Travel time estimation based on historical congestion maps and identification of consensual days

Nicolas CHIABAUT[a,c,*], Rémi FAITOUT[b,c]

[a] Univ. Lyon, Univ. Gustave Eiffel, ENTPE, LICIT, F-69518, Lyon, France

[b] SPIE CityNetworks, F-69320, Feyzin, France

[c] IRT System-X, Lyon, France

[*] Corresponding author : nicolas.chiabaut@entpe.fr

Abstract

In this paper, a new method for real-time estimation of traffic conditions and travel times on freeways is introduced. Using a combination of a Principal Component Analysis and a Gaussian Mixture Model, observation days of historical data are first clustered. Then, a consensus day is identified in each group as the most representative day of the community according to the congestion maps. Such a map is binary visualisation of the congestion propagation on the freeway giving more important to the traffic dynamics. Then, the first measurements of a new day are then used to determine in real-time which consensual day is closest to this new day. The past observations recorded for that consensus day are then used to predict future traffic conditions and travel times. This method is tested using two years of data collected on a French freeway and shows very encouraging results.

1 Introduction

Prediction of traffic states and travel times evolution is a key component of any traffic monitoring system. Their accurate estimation is critical for freeway managers, mainly when the network becomes congested. This problem has been extensively investigated in the transportation literature using model-based, simulation-based and data-driven approaches. For short-time prediction, model-based and simulation-based approaches use traffic flow models in conjunction with data assimilation techniques such as recursive Bayesian estimators to predict the traffic states and the resulting travel times [1, 2, 3, 4]. Most data-driven approaches use general purpose parameterized mathematical model such as linear regression [5], Kalman filtering [6], support vector regression [7], random forest, Bayesan network, artificial neural networks [6] and many other techniques to capture and learn from data the correlations between traffic variables (speed, travel-time) over space and time. As pointed out by [8], these approaches suffer from various limitations. To quote only a few, they often use instantaneous travel times, i.e. travel times calculated combining the speed measurements in different locations at time t, which is inconsistent with traffic dynamic because it does not account for congestion evolution. To overcome this drawback, some of the existing methods resort to experienced travel times, i.e. travel times calculated by traveling a trajectory through the velocity field, but this information is rarely available in real time because experienced travel time is usually greater than the prediction horizon.

Consequently, the purpose of this paper is to predict congestion evolution and travel times with a simple and fully explainable method that overcomes these drawbacks. Inspired by the work of [8], the proposed method uses both historical and real time traffic information to make short-term congestion and travel time evolution forecast. To this end, we used the same concept of *congestion map* as [8] to consider queue propagation rather than traffic states variables evolution, such as density or speed. To learn from past situations, historical information is partitioned into clusters with similar characteristics based on the traffic patterns observed in the freeway. Then, the proposed method differs from the one of [8]: rather than considering the global behavior of the clusters, we try to identify which day within the cluster is the most representative of the group. This so-called *consensual day* is determined based on the congestion maps of the clustered days. Once a set of consensual days has been established, the new observation days are processed in real-time to identify in this set which is the closest consensual day. The congestion maps and the observed speed of this closest consensual day are then used to predict the congestion and travel times evolution of the new observation days. The main benefit of using past measurements to compute future traffic conditions is to ensure realistic value that are consistent with traffic dynamics. Figure 1 presents the mechanism of the algorithm of the proposed method.

