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VANET-assisted Cooperative Traffic Congestion Forecasting

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Existing mechanisms to monitor vehicular traffic, such as the use of induction loops or cameras are expensive to deploy and maintain. Vehicular communications open a new world of optimization opportunities as each vehicle can be used as a sensor to measure the fundamental variables defining the traffic state (flow, density and speed). In this article we propose ABEONA, a distributed algorithm for traffic monitoring that captures current and recent-past traffic trends to forecast near future road conditions. Compared to existing monitoring approaches, ABEONA allows estimating the vehicular density and, reducing installation and maintenance costs. ABEONA's algorithm incurs in low overhead and enables drivers to use forecast traffic congestion events to re-plan their route accordingly.

Introduction

Traffic congestion is a major economic and collective problem of the modern world. While social aspects are difficult to quantify, the economic impact is easier to estimate. The 2011 Urban Mobility Report published by Texas University[1] claims that the total cost for traffic jams in the U.S. that year was $100 billion. Traffic congestion does not only make an impact on factors like fuel consumption or increased pollution, but also on loss of working hours.

There are three key aspects in traffic management systems: *i)* traffic monitoring, *ii)* congestion detection/prediction, and *iii)* efficient information dissemination. Existing traffic monitoring techniques, such as induction loops and video cameras, present several drawbacks, as they are not flexible (measurement points cannot be easily moved) and are very expensive to deploy and maintain. Congestion prediction is challenging, as current methods (e.g., use of floating car data) lack flexibility and might be inaccurate (e.g., those based on off-line seasonal data). Moreover, current systems do not yet exploit vehicular communication capabilities that could be used to gather and disseminate data.

[1]http://tti.tamu.edu/documents/mobility-report-2011.pdf

Vehicular communications have been extensively researched with the aim of enabling vehicles to exchange information among them and also with the infrastructure. In addition to the use of cellular networks, vehicular ad-hoc networks (VANETs) are expected to be a complementary technology, allowing vehicles to share information in real time, especially within a limited geographical region [1,2].

This article proposes a traffic management solution – called ABEONA (A BEacON based Traffic Congestion Forecasting Algorithm), which benefits from the use of vehicular communications technologies. The key points of the solution are: *i)* ABEONA allows monitoring traffic conditions in real-time in a flexible and cost-feasible way; *ii)* ABEONA is based on a cooperative and distributed knowledge of traffic conditions (average vehicular speed, flow and density); *iii)* ABEONA is able to forecast short-term traffic conditions (with a window of 15 to 20 minutes). This makes possible to warn drivers of future forecast traffic congestion events, so alternative routes can be planned, reducing the overall travel time. Note that this article does not specifically address how predicted events are disseminated, but focuses on how the prediction is actually performed.

This article is organized as follows; we first overview the classical theory used to model vehicular traffic including a validation analysis using real traces. Then, we introduce the theoretical basis for traffic density and flow estimation, and their prediction, before presenting and validating our solution using real vehicular traces.

Modeling vehicular traffic

Vehicular traffic has been investigated since the 1950s and we can now find micro-, meso- and macroscopic models available, many of them reviewed in [3].

Macroscopic models are based on drivers' behavior and analyze three fundamental factors: speed v [km/h], flow q [veh/h] and density k [veh/m]. Parameters q and k are directly proportional until reaching a critical density k_c that corresponds to a maximum flow q_m. For lower densities, vehicles travel under free-flow conditions, while for higher densities, vehicles' behavior depends on their neighbors. For density values k

higher than k_c, q and k are inversely proportional. When k is equal to the traffic jam density k_m, q is equal to 0 (i.e., vehicles are not moving). The vehicular speed v fixes the shape of the relation function.

Among the many theories proposed since the 1970's analyzing the interaction of vehicles, one of the most accepted studies is the "Three-phase traffic theory" – firstly proposed by Kerner in [4] and then extended by the same author in [5] – that classifies traffic state into three categories:

- Free flow: when the vehicular density is reasonably low and drivers can easily keep their desired speed and overtake slower vehicles. The average speed of each lane is independent.
- Synchronized traffic: when the density is such that overtaking is not easy, so that the average speed of each lane sharply decreases and synchronizes. Drivers' behavior is influenced by other drivers.
- Traffic jam: when vehicles are stopped or follow a "stop and go" pattern.

