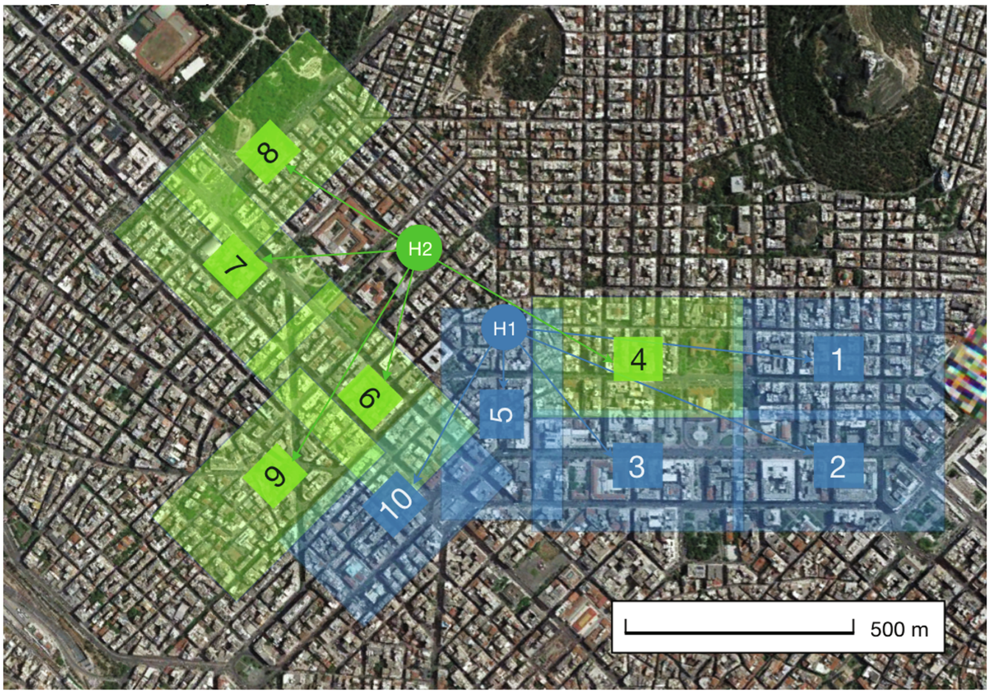

Fig. 3. The route for each drone of the swarm and the two clusters formed.

avoided in the 3-dimensional airspace with different altitudes, their routes were updated so that the drones would not be at the same altitude when being at the intercepting point.

3.2. Flying the swarm

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

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

3.3. General information

The specific experiment is first-of-its-kind in scale and for flying a swarm of drones for transportation purposes over a congested city center. As seen in previous sections, while a future monitoring system is expected to require real time operations and communications, such subjects go beyond the scope of this experiment. In order to acquire a high-accuracy detailed dataset, all operations take place off-line. As far as the aerial video footage is concerned, the videos were recorded in 4K (4096 $\times$ 2160) resolution at 25 frames-per-second (FPS) using consumer quadcopter DJI drones, and specifically the Phantom 4 Advanced. The total duration of the recordings is 59 h, sizing more than 2 TB. The study area to be analyzed includes:

i) a total of 1.3 km^2 area
ii) a 10 km road network
iii) low, medium and high-volume arterials
iv) more than 100 intersections (signalized or not)
v) more than 30 bus stops

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

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

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

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

Except for the features that can be produced using the position information, for example speed (first derivative of position), acceleration (second derivative of position), distance traveled etc., the type of each vehicle (car, taxi, motorcycle, bus, heavy vehicle) is also available.

Finally, as the speeds and accelerations are produced using the position information, the accuracy of the data is based solely on how well the vehicle is tracked and how well the study area has been geo-registered, a process that includes assigning real-world coordinates to video image coordinates (pixels). More information for the accuracy of the position for the specific algorithms can be found in (Babinec and Apeltauer, 2016). For the *pNEUMA* dataset, at least 10 characteristic points per drone measured with GNSS technology in WGS coordinates with less than 5 mm accuracy were provided. Then, these coordinates were assigned to the corresponding pixels in the stabilized video and the average ground sampling distance is calculated to 16.5 cm/px. As the vehicle positioning may have an error of 2 pixels, the maximum error is equal to 33 cm in every frame. Finally, an advanced Kalman filter that is able to filter out the noise in the measurements up to a level of 3.3 cm is applied, which is equivalent to 2.97 km/h in terms of speed error. While this is the error of a single point speed estimation due to pixel size, if a sequence of multiple points is considered then the error is significantly smaller, as the absolute distance error remains the same, but the time interval is longer (and speed more accurate).

3.4. Vehicle reidentification

The overlap between the area of visibility of each drone with its neighboring ones, allows us to properly synchronize the videos, automatically re-identify vehicles from one drone to the other based on features such as vehicle type, vehicle color, time information,

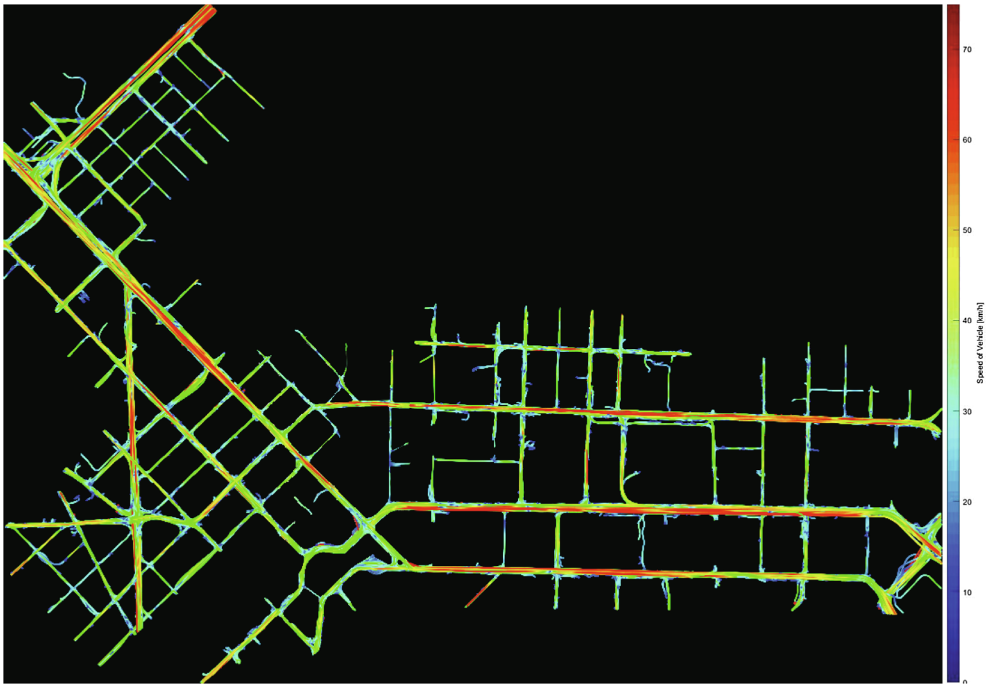

Fig. 4. Extracted trajectories covering the road network of the study area.

