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# Traffic Monitoring on City Roads Using UAVs

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**Abstract.** Unmanned Aerial Vehicles (UAVs) based systems are a suitable solution for monitoring, more particularly for traffic monitoring. The mobility, the low cost, and the broad view range of UAVs make them an attractive solution for traffic monitoring of city roads. UAVs are used to collect and send information about vehicles and unusual events to a traffic processing center, for traffic regulation. Existing UAVs based systems use only one UAV with a fixed trajectory. In this paper, we are using multiple cooperative UAVs to monitor the road traffic. This approach is based on adaptive UAVs trajectories, adjusted by moving points in UAVs fields of view. We introduced a learning phase to search for events locations with a frequent occurrence and to place UAVs above those locations. Our approach allows the detection of a lot of events and permits the reduction of UAVs energy consumption.

**Keywords:** Unmanned Aerial Vehicles (UAVs) · Traffic monitoring · UAVs trajectories · Events detection process · Learning strategy

## 1 Introduction

Unmanned aerial vehicles (UAVs) are gaining popularity in civil and commercial applications. They are considered as a new traffic monitoring technology used to collect information about road traffic conditions. This paper addresses the design of a UAV-based system for the management of road traffic within a city.

Several road traffic monitoring systems already exist. They have many objectives, among them the detection of infractions like speeding violations and the discovery of congestion. To fulfill these goals, monitoring systems should first collect traffic data from deployed devices. Traffic data consist of the number of vehicles, their position, and their speed. The data should then be transmitted to a processing center. The processed data can be used offline or online. For example, notification can be sent online to vehicles owners to avoid congested

roads, or emergency measures can be triggered automatically like calling rescue in the case of cars accidents [1–3]. For the regulation of traffic offline, statistics are generated using the collected data, then, for example, red lights and traffic displays are reorganized [2,4].

A lot of researches treated the congestion detection [5–7] and the early congestion detection [8–11] to overcome the low efficiency of transportation, which is a significant problem on roads in urban cities. The numbers of vehicles in an area and their velocities are the two main parameters that indicate whether there is congestion or not.

Several road traffic monitoring systems exist, they can be mobile or fixed. Fixed systems are for example sensors, detectors, and fixed cameras [12]. They enable the monitoring of a specific and limited area, their implementation and maintenance costs are very high, and they are generally affected by bad weather conditions. While for mobile systems, UAVs is the best solution for traffic monitoring [13]. In fact UAVs are mobile and equipped with cameras, sensors, and detectors. Using UAVs in the context of traffic monitoring have many advantages. UAVs can cover large areas and access specific locations; they can be deployed in any area, at any time, for any duration, and at no additional cost. UAVs can also perform vehicle identification, positions, and velocities estimation because they are equipped with cameras and have image processing capabilities.

For traffic monitoring systems based on UAVs, UAVs trajectories are predefined in advance by fixed points of interest. Those fixed points of interest can be intersections where there is a lot of traffic, critical areas, or positions of sensors placed on the ground. UAVs move from a fixed point of interest to another to get information about the traffic and vehicles. One or multiple UAVs can be used to collect data from various ground sensors placed on city roads [3,14]. UAVs fly over the sensors and collect the data after establishing a connection with them. Also, the UAV can receive data only from clusters heads nodes [15]. In other systems, a single UAV with image processing capabilities is responsible for the measurement of relevant vehicles parameters [16,17].

In [18], we proposed a road traffic monitoring solution based on the use of multiple cooperative UAVs with image processing capabilities. The goal is to detect as many events as possible. UAVs trajectories are adapted according to the position of vehicles in their field of view, which is not enough to detect all events, and which is consuming a lot of energy due to unnecessary movements. Vehicles trajectories are not from real traces; they were generated according to a mobility model, this can cause the computation of events detection percentages far from the reality.