Kerner also studied the transitions between the different phases, concluding that they can be modeled as first-order phase transitions.

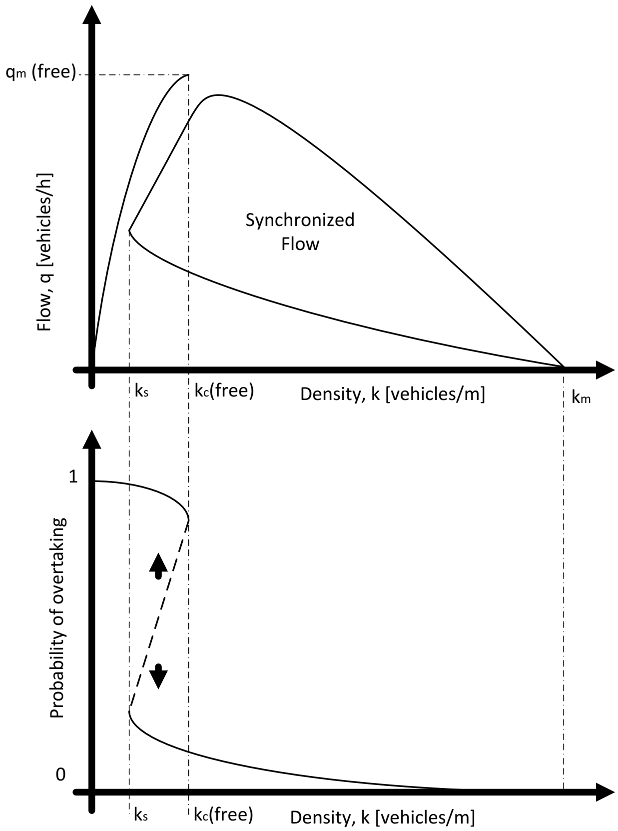

Figure 1 *Phase transitions diagram.*

Figure 1 shows an example of a "Free flow → Synchronized traffic" transition. The phase transition is (mostly) related to the easiness of overtaking experienced by drivers. When the road is in *Free flow* state, the probability of overtaking is quite high. When the road is congested, this probability is close to zero, as vehicles are travelling at similar speed and it is difficult to find room for possible overtakes. There is an "undefined area" (between k_s and $k_c(free)$), where a perturbation of one of the three variables can result in a different outcome: for example, a wrong maneuvering can lead to other drivers to temporarily slow down and then come back to *Free flow* state, while a road suffering a continued increase in the traffic demand will end up in the transition from the *Free flow* to the *Synchronized traffic* state. In *Free flow* conditions, vehicles travel at a speed that depends on the road state, the vehicle type and the weather conditions, and it is ultimately limited by the road's speed limit. Interestingly, the speed is the variable that has the least linear behavior, being an abrupt decrease possible when traffic experiences a change from *Free flow* to *Synchronized traffic* state.

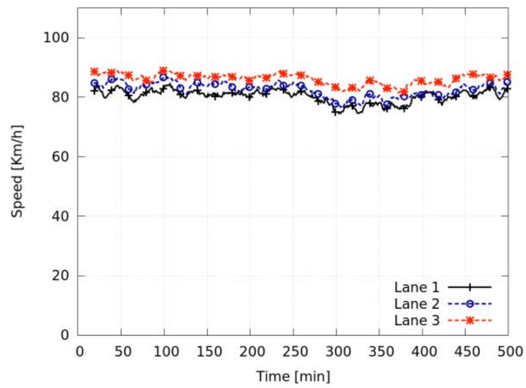

Figure 2 *Average speeds in "Free flow" state.*

In order to assess the correctness of Kerner's model we have used real traffic measurements from the city of Madrid, specifically from a 24-hour trace collected by an induction loop placed at the km 4.4 of the M30 orbital motorway, northbound, which at this point has three central lanes available and a speed limit of 90 km/h. Figures 2and 3 show the relation between the average speed of different lanes in *Free flow* and *Synchronized traffic* states, respectively. Similarly, Figures 4 and 5 show the complete relations of the two variables that can be directly captured by an induction loop: flow and speed. Figure 4 depicts the complete speed and flow time series[2] and it can be observed that the transition between *Free flow* and *Synchronized traffic* states is a first order transition that involves both flow and density variables. As already shown in Figure 1, the state transition triggers an hysteresis that can also be noticed in Figure 5: for the same flow rate q=150 veh/min, values around 40-50 km/h and around 90 km/h are possible.