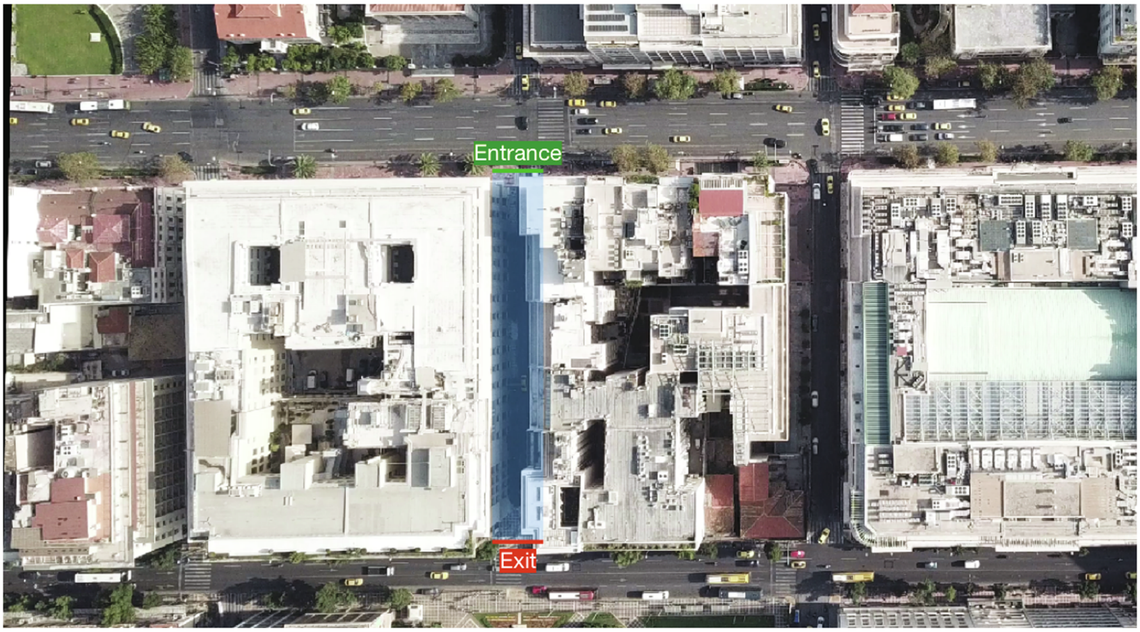

Fig. 5. A minor road between two main arterial that is not visible.

spatial information etc. and to collect consistent information while it is being tracked throughout the period it remains in the study area.

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

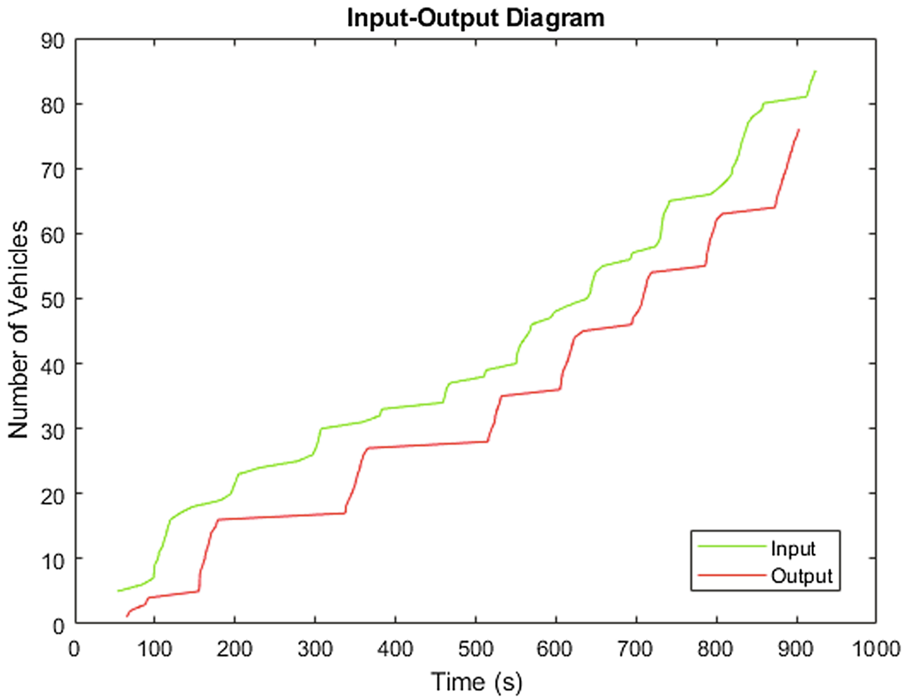

Fig. 6. Input-Output diagram of a minor road with reduced visibility.

Fig. 7. The trajectory of a vehicle tracked continuously by different drones throughout the study area.

4. Primary results and future research possibilities

The aim of the experiment is to record traffic streams in a multi-modal congested environment over an urban setting using a swarm of drones 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. In this section we provide some preliminary results to highlight a few concrete examples of research domains that *pNEUMA* can facilitate the development of the new era of traffic models. The emphasis of this paper is not on fundamental contributions per se in traffic flow theory, but on the design of an experiment that intends to revolutionize how emerging technologies reshape our understanding of traffic congestion mechanisms, by putting the emphasis on urban networks with disturbances generated by interactions among different types of vehicles. The developed dataset targets to better explain the mechanism of congestion formation and propagation in congested multimodal urban environments through massive data from aerial footage and fundamental research prospective. In this