So in this paper, we propose to adjust the position of UAVs not only according to the position of vehicles in their fields of view but also according to the position of events. We propose to place some UAVs at positions where events frequently occur. The choice of UAVs to place can be according to the distance that separates them from those positions, or according to the number of targets in their fields of view. This solution is applied to all types of events like speeding violations and congestion. For that, we introduced a learning phase to

predict event positions with frequent occurrences, that we call Strategic Points (SPs). Because we want to group events positions that happened close to each other, we choose the unsupervised learning as the learning method to work with. The unsupervised learning is used to learn more about the data by exploring it and finding some structure or distribution within. After the learning phase, we propose to place UAVs above some SPs, to increase percentages of events detection, and to reduce the total traveled distance by UAVs. We also propose to use real vehicles traces to work on real conditions and to get realistic results while applying our approach. Finally, we improve the events detection process by better defining the conditions for events detection. We are interested mainly in the congestion detection and the speeding violation detection. For congestion detection, we use a vehicles clustering approach. For speeding violation detection, we use a velocity threshold approach.

The purpose is to show the positive impact of applying our approach on events detection percentages, on the number of covered vehicles, and on the UAVs total traveled distance, while using real vehicles traces. In fact, due to the limited number of UAVs, and due to their limited autonomy, having some moving UAVs and others placed above SPs is a good solution.

The rest of the paper is organized as follows. In Sect. 2, we present the system model. In Sect. 3, we present our contributions. In Sect. 4, we analyze simulation results for real traces and mobility model traces. We conclude in Sect. 5.

## 2 System Model

The system consist of multiple UAVs ( $U_1, U_2, \dots, U_i$ ), characterized by their positions ( $P_1, P_2, \dots, P_i$ ), velocities ( $V_1, V_2, \dots, V_i$ ), and labels  $i$  with  $1 \leq i \leq U_{max}$ , where  $U_{max}$  is the maximal number of UAVs. We assume that all UAV are flying at the same altitude ( $A$ ) and have the same radius ( $R$ ) of fields of view. They are monitoring the road traffic during an observation time ( $St$ ).

The system consist also of multiple targets ( $T_1, T_2, \dots, T_j$ ), characterized by their positions ( $Pt_1, Pt_2, \dots, Pt_j$ ), velocities ( $Vt_1, Vt_2, \dots, Vt_j$ ), and label  $j$  with  $1 \leq j \leq T_{max}$ , where  $T_{max}$  is the maximal number of targets. Targets are vehicles moving on city road, their positions and velocities are updated according to a mobility model or updated from real traces for the period  $St$ .  $St$  is divided into times slots. Updates, instructions, and decisions are made at each time slot.

We assume that all UAVs have image processing capabilities. They are capable of detecting targets in their field of view and estimating relevant targets parameters (label, position, and velocity). A processing delay  $Du$  can occur at UAVs. Targets information are used to detect events and to adjust UAVs trajectories. Those information are processed at a processing center. We assume that there is a processing delay  $Dp$  at the processing center.

All UAVs send the collected information to the processing center, it deduces if events occur and send new positions to UAVs for the adjustment of their trajectories. The control is centralized because decisions are made at a single point. LTE connections are used for the exchange of information. Some delays can occur while transmitting ( $Dt$ ) and receiving ( $Dr$ ) information.

Delays differ from a time slot to another because the distance between the processing center and UAVs vary. UAVs transmit new information to the processing center at each time slot. While the processing center sends back new instructions to UAVs only when they arrive at destination, because it can take several times slots for UAVs to reach the final destination.

We assume that no obstacle is obstructing UAVs line of sight and that they temporarily change their altitude to avoid collisions between each other. While changing the altitude, the minimal and the maximal altitude ( $A_{min}$ ,  $A_{max}$ ) must be respected.

### 3 Contributions

#### 3.1 Events Detection

UAVs are deployed over an area to monitor the traffic and to detect abnormal events. Several parameters are observed and measured: vehicles positions, vehicles speeds, and vehicles number. Specific events are detected through value changes of the above mentioned parameters [5–7]. We propose algorithms to perform the congestion detection and the speeding violation detection. We assign a speed threshold  $V_{max1}$  and a density threshold  $N_{min}$  to detect congestion, and another speed threshold  $V_{max2}$  to detect speeding violations.