[2]Values are window-averaged with a window equal to 10 minutes to avoid excessive glitches.

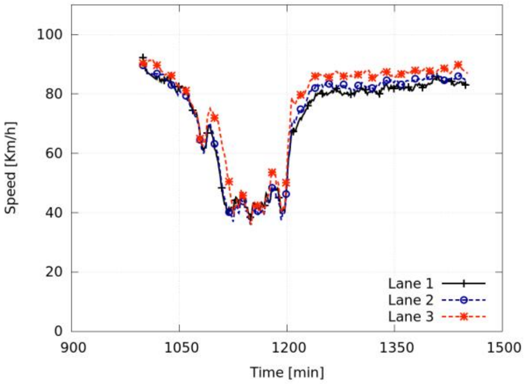

Figure 3 *Average speeds in "Synchronized traffic" state.*

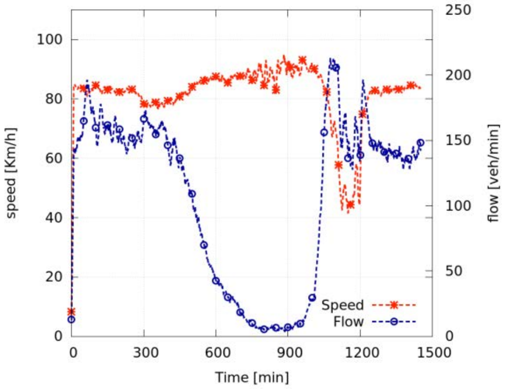

Figure 4 *Flow-speed vs. time plot from real measurements.*

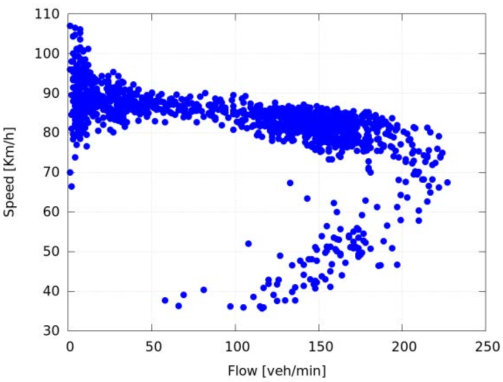

Figure 5 *Flow-speed plot from real measurements.*

Traffic monitoring and congestion prediction

Nowadays there are three main approaches in use to monitor traffic in real-time: induction loops, cameras and floating cars. The oldest and still more widely deployed mechanism is the use of induction loops, which consist in a continuous loop of wires buried under the pavement that are able to detect when a vehicle passes over it by a sensor measuring a change in the magnetic field. The use of subsequent loops allows detecting the type of vehicle and its speed. With the latest advances in license plate recognition software, cameras installed on poles or bridges along the road are now also used as traffic monitoring systems, being capable of providing additional information compared to the induction loops. Third and most recent technique (called floating cars) comes from the use of data gathered anonymously from wireless devices present inside vehicles (e.g., mobile phones)[3].

In order to correctly understand the traffic state, the three variables (speed, density and flow) have to be monitored, as a perturbation in one of them can trigger a transition. However, it is difficult to measure or estimate density using the three classic monitoring techniques revised above. While the floating cars technique is a cheap mechanism, data from every vehicle cannot be easily obtained and it is not straightforward to extend it for monitoring flow and density. Alternatively, cameras can measure all the three variables, but they have high deployment and maintenance costs, and introduce privacy issues. Last but not least, induction loops, although cheaper than cameras, can only measure speed and flow.

Vehicular traffic forecasting can be divided into long-term and short-term prediction. The former exploits the so-called seasonality property of vehicular traffic: people tend to move following regular patterns [6]. The threshold between long term and short-term prediction is usually set around 15-20 minutes.