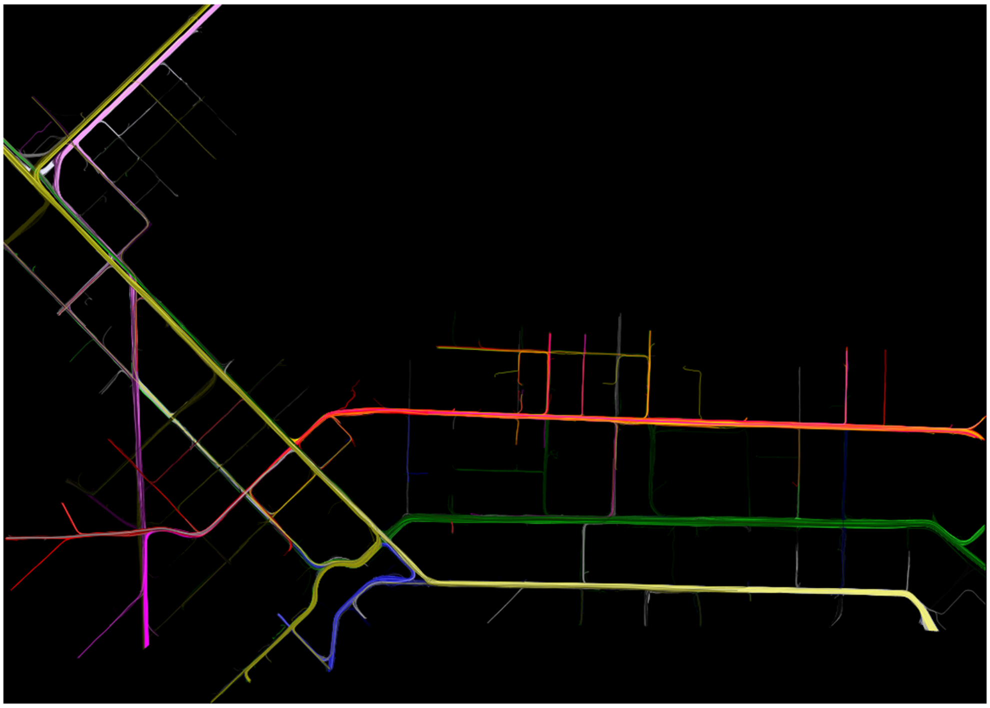

Fig. 8. Origin Destination illustration for different movements.

paper, we put effort to ensure that this objective is feasible and that the data is of high quality. We decided to work on breadth more than depth and investigate how well a complete information of the local environment could be extracted by these trajectories. We are able to observe almost every lane-change in all major roads, accurate travel time estimation, interactions between cars, taxis and public transport and many other phenomena that will allow researchers to revisit many fundamental concepts of traffic modeling.

4.1. Origin-Destination information

An Origin-Destination (OD) matrix has been one of the most critical tools for network loading and traffic assignment. An effective, reliable and handy OD is mainly depended on the quality of the input data, and the number and locations of traffic counting points in the road network (Yang and Zhou, 2002). A detailed review is provided in (Antoniou et al., 2016). It is evident that when all vehicles have been tracked and geotagged information has been extracted, virtual loop detectors can be placed in every part of the recorded area, as also seen in Fig. 6. Additionally, until now, OD information in urban areas was extracted only at intersection level for a big number of vehicles using computer vision techniques that observed the intersections entries and exits. For larger areas, OD information was mainly based on personal interviews or GPS devices that do not allow a large sample to be collected. Thus, the specific experiment allows (i) extracting massive OD matrices at a network level, (ii) a less costly and time-consuming process, (iii) eliminating manual errors and (iv) estimating dynamic OD matrices. The results of such a process can be illustrated in Fig. 8 where the different OD combinations are illustrated with different colors.

4.2. Arterial travel time and congestion propagation

While there is a vast literature in travel time estimation in arterials, there are challenges involved since it requires extensive sensor infrastructure that is less dense than in freeways. Moreover, speed of vehicles at a given time in the network is not a deterministic quantity over space because of different type of vehicles, drivers' behaviors and the queueing effects due to signals (near the stop line vs. further upstream). This creates local speeds that are temporarily different than the widespread average, even for vehicles traveling in the same link during the same cycle length. Reduction in travel time variability is at least as desirable as reduction in mean travel time (Jenelius, 2012), since it decreases commuting stress and uncertainty of decision making. Different indexes of travel time stochasticity-reliability can be found in (Kaparias et al., 2008). The *pNEUMA* database can create unique opportunities for monitoring and modeling travel time variability.

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

Travel time reliability on arterials depends on the efficient progression of vehicles from one traffic signal to another. Various works have considered that spatial correlations and offsets of traffic light phases can influence the variability (e.g. (Chen et al., 2017;

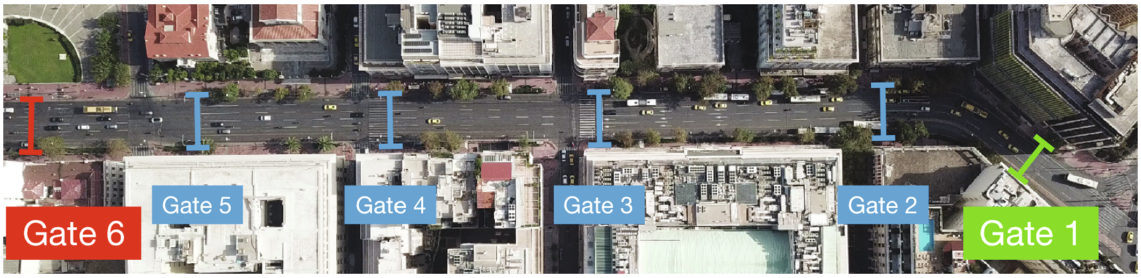

Fig. 9. A main arterial of the study area with installed virtual loops (gates).

Feng et al., 2011; Guo et al., 2013; Herring et al., 2010; Kwong et al., 2009; Ma et al., 2017; Park et al., 2011; Ramezani and Geroliminis, 2012; Zheng et al., 2017). While estimating joint distributions of travel times for successive links, can provide a useful connection with reliability, this time of information is difficult to be collected with loop detectors or low penetration mobile sensors. Building on *pNEUMA* database, using the concept of virtual loop detectors (Fig. 9) put at the various intersections of a road section significant information can be extracted regarding travel times.