The Congestion Detection is performed according to a clustering approach. First, vehicles in the field of view (FoV) of UAVs with a velocity lower than the velocity threshold  $V_{max1}$  are selected. Then, for each selected vehicle, we search for neighbors within a radius equal to the radius of the FoV of UAVs. For each constituted group, if the number of vehicles is equal to or higher than the density threshold ( $N_{min}$ ) we consider that the group is in congestion. Centers of congested areas are centers of gravity of groups in congestion. We form a list of congested vehicles, updated with members of the congested group. It is necessary to have that list for each time slot. In fact, the duration of congestion increases if from, one time slot to another, a vehicle still in the list of congested vehicles.

For the Speeding Violation Detection, first we select vehicles in the FoV of UAVs, then we compare their velocity to  $V_{max2}$ . If the velocity of a vehicle exceeds the threshold, we consider that there is a speeding violation and we tag the vehicle. For the next time slots, the velocity of a tagged vehicle can still be higher than the threshold or can go under it. If the vehicle keeps traveling with a high velocity, we do not consider that there is another speeding violation, only the duration of speeding violation increases. If the velocity goes under the threshold we remove the tag. That way, the number of infraction increases only if the velocity of a non-tagged car exceeds the threshold. Also, when a tagged car goes out from the FoV of UAVs, we remove the tag.

## 3.2 UAVs Trajectories

Now we address the design of UAVs trajectories and placement. UAVs position and trajectories have an impact on the number of covered vehicles, on the number of detected events, and on detected events duration.

The proposed methods are based on the use of multiple cooperative UAVs. UAVs are capable of detecting and identifying vehicles in their field of view, perfectly estimating their positions and velocities values, and exchanging relevant information with each other and with a processing center.

**Opportunistic Method.** We proposed this approach in [18]. UAVs trajectories are adapted by mobile points. Those mobile points are centers of gravity of vehicles groups in the field of view of UAVs. The motion of UAVs depends on the motion of their groups of vehicles, so they adjust their position and fly over the centers of gravity of their groups. In this method, the goal is that every UAV keeps in its field of view the maximum number of targets, keeps tracking them, and detect as many events as possible for as long as possible. UAVs keep tracking and monitoring the same group of targets while considering the new targets entries. If from one observation to another groups disappear, UAVs randomly choose other groups to track and supervise.

**Opportunistic Method with Learning.** The Opportunistic Method with learning is based on the Opportunistic Method because UAVs are moving according to this method. However, some UAVs will be placed above Strategic Points (SPs) after a learning phase. SPs are locations where events frequently occur. So, this method is characterized by a learning phase performed at the beginning. During this phase, all UAVs are mobile. They are collecting information about vehicles, detecting abnormal events, and estimating the positions of those events.

At the end of this phase, all events positions are processed by a processing center. The goal is to find the SPs. In our case, SPs are locations where congestion or speeding violation frequently occur. To find the SPs, the processing center uses a machine learning approach to process the data, and make decisions and predictions regarding it. Two of the most adopted machine learning methods are the supervised learning and the unsupervised learning [19,20]. We choose the unsupervised learning because we want to explore the data and split it into groups.

In our learning method, the data that we want to split into group is all events positions that were collected during the learning phase. The clustering criterion is the distance. Indeed, the position of each event is compared to the positions of all other events of the same nature. If the distance between them is less than a given value, this means that they are part of the same group. The occurrence frequencies of events are equal to the number of positions in the groups. For example, for a given event position  $p_1$ , if other events were observed in the same position or in a circular area with a radius  $r_a$  and with a center  $p_1$ , the occurrence frequency of events at this position will increase. If the frequency of occurrence

is higher than a given threshold, the center of this group will be considered as a SP. The frequency threshold is not fixed in advance, but it must be at least equal to 2 to consider that the center of a group is a candidate SP. Indeed, an event must have occurred at least twice in a circular area with a radius  $r_a$ . The frequency of occurrence depends on the total number of vehicles, the observation period and the number of deployed UAVs.

At the end of the learning phase, a certain number of UAVs are placed above the previously calculated SPs. UAVs are placed in priority above SPs with the highest frequency of occurrence, so that they can observe more events.