In [7], Kanoh *et al.* propose a neural-network based solution. A different approach, using the analysis of the flow time series, was presented by Thomas *et al.* in [8]. Both of them are validated using real measurements and claim that, if used in conjunction with intelligent transportation systems, prediction techniques can help optimizing flows and other aspects of road conditions (e.g., waiting times at traffic lights). These two works propose algorithms both for long-term and short-term forecasting. However, while the analysis for long-term forecasting is more complex, the short-term part is easier, depending on the conditions from the previous 15-20 minutes.

Chrobok *et al.* propose in [9] different methods for short-term traffic forecasting, and they find out that even a very simple forecasting method like linear prediction can achieve good results in estimating the short-term traffic demand.

All the aforementioned methods do not specify any procedure to gather the data needed by the prediction algorithm as they work on off-line data.

Bauza *et al*. in [10] propose a mechanism to evaluate the length and intensity of a traffic jam using V2V techniques. In [1], Leontiadis et al. present a vehicular navigation system based on the dissemination of data sensed by vehicles. While both of them use vehicular communication concepts, none of them work with the concept of flow and density variables to provide forecasting capabilities for future traffic conditions.

In the next sections we describe our traffic congestion prediction framework, which is composed of two main aspects: *i)* VANET-based traffic monitoring (i.e., collaborative flow and density estimation), and *ii)* traffic forecasting (i.e., short-term prediction).

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[3]TomTom HD Traffic™: http://www.tomtom.com/en_gb/services/live/hd-traffic/

ABEONA: VANET-based traffic monitoring

The flexibility and infrastructure independence of vehicular ad-hoc networks (VANETs) make them suitable for the implementation of distributed algorithms for traffic monitoring. A VANET can be briefly described as a set of On Board Units (OBUs) deployed inside vehicles, and Road Side Units (RSUs) installed along roads to provide access to the infrastructure. OBUs and RSUs can communicate among them using Dedicate Short Range Communications (DSRC), like the widely used 802.11 standard. Application Units (AUs) inside the vehicles run automotive or infotainment software and rely on OBUs for obtaining connectivity. Vehicular communications can be divided into two main families: Vehicle-to-Vehicle communications (V2V), and Vehicle-to-Infrastructure (V2I).

ABEONA makes use of V2V communications to exchange data among vehicles – which are used as distributed "sensors". It should be noted that ABEONA assumes that all the vehicles have V2V capabilities. ABEONA needs a spatial-temporal reference which can be provided by a GPS device with an accuracy of 1s. Each vehicle groups the monitored data in 1-minute sets, identified by an epoch value (i.e., the current minute) called *EpochId*. The spatial reference is provided by dividing the road into different regions, each of them identified by a unique *RoadId* identifier, and including this information into an enriched version of the digital map or Local Dynamic Map (LDM) [12] used by the in-vehicle navigation system. The knowledge of the *RoadId* and *EpochId* values allows the use of time persistent content distribution techniques, firstly proposed by Leontiadis *et al.* in [11].

Each vehicle periodically broadcasts the sensed information within its region (identified by the *RoadId*), not only about the current epoch, but also about the most recent past ones (i.e., historical data). This ensures that the information required at each region to forecast future traffic conditions remains available at the area. Vehicles traveling within the region cooperatively store and share this information. For example, when a vehicle leaves `RoadId A` and enters `RoadId B`, it stops broadcasting `RoadId A` related information and waits to receive information about `RoadId B` sent by other vehicles that are currently in that region. The messages exchanged by vehicles staying in the same road region include both data related to the current epoch and historical data.

Current epoch data estimation

A first goal of ABEONA is to correctly estimate the flow and the density for the current *EpochId*. In order to do so, there are two key parameters that need to be exchanged by cars: a *VehicleId* that uniquely identifies each vehicle, and the current position (i.e., a<*Latitude, Longitude*> pair). Vehicles include this information in ABEONA beacons that are broadcast periodically (i.e., typically every 1 or 2 seconds).

Density Estimation

The density of a given road region can be independently estimated by each vehicle using the information included in the beacons received from other vehicles. First, each vehicle, by listening to these beacons, can build an updated map of the surrounding vehicles (i.e., a neighbors' table). A local estimation of the density can be inferred by taking the distance between the pair of neighbors that are furthest away from each other and dividing it by the current number of neighbors (see Figure 6). This value, calculated independently by each vehicle, is included in the ABEONA beacon. With the information collected from the neighbors, each vehicle calculates a weighted average of the density estimated locally and the one estimated by its neighbors. This estimation can be even furthermore improved by time-averaging it (i.e., among 30 and 60 beacons are received in an epoch).