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

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

Additionally, another useful tool to study how traffic moves, to analyze its delays, to coordinate signal timings, to estimate shockwaves and calculate of individual headways and spacings is the time-space (x-t) diagram. Especially when roads become more congested, the time-space diagram can be a significant tool to study and visualize the speed of the shockwaves formed, as well as

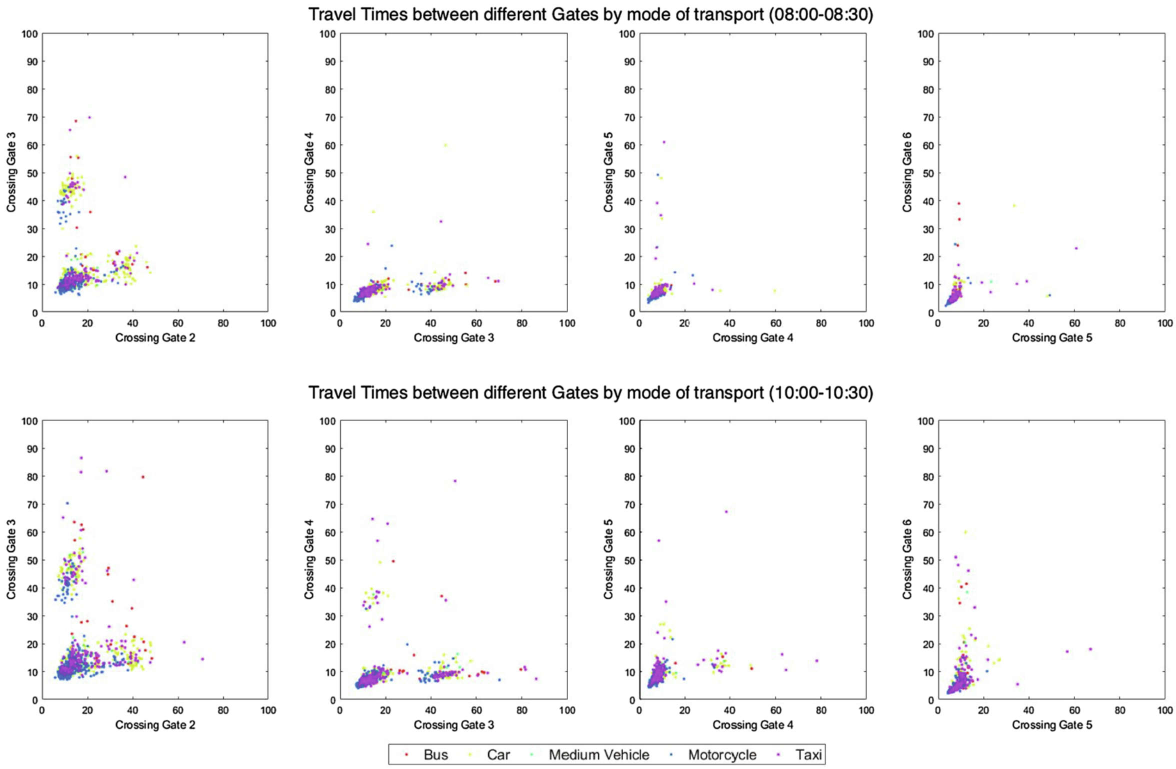

Fig. 10. Travel times between different gates grouped by transport mode.

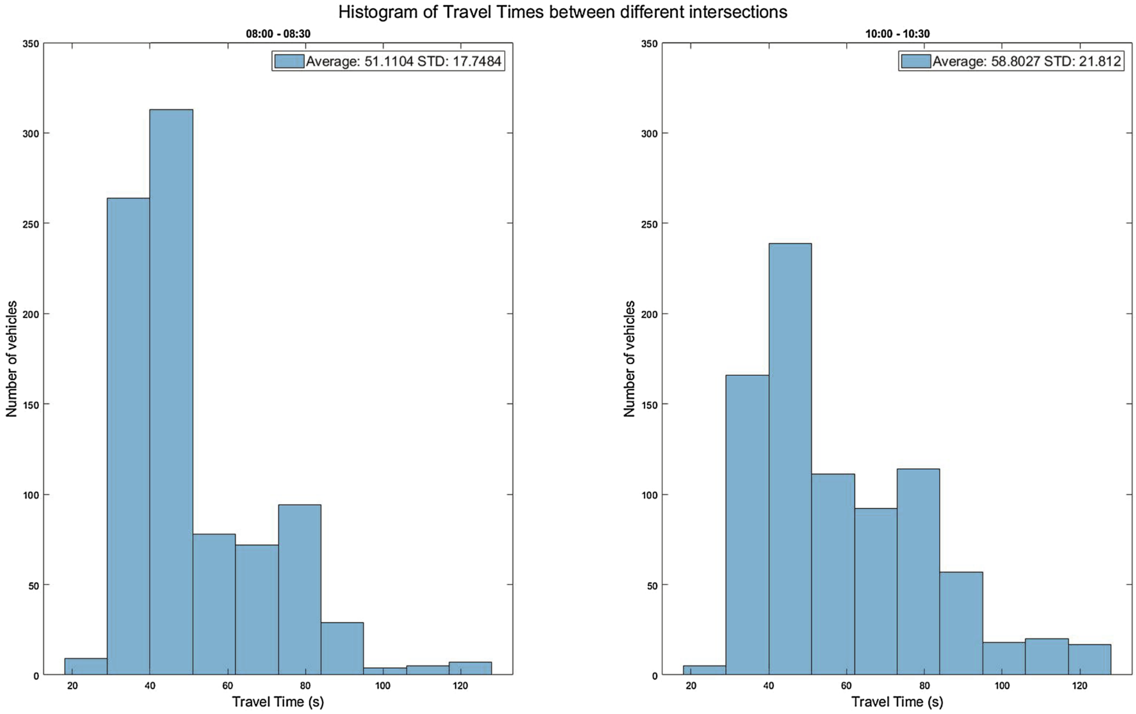

Fig. 11. Histogram of travel time between an extended arterial during different time periods.

information about when and where they started forming.

Fig. 12 presents an x-t diagram for a period of 15 min extracted from drone 8, covering 450 m of the central lane of a major arterial (Alexandras Avenue) and three signalized intersections. The color represents the instantaneous speed (measured in km/h). Note the significant heterogeneity in driving behavior when vehicles are joining or leaving a queue. Despite this, the queue evolution, shockwaves and spillbacks can be studied at the lane-detail. For example, the maximum wave speed *w* (as per LWR theory) is almost the same for all cycles and intersections. The speed scale provides a quick overview on the traffic conditions that were present, as the number of stop-and-go due to traffic lights or not. It should be noted that this diagram does not include data from motorcycles, but only from cars, trucks, buses and taxis, as their chaotic trajectories would be illustrated with intercepting points between the different vehicle trajectories and make the diagram less readable. For the same reason, we can distinguish some characteristic issues that appear in this time space diagram compared to traditional ones. Specifically, there is an unexpectedly large headway between the two