The choice of UAVs to place can be:

- Random: UAVs are randomly assigned to SPs.
- According to a distance criterion: the distance here refers to the distance between UAVs and SPs. For each SP, the closest UAV to it will be placed above it.
- According to a coverage criterion: the coverage here refers to the number of vehicles in the field of views of UAVs. UAVs with the smallest number of vehicles under their coverage will be placed above SPs.

The non-placed UAVs continue moving according to the Opportunistic Method, and all UAVs, fixed and mobile, continue monitoring the traffic.

The idea behind this proposal is to reduce the energy consumption of UAVs and to ensure better performances in terms of events detection than in the case where all UAVs are mobile. In fact, when UAVs are fixed the energy consumption due to movement decreases and the battery lives longer, and when they are fixed above points where events frequently occur the chance to observe more events is better.

## 4 Simulation

For the computation of events rates and events duration, we do simulation for real vehicles traces and for vehicles traces generated by a mobility model. We opted for the Opportunistic Network Environment (ONE) simulator to generate car mobility traces based on roads of the city of Helsinki, Finland [21]. For the real mobility traces, we opted for mobility traces of cars moving on the city of Cologne, Germany [22]. Using real traces of vehicles is very important to see how our approaches react in real conditions.

UAVs are flying over the areas, trying to collect as much data as possible. We evaluate the coverage percentage of vehicles, the percentage of occurrence of the abnormal events (congestion and infractions), and the duration of detected events. Also, we study the impact of two types of traces on the performances criteria.

### 4.1 Parameters

For the mobility model, we work on the Helsinki downtown to generate car mobility traces using the ONE simulator. The total surface of the area is

(4500 m × 3400 m) and we consider scenarios with 1000 cars spread over that area. We use the Shortest Path Map-Based Movement model (SPMBM), which is integrated into the simulator, to compute the path between a starting point and a point of arrival. Paths are computed according to the Dijkstra's shortest path algorithm. Vehicle velocities are uniformly distributed between 0 m/s and 15 m/s. The wait time when vehicles arrive at their destination is null. For our observations, we only consider the central area (1600 m × 1500 m).

For real traces, we work on Cologne city area to investigate real traces of cars. The total surface of the city is 400 km<sup>2</sup>, with more than 700000 cars passing by. Real cars data is available for 24 h in a typical working day. For our investigations, we only consider the central area (225 km<sup>2</sup>). We did observations in a rush period (at 4 pm). A rush period is a period where we observe a lot of cars transiting. The total number of cars transiting in the selected area is 25800 cars in the rush period.

The observation time is only 1000 s because it approximately the autonomy duration of a commercial UAV. The radius of UAVs field of view is related to the maximal authorized altitude of UAVs flying on a city. Velocities, density thresholds, and velocities intervals are related to the nature of the city roads and the traffic. Other parameters are presented in Table 1.

The processing center is placed in the center of areas to monitor. In the case of Helsinki city, the maximal distance between the processing center and an UAV is approximately 1 km. In the case of Cologne city, the maximal distance between the processing center and an UAV is about 15 km.

UAVs send information about vehicles (positions, velocities, and number) and information about events (positions and duration) to the processing center using LTE links. When the processing center receives the data, it processes it and sends back positions to UAVs for their positions adjustments using also LTE link.

The transmission delay and the propagation delay depend on the distance between the processing center and UAVs and the speed of the light. For Helsinki city, the maximal transmission delay is about  $3.33 \times 10^{-6}$  s. For Cologne city, the maximal transmission delay is about  $5 \times 10^{-5}$  s. UAVs observe the traffic, they detect vehicles and estimate their velocity and position. So, part of the processing delay in UAVs is due to the detection process and the other part is due to the state estimation process. When using the Extended Kalman filter, the execution time is around  $3.69 \times 10^{-2}$  s [23]. When using new detection techniques like Wave3D, the execution time is around  $6.306 \times 10^{-3}$  s [24].

The processing center processes the position, the speed, and the number of vehicle to deduce new positions (centers of gravity of vehicles in UAVs Field of View that they are tracking) of UAVs and positions of strategic points (centers of gravity of vehicles in UAVs Field of View that verify conditions of events detection).