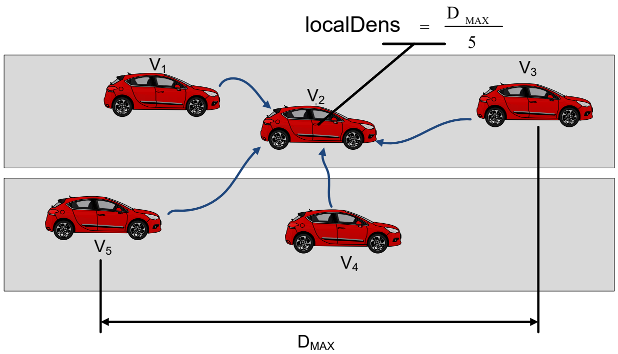

Figure 6 *Local estimation of the traffic density.*

Flow Estimation

Estimating the vehicular flow in a distributed way is a more complex task, as vehicles need to agree on a common observation reference point. In order to do so, ABEONA uses the concept of *Virtual Induction Loop* (VIL) [13], which is a virtual reference line crossing the road. The information about the position of the VIL of each road segment (there is only one per *RoadId*) is included in the enriched digital map used by the in-vehicle navigation system. ABEONA's flow estimation algorithm works as follows (see Figure 7). Each vehicle maintains a VIL table, containing the list of the vehicles that have already crossed the VIL reference line during the current epoch. When a vehicle traverses the VIL reference line, it adds its own *VehicleId* in its VIL table. Information from the VIL table is included in the ABEONA beacons broadcast by each vehicle, so neighbors can merge this information with the one contained in their local VIL table. By doing this, information is kept consistent among all the vehicles from the same road region. However, to limit the beacon size and avoid sending too much redundant information, only a small set of random entries from the VIL table is included in each beacon. As beacons are sent often and each vehicle is receiving information from multiple sources, vehicles end up building a consistent VIL table or just with negligible deviations.

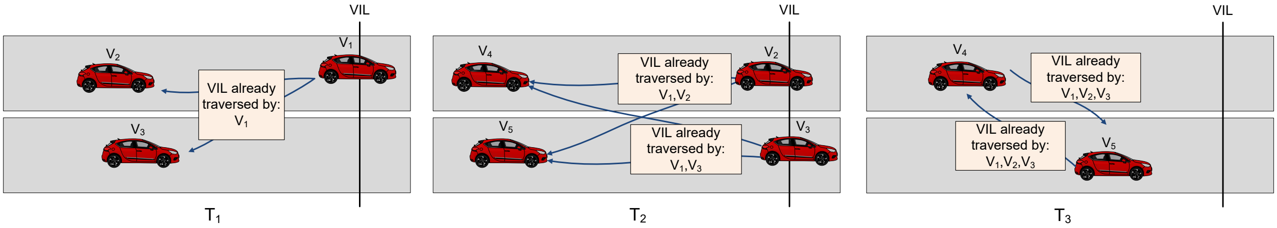

Figure 7 Cooperative estimation of the traffic flow.

Historical data management

Congestion prediction is based on the analysis of current and recent past traffic conditions. Each vehicle tracks the density and flow values estimated per epoch, storing them in a *historical epoch local table*. The amount of data maintained by each vehicle is limited in size, discarding older values (i.e., a historical data length of 20 epochs). Since the *historical epoch local tables* are shared among the different vehicles within the same road region, the information used by each participant tends to be consistent, though minor deviations may appear. Vehicles merge the information locally maintained for each *EpochId* with the data received from beacons as follows. Upon receiving a beacon, if a vehicle does not have information about a particular past epoch, then the *historical epoch local table* is updated with the data in the beacon. On the contrary, if the vehicle already has information for this epoch, a new density value is calculated as the average of the densities contained in the beacon and in the *current value.* Regarding the flow, the highest value is taken as new estimated flow value for this epoch.