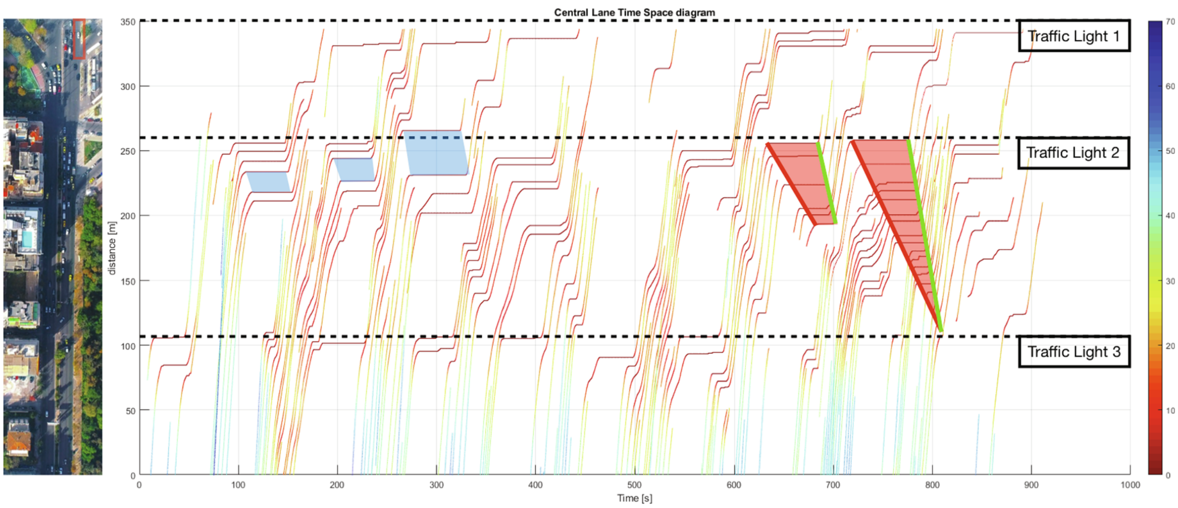

Fig. 12. x-t diagram of the central lane of a three-lane 450 m arterial with sequential traffic signals for a 15-minute period (a 4th lane is developed in the downstream end – see the red box). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

stopped vehicles, highlighted with light blue color. Such cases were reviewed manually and it was identified that in between there was a motorcycle, whose trajectory does not appear in Fig. 12. It should be noted that the motorcycle was properly identified, but Fig. 12 focuses on the rest of the vehicles' trajectories as motorcycles can have non-smooth trajectories with multiple lane changes and driving on the border of a lane and between vehicles. The non-continuous lines refer to lane changing phenomena that are discussed in the next section. This figure contains a significant amount of information that is rarely available for arterial networks (e.g. detailed interactions for almost every pair of vehicles moving in a congested urban environment). Clearly, this will allow to revisit and create a new era of microscopic traffic flow models and improve the accuracy, calibration and validation of micro-simulation tools.

4.3. Lane changing

Lane-changing modeling has attracted significant interest, especially for freeway systems (Coifman et al., 2005; Kesting et al., 2007; Laval and Daganzo 2006; Nagel et al., 1998; Wei et al., 2007). As lane-changing maneuvers often act as initial local disturbances, it is crucial to understand their impact on the capacity, stability and breakdown of traffic flows (Kesting et al., 2007). Most of lane-changing models attempt to identify if an immediate lane change will improve the vehicle's speed given safety constraints (Gipps, 1986). This is typically modeled with gap-acceptance models (Gipps, 1986), (Toledo et al., 2003). One of the most general lane-changing models is described in (Kesting et al., 2007). Authors introduce a utility of a given lane and the risk of a lane change is determined in terms of longitudinal accelerations. This allows the formulation of safety and incentive criteria both for various passing rules. While these phenomena have been studied in details after the development of NGSIM freeway database (NGSIM, 2006), their effect in urban settings is unexplored. Reasons for this research gap is the scarcity of complete trajectory data and the fact that bottleneck locations and the breakdown mechanism are more difficult to be identified compared to freeways. For measuring lane changes, conventional cross-sectional data from detectors are not sufficient. Recent progress in video tracking methods, however, allows for a collection of high-quality trajectory data from aerial observations (Hoogendoorn et al., 2003; NGSIM, 2006). Data collected from drones in urban environments can allow a careful study of lane-changing behavior and investigate the effect of the local phenomenon to network congestion.

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

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

In Fig. 13 all red circles represent lane changes that remained in the study are while the black circles represent the vehicles that exited the study area from the right lane to adjacent roads of the network. What is interesting to notice is that many lane changes occur close to the most downstream traffic light at the end of the road section (x = 340 m), which suggests that some drivers will conduct a lane-changing maneuver for a better position in the queue upstream of the traffic light. It is seen that the use of lane-level x-t diagrams allows the study and modeling of queue evolution and spillbacks, phenomena which are directly connected with excessive delays and congested environments. Note for example the spillbacks occurring in the central and right lane at location x = 150 m, t = 420 s. Interestingly, the spillback is active only on the right lane at the next cycle (same x, t = 500 s). These phenomena of lane-specific spillbacks have not been studied properly in the traffic community because of lack of available data and microscopic traffic simulators (and models) have never been calibrated at this level of detail. Finally, since the x-t diagrams have not been used massively for multi-lane environment, we expect new ways of illustrating vehicles' trajectories to be proposed that will incorporate the unique cases that occur in dense urban environments.