**Table 1.** Parameters.

Parameters	Helsinki	Cologne
Observation time	1000 s	1000 s
Cars velocity interval	[0–15 m/s]	[0–50 m/s]
Maximal velocity for congestion ( $V_{max1}$ )	8 m/s	5 m/s
Maximal velocity on roads ( $V_{max2}$ )	12 m/s	20 m/s
Minimal congested group members ( $N_{min}$ )	10	20
Radius of the field of view of UAVs ( $R$ )	100 m	100 m
UAVs altitude ( $A$ )	200 m	200 m
Supervised area	2.4 km <sup>2</sup>	225 km <sup>2</sup>

## 4.2 Performances of UAVs Monitoring Methods

In this section, we study the performance of the Opportunistic Method with learning in terms of events detection, coverage percentage and UAVs total traveled distance. We study the influence of parameters like the learning duration, UAVs placement criteria, and the number of UAVs to place.

Then, we compare the performance of the Opportunistic Method, the Opportunistic Method with learning, and the Fixed Method in terms of congestion detection. The Fixed Method is an existing method [16,17]. In this method, only one UAV is used to monitor the traffic. The UAV trajectory is predefined in advance, the UAV moves from one fixed Point of Interest (PoI) to another to do the monitoring task. PoIs are intersections where there is a lot of traffic.

For the Opportunistic Method with learning, the placement of UAVs above SPs can be done according to the Distance Criterion (DC) or to the Coverage Criterion (CC). In the Fixed Method, in the case of our simulations, to be fair, the number of UAVs will be equal to the number of PoIs. UAVs move from their initial locations to their respective closest PoI, and hover over those points with a null speed. For all methods, initially, all UAVs are randomly placed.

We use the following metrics:

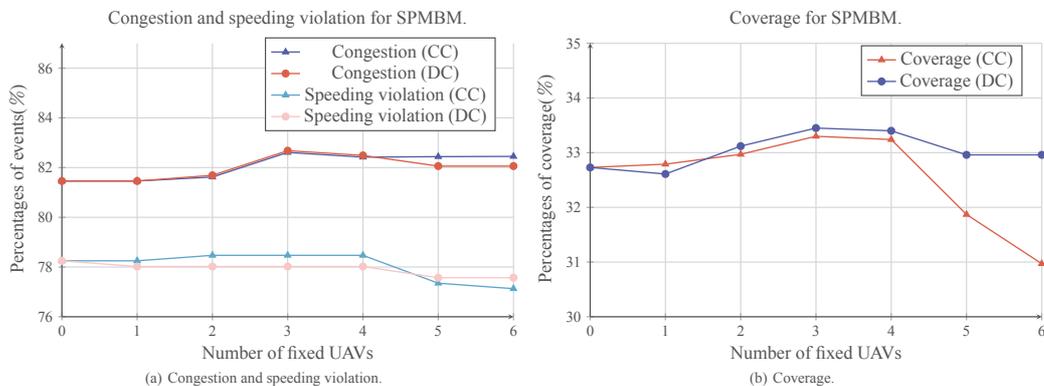
- Coverage percentage: the percentage of vehicles in the UAV’s field of view.
- Percentage of detection of the number of speeding violations: speeding violations are detected when vehicles velocities exceed  $V_{max2}$ .
- Percentage of detection of congestion duration: congestion events occur in a group of vehicles, so when members velocities are lower than  $V_{max1}$  and members number is at least equal to  $N_{min}$ , we conclude that a group of vehicles is in congestion.

We did simulations offline to compute the number of UAVs to deploy. When using the Opportunistic Method, we observed a stabilisation of the performance criteria for 25 UAVs in the case of the mobility model, and for 150 UAVs in the case of the real traces. UAVs velocity will be 5 m/s which is a typical velocity of a commercial UAV.

**Performances of the Opportunistic Method with Learning.** For the next simulations, SPs will be positions where congestion frequently occur, and the radius  $r_a$  of the area that allows as to split events positions into groups will be equal to the radius of the UAVs field of views.