Beacon size and possible implementation

A beacon basically contains the following information: *VehicleId*, vehicle' position, *RoadId*, current *EpochId*, the density estimation for the current *EpochId*, VIL table (containing the *VehicleId* of a random set of cars that have traversed the VIL reference line during current *EpochId*) and historical data (i.e., containing the estimated <flow, density> pairs for the past recent epochs).

ABEONA's beacon could be contained into the Context Awareness Messages (CAMs) defined by the European Telecommunications Standards Institute (ETSI) for the dissemination of data of local interest. As the CAM messages are defined in ASN.1 notation, there are fields that can be extended to achieve a flexible management of the different packet format versions. Moreover, CAMs are already used to broadcast vehicles' position. Using a 10-entry VIL table (containing 64 bit long *VehicleIds*) and 20min historical data, the total CAM size would be increased by 240 bytes.

Traffic efficiency applications may not be classified as meritorious of being broadcast on the high priority control channel. So the information needed by ABEONA can be split into CAMs (which deliver *Vehicle Ids* and their positions) and an application packet that provides all the rest of the information.

ABEONA can use its knowledge of the vehicular traffic conditions to reduce the saturation of the wireless channel in crowded situations. When the traffic goes to *Synchronized traffic* state (i.e., the vehicular network is crowded), there is no need for ABEONA's beacons to be broadcast, thus ABEONA beacons could be reduced or even disabled.

Lack of connectivity issues

One of the main barriers of VANET-based approaches is the intermittent connectivity problem. This problem, already studied in [14], does not impact ABEONA as we can argue that in the previous moments leading to a congestion event, the traffic density will be such that guarantees that there is connectivity between the vehicles. This observation is supported by the empirical results shown in Figure 4.

ABEONA: VANET-assisted traffic forecasting

Each vehicle can autonomously forecast the future values of density and flow (q_e and k_e), using the current and historical epoch information, and compare them with a set of reference values (q_r and k_r). These reference values represent the threshold leading to a state transition between *Free flow* and *Synchronized traffic* states, and are characteristic for each road region, so they can be included in the enriched digital map. Note that these values are quite stable for a given road, so the typical update pattern of navigation software is sufficient to keep these parameters up-to-date.

To forecast future density and flow values, ABEONA uses a linear prediction algorithm [9], namely the linear least squares. Although more complex estimators could be used to furthermore refine the prediction outcome, this simple algorithm has proven to be more than sufficient. When a vehicle detects that $q_e > q_r$ and $k_e > k_r$ this means that a traffic state change is forecast, triggering a warning message to be sent to the traffic control center. The traffic control center keeps track of the warning messages received, marking a given road region to be "likely to become congested" if more than a preconfigured number of warning messages is received from different vehicles over a preconfigured window time. The traffic control center shares this information with all the vehicles that can benefit from knowing it.

Experimental evaluation

In order to conduct a performance evaluation, and given the difficulties associated to conducting real experiments with a vehicular mechanism under real-life traffic conditions, we decided to use trace-driven simulations. The simulation environment is the following: ABEONA has been implemented in OMNeT++[4], and SUMO[5] has been used to emulate vehicles behavior. A three-lane wide, 1 km-length road region has been used, placing the VIL reference line at a fixed point in each simulation run. Vehicles are equipped with standard IEEE 802.11g connectivity, being their initial positions and speeds taken from real traces collected at the M30 road (Madrid).

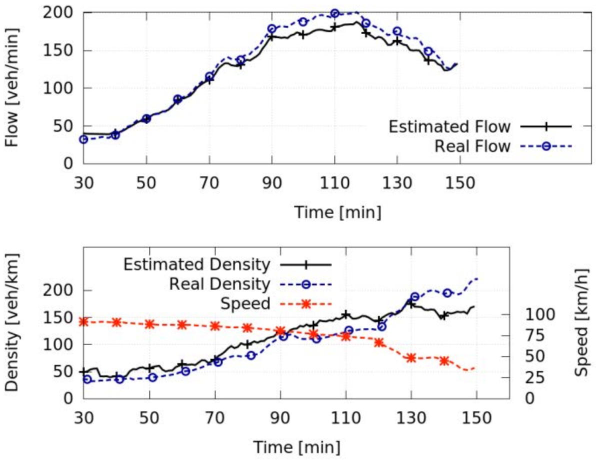

Figure 8 ABEONA flow and density estimation.