4.4. Fundamental diagrams (FD) and Macroscopic fundamental diagrams (MFD)

4.4.1. Fundamental Diagrams (FD)

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

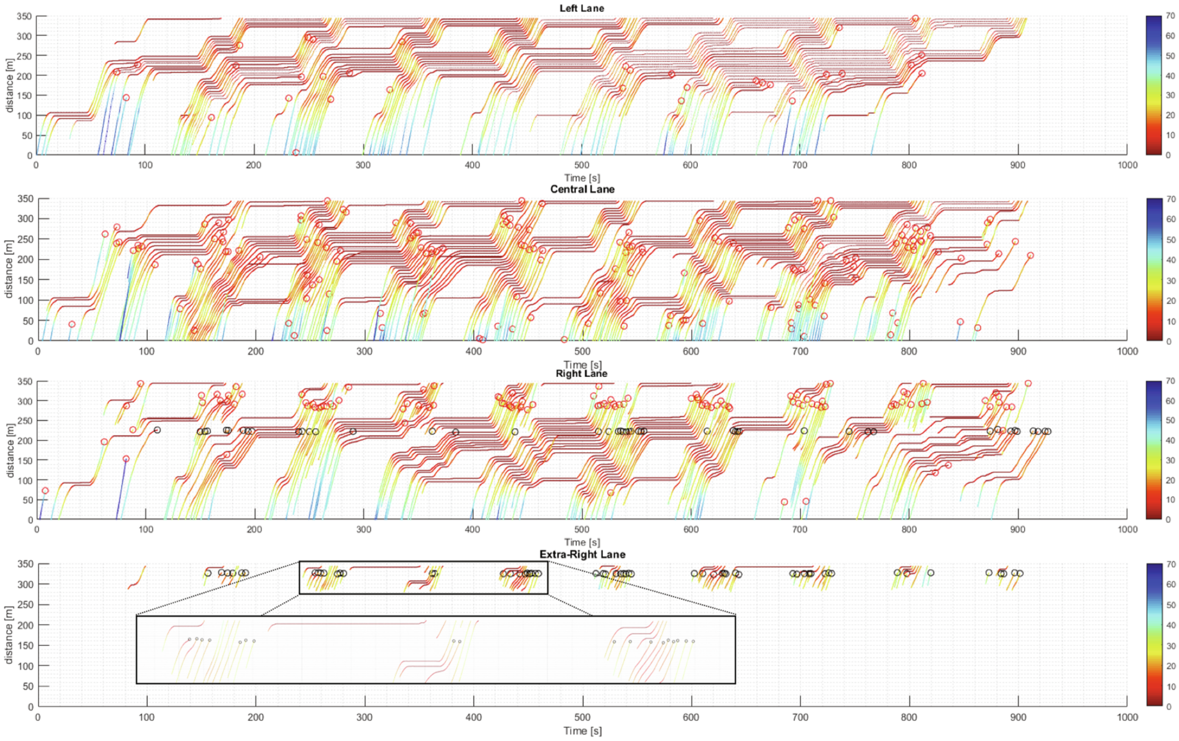

Fig. 13. Time-Space diagram of a 3-lane arterial illustrating lane-changing phenomena.

et al., 2012b; Coifman, 2015; Deng and Zhang, 2015) but mostly for freeway data.

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

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

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

4.4.2. Macroscopic fundamental diagrams (MFDs)

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

pNEUMA provides a unique opportunity to investigate many aspects of MFD modeling with this data. Traffic researchers will be able to test many of the MFD assumptions that have been made in the literature and cannot been verified with existing empirical data due to low penetration rate (from moving vehicles) or local information due to loop detectors. Some examples are distribution of trip lengths, trip based vs. accumulation-based models, the relationship between outflow and production, a 3-D bimodal MFD and other

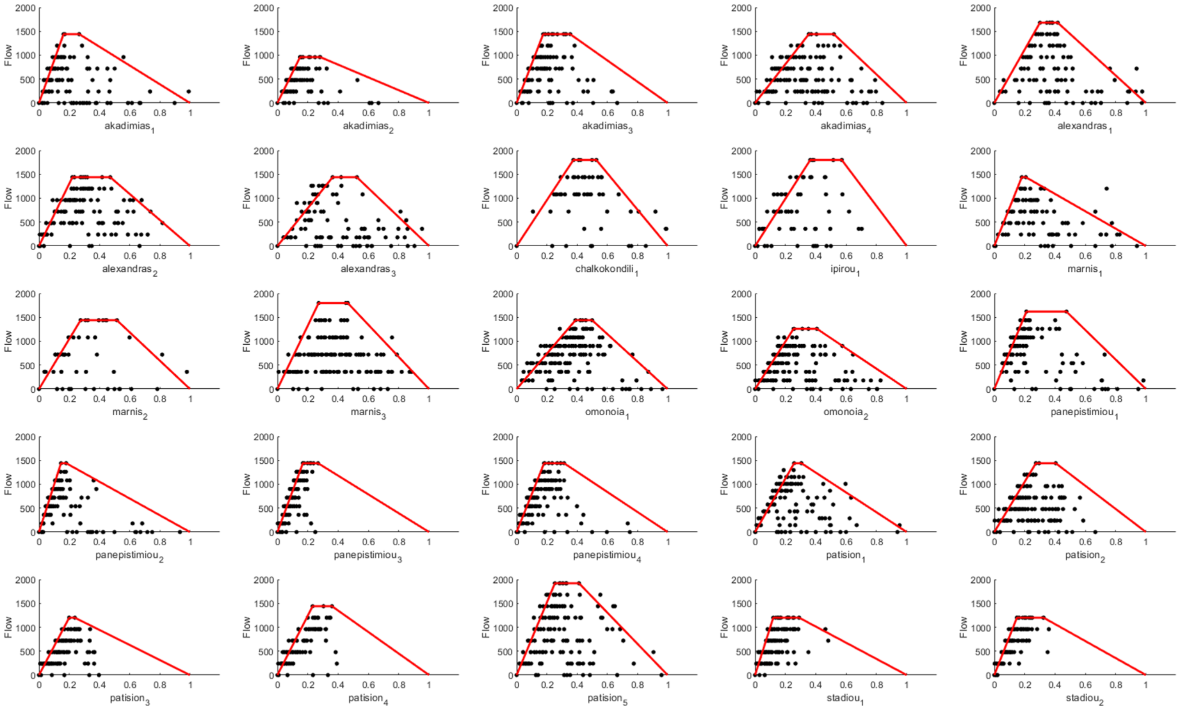

Fig. 14. Flow vs Occupancy for various for 25 different locations.