In the case of the mobility model traces, with observations made by 25 UAVs, the processing center computed a maximum number of SPs equal to 6. In the case of the real traces, the processing center calculated up to 20 SPs with data collected from 150 UAVs. The processing center collects during the learning phase all congestion positions and computes positions where congestion frequently occur.

Because hovering consumes less energy than flying, fixing UAVs lead to less energy consumption and longer battery lifetime. To evaluate the gain when using the Opportunistic Method with learning rather than the Opportunistic Method, we introduce another criterion: the UAVs total traveled distance. The less traveled distance, the less energy consumed.



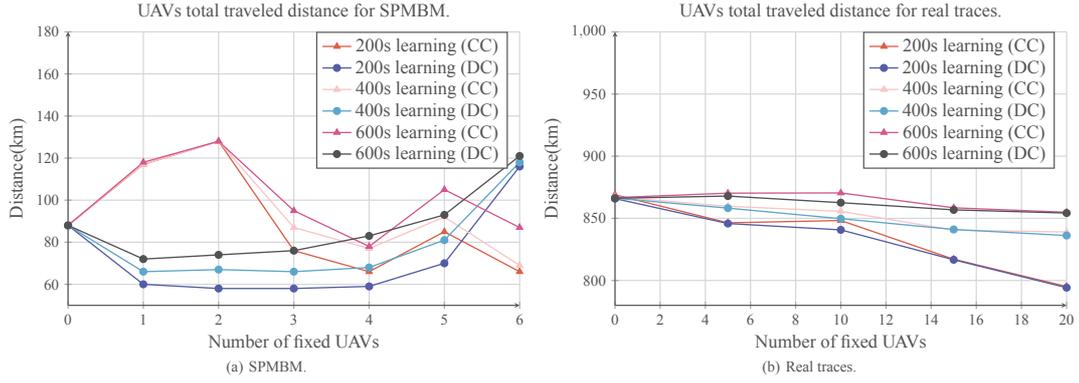
**Fig. 1.** Influence of UAVs placement on events detection and coverage.

For real and mobility model traces (Fig. 2(a) and (b)), we observe that when the learning phase is shorter the traveled distance is lower, thus, the energy consumption decreases. We compute the total traveled distance for the two criteria of UAVs placement above SPs: the Distance Criterion (DC) and the Coverage Criterion (CC).

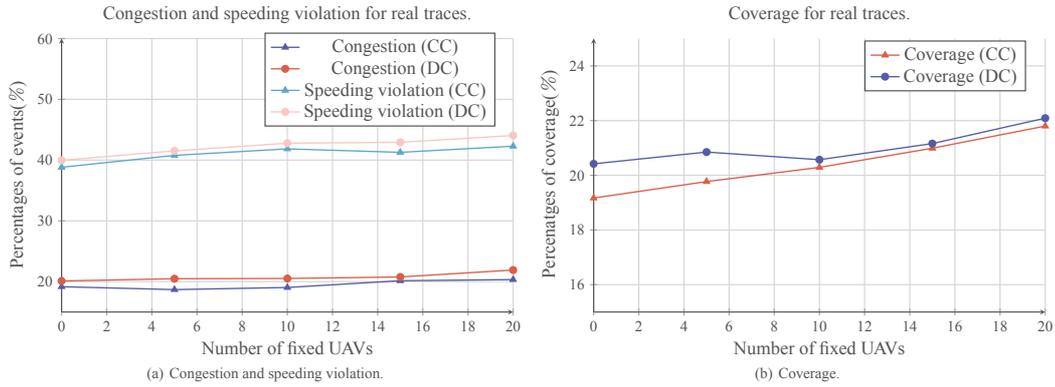
From Figs. 1(a) and 3(a), Figs. 1(b) and 3(b), we observe that the percentages of coverage, congestion detection, and speeding violation detection are better when using the DC rather than the CC. For SPMBM, we can select 3 SPs, because we got better performance with this number. While, for the real traces, we can select 20 SPs.

We observe that when we choose the DC, less distance is traveled because the closest UAVs to the selected SPs are placed above them. We observe fluctuations especially when we use the CC because sometimes the selected UAV can be close to the SP and sometimes not.