We first introduce some terminology that will be used in this section. By *real values* we refer to the ones coming directly from the vehicular traces: flow and speed, as density cannot be measured with induction loops. By *estimated values* we refer to the outcomes of the *current epoch* data estimation procedure detailed before, and which are broadcast in beacons. Finally, *predicted values* are those derived from ABEONA's prediction algorithm.

We first assess ABEONA's capability of estimating the traffic flow variable. The upper part of Figure 8 shows the real flow and the estimated one before and during a traffic congestion situation (around t=120 min). The lower part of the figure depicts the vehicular density. Speed is also shown, in order to better identifying when a traffic congestion event happens. The estimated density is compared with the real one generated by the mobility simulator (i.e., the actual one that ABEONA has to monitor). The main performance metric of ABEONA is its capacity to forecast future traffic state transitions based on the estimated flow and density variables. We next evaluate this performance using 20-minute historical data and a prediction window of 10 minutes (i.e., the density and flow are forecast 10 minutes in advance). Figure 9 shows the estimated and predicted density (top) and flow (bottom), as well as the speed (to help identifying the transition to *Synchronized traffic* state). It can be observed that ABEONA predicted density and flow closely follow the estimated values (which are a good approximation of the real traffic variables), therefore enabling the forecast of future traffic conditions.

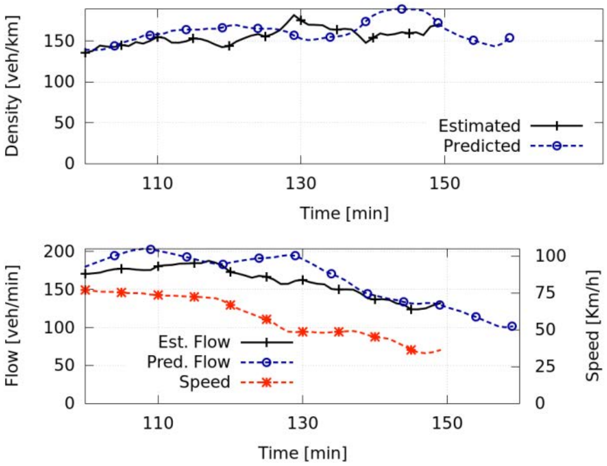

Figure 9 ABEONA flow and density prediction.

ABEONA's goal is to anticipate the transition from *Free Flow* to *Synchronized traffic* state, in order to effectively warn the approaching vehicles about the forthcoming major change of the traffic conditions. ABEONA prediction is based on the use of two different thresholds: q_r and k_r, which have to be carefully chosen to minimize false positives or undetected congestion events. These values are derived offline using past historical data observed for each road region. Note, that in this article we have experimentally validated the feasibility of ABEONA using real traces from one road of Madrid. Future work includes analyzing traces from additional roads in order to infer the appropriate thresholds.

Additionally, there are two more parameters that affect ABEONA's performance: the size of the past data used to make the prediction (historical data), and the time in advance that this prediction is made (prediction window). In the results shown in Figure 9, we set up these values to be 20 and 10 minutes respectively, which are the ones providing the best results for this road. We also evaluated the impact of using different values for these two parameters. Using longer past data sets makes the prediction algorithm to react more slowly, and using shorter data sets leads to the opposite effect, which may result in potential false alarms. Finally, as expected, using shorter prediction windows leads to more accurate predictions, but at the cost of leaving less time to react and re-plan the route.

[4] http://www.omnetpp.org/

[5] http://sumo.sourceforge.net/

Conclusions

This article proposes ABEONA, a traffic congestion prediction framework based on the cooperative monitoring and estimation of two of the three principal variables that define macroscopic traffic behavior: density and flow. ABEONA is a VANET-assisted mechanism that enables vehicles equipped with a GPS navigation system to estimate current flow and density, by cooperating and sharing locally monitored information. The availability of these accurate estimated parameters (density and flow), enables vehicles to perform a short-term forecast of a potential congestion event.

We have conducted a simulation-based validation analysis, using real traffic traces collected at one road of the city of Madrid. Obtained results support the feasibility and correctness of our proposal, which can help drivers to properly re-plan their routes, leading to important savings in commuting time.

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