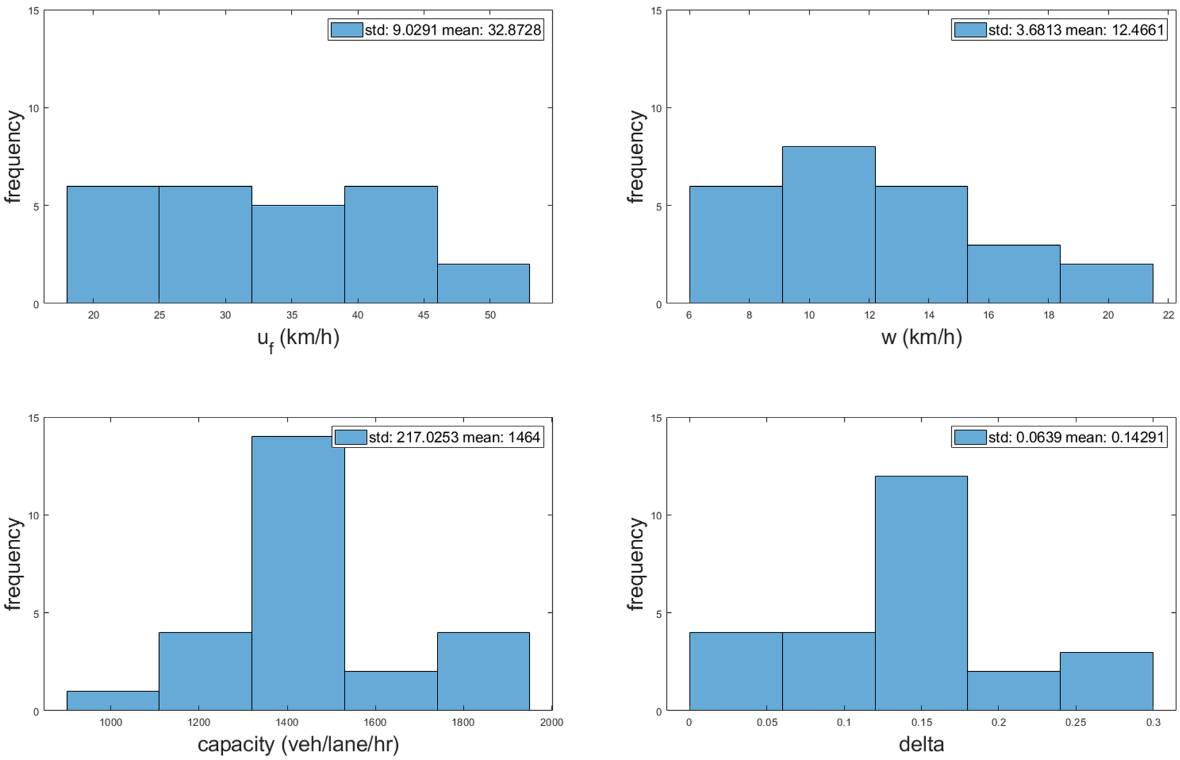

Fig. 15. Distribution of the four different FD parameters.

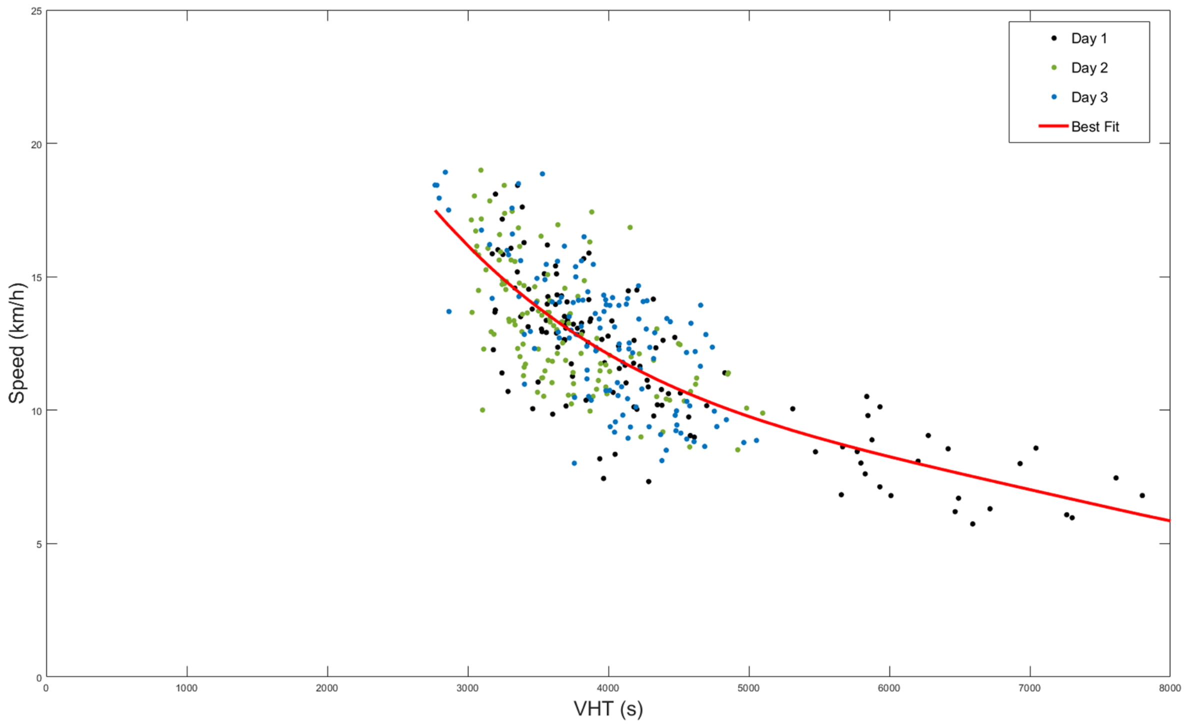

Fig. 16. Speed vs VHT for Omonoia square in three different days.

directions. While MFD literature is vast in the last few years, a few examples can be found in (Haddad, 2017; Lamotte and Geroliminis, 2018; Mahmassani et al., 2013; Mariotte et al., 2017).

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

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

In Fig. 16 the MFDs of the congested area are illustrated for the time window of 2.5 h for three different days. It can be seen in Fig. 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 was normalized.

4.5. Research on multimodal interactions and specialized urban driving phenomena

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.

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

Fig. 17. The effect of a taxi (red oval) that stopped to pick-up a passenger. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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 (30–40 s), while taxis might stop in random locations for shorter durations (5–15 s) 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 data to study such cases for different traffic conditions (Fig. 17).

As can be seen in Fig. 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 s, 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.

Another characteristic example of multi-modal interactions is illustrated in Fig. 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 ($x = 110$ m) 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 developed queue has almost discharged and vehicle C experiences a short waiting due to the traffic light red phase. Nevertheless, the first bus stops when the traffic light is green at interval (210, 235), resulting in a queue of vehicles behind it and a underutilization of green phase. Note that no vehicles are passing the traffic light stopline in the interval (225, 245) at the right lane, while the central lane operates at capacity during the same time. Specifically, the queue that is formed in the right lane shoud start reducing when vehicle C accelerates. However, as the first bus has already stopped at the bus stop, the queue does not reduce until the bus leaves the bus stop. The second bus even if it stops for about the same duration, it does not create any capacity loss and the traffic light operates mostly at capacity at the next cycle.