We choose 200s as a possible duration of the learning phase, because for that duration the traveled distance is the lowest comparing to other learning



**Fig. 2.** Influence of the learning on the total travelled distance.



**Fig. 3.** Influence of UAVs placement on events detection and coverage.

duration. For UAVs placement, it is better to do it according to the DC because less distance is traveled and the performances criteria are better than for the CC.

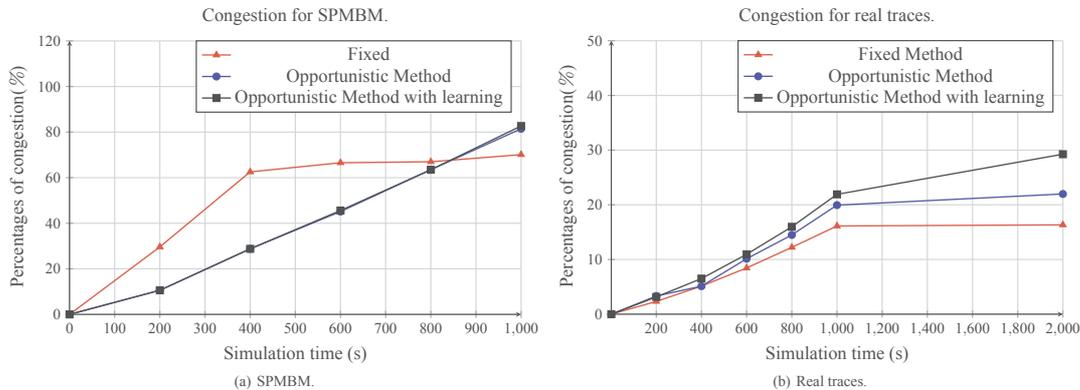
For 200s of learning, for the SPMBM, with 3 fixed UAVs, we got 12 km less traveled distance when the CC is applied. While, when the DC is applied, we got 30 km less traveled distance. For real traces, the total UAVs traveled distance is 70 km lower in the Opportunistic Method with learning because we placed 20 UAVs above SPs at the end of the learning phase.

### Comparison of Performances of Monitoring Methods Based on UAVs.

SPs are positions where congestion frequently occurs. So, we will compute percentages of congestion detection. We compare the performance of Opportunistic Method with learning to the performance of the Opportunistic Method, and to the performance of the Fixed Method regarding congestion detection.

For mobility model traces (Fig. 4(a)), we observe that the performance of the Opportunistic Method with learning and the performance of the Opportunistic Method are almost the same regarding congestion detection. The performance of the Fixed Method become the worst at the end of the simulation, because UAVs will be monitoring fixed PoI and miss a lot of vehicles and events, while

UAVs are all mobile in the Opportunistic Method, and placed above SPs in the Opportunistic Method with learning.



**Fig. 4.** Influence of the simulation time and the monitoring method on congestion detection.

For real traces (Fig. 4(b)), the performance of the Opportunistic Method with learning is the best regarding congestion detection. In fact, 20 UAVs are placed above positions where congestion frequently occur, so the discovery of this event is better. Also, mobile UAVs are tracking groups of vehicles, and probably they follow them much longer when they are moving with low velocities.

We observe that, in the Fixed Method after a certain period of observation, the percentage of congestion detection becomes almost stable. This method becomes inefficient because in the fixed PoI no more congestion can be observed after 400s for SPMBM and 1000s for real traces.

## 5 Conclusion

In this paper, we used multiple UAVs to monitor the road traffic. We proposed a method characterized by a learning phase and by adaptive UAVs trajectories. During the learning phase, UAVs collect events positions, after this phase, positions where events frequently occur are computed, and UAVs are placed above some of them. We defined also a process for the detection of speeding violations and a process for the detection of congestion. Our method has two goals, the first one is to detect the highest number of events and the second one is to save the energy of UAVs by limiting their traveled distance. To evaluate the performance of our proposal, we used real vehicles traces and traces generated by a mobility model. We observed, especially for real vehicles traces, better events detection comparing to the Opportunistic and the Fixed Methods, and less traveled distance comparing to the Opportunistic Method.

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