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

4.6. Other future directions

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

i. Develop methodologies to automatically identify lane-changing maneuvers in the complete set of trajectory data. For example, given proper coordinates of the lanes for each road and the direction of travel, events that trigger deviations from a direct straight line will be considered as lane changes. This is one of our current research priorities.
ii. Investigate congestion mechanisms and the effect of local disturbances at network level. Local disturbances are associated with stop-and-go situations that involve few or more vehicles. An important challenge is to identify how many vehicles are influenced upstream from a lane-changing event. It is expected that small shockwaves may be developed during the formation that might expand or not in time and space. These observations will allow for the development of proper locally aggregated variables that can explain the congestion mechanism. While the literature of lane-changing mainly models an event by comparing the spacing with the leading vehicle of the same lane and the lead and lag gap of vehicles in the target lane, *pNEUMA* experiments will allow to investigate more advanced models that quantify the effect of the local environment. Even if *pNEUMA* does not have a direct

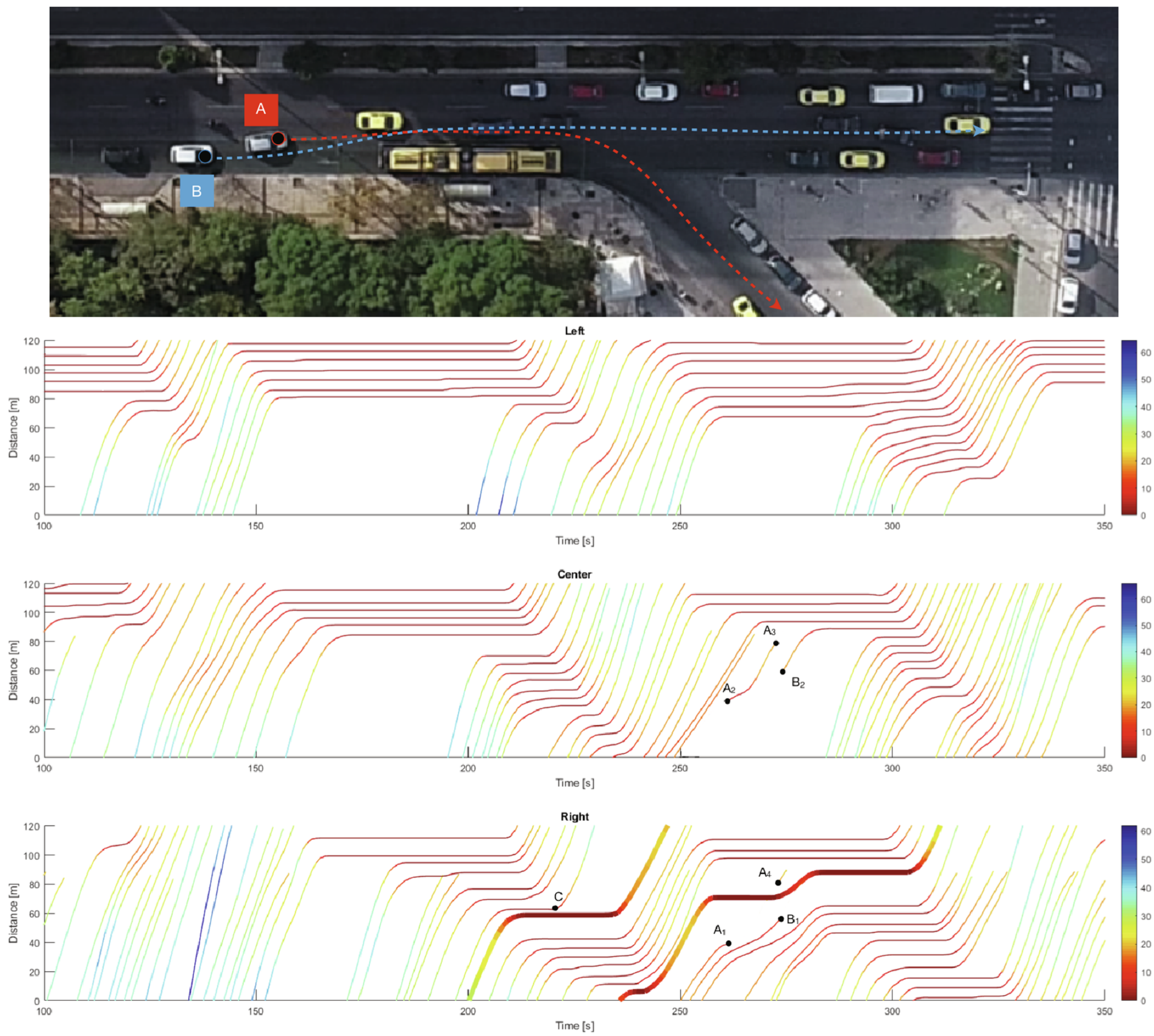

Fig. 18. Time-Space diagram of a 3-lane arterial illustrating the effect of bus stops.

interest on AVs, it can create accurate lane-changing models that AVs can integrate in their design for movements in mixed-usage with conventional cars.

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

iv. Investigate lane-changing mechanisms as in points (ii) and (iii) above for multimodal interactions (similar to those of Fig. 18) will unhide models of additional complexity, with important consequences for traffic engineering. Data extracted contain the type of vehicle, so the contributions of this task will mainly be in the exploration of dynamic congestion formation and propagation for mixed environments. For example, similar cases apply for motorcycles and Powered Two Wheelers (PTW) in general, which have not been studied in detail until now mostly due to lack of naturalistic datasets (Barmpounakis et al., 2016b).

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

5. Discussion – open dataset initiative

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 decentralized or simulation-based approaches of modeling and managing mobility. How local disturbances, such as lane changes, service-related stops (of taxis, ride-hailing or buses) influence the network performance and the propagation of congestion especially under congested conditions still requires careful consideration. While UAS are not yet ready for continuous operation to monitor traffic, the focus of our work is on the potential of a full coverage of a large region that will allow the deep investigation of critical traffic phenomena. The emphasis is on local disturbances that often occur in urban networks and can be associated with a reduced performance at the network level. Observing, understanding, modeling and validating these phenomena for congested urban multimodal settings with an accurate monitoring of almost every vehicle has not been done before at such a scale.

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

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

Therefore, it is of our best interest to create an Open Data initiative at a scale an-order-of-magnitude higher than what was available until now and many communities can benefit for research purposes. Putting together this information and sharing it widely and openly will allow different research communities to test models and hypotheses far beyond our main research interests ranging from modeling microscopic phenomena and vehicle-to-vehicle interactions to network level models and road safety. This dataset can be utilized by the whole research community of transportation science and other disciplines, such as Machine Learning or Artificial Intelligence, to study, model and improve traffic congestion. This dataset can become a benchmark dataset for a new era of traffic models that will be utilized for understanding how people behave and what really causes traffic congestion. The *pNEUMA* database is enhanced continuously and data can be downloaded from open-traffic.epfl.ch.

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