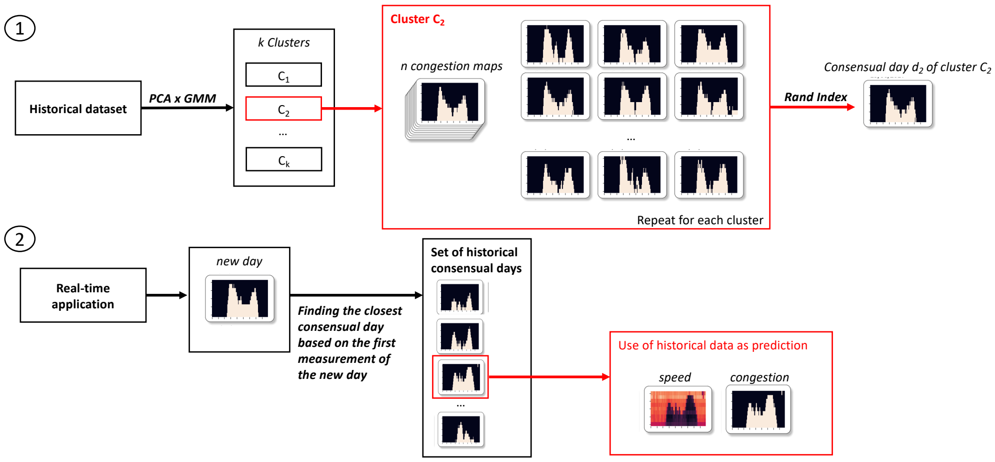

Figure 1: Graphical representation of the proposed method

The remainder of the paper is organized as follows: Section 2 presents the case study and the dataset used in the paper, Section 3 introduces the prediction methods, Section 4 is devoted to the results while Section 5 includes a brief a conclusion.

2 Case study and dataset

In this paper, we focus on the A6 highway near Lyon, France. A sketch of the site is depicted in Figure 2. It is important to notice that this highway is used to access the city center through a tunnel, which is a recurrent active bottleneck. Moreover, this highway is one of the most important in France because it connects Paris to the south of France (beaches) and to the Alps. Consequently, major congestions are always observed during holidays. The maximal authorized speed varies from 70 km/h to 90 km/h.

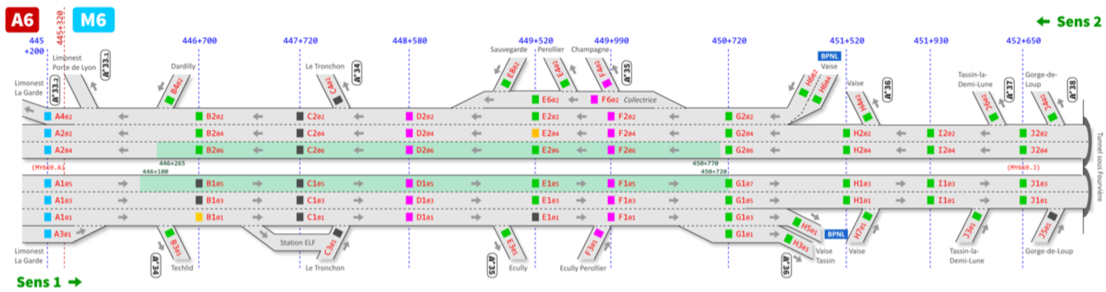

Figure 2: Sketch of the studied site. We focus on loop detectors B (then labeled 0) to J (then labeled 8) in the direction *Sens 1*.

Regularly staggered loop detectors can be found on this highway section. These detectors provide average flow, speed and occupancy rate per lane every 1 minute. In this study, we mainly focus on data from 9 detectors of a 6 km long section, see Figure 2. In the remainder of the paper, detectors are labeled by increasing positions from 0 to 8. We consider that traffic conditions between detectors can be interpolated by using observations of the closest detector. All data from Mai 2017 to December 2018 is available. We partitioned the data by day from 0:00 to 23:59 (1440 observations per day). Finally, data has been roughly cleaned up to remove unrealistic values or problem of acquisition.

3 Methodology

3.1 Congestion maps

To mainly focus on traffic dynamic rather than speed evolution, we used the concept of congestion map. For each loop detector $l \in [0, 8]$, we consider therefore a variable x that, at time t, is equal to 1 if the observed speed $v_l(t)$ is lower than a congested speed threshold v_{cong} (fixed here at 50 km/h) and equal to 0 otherwise. It makes it possible to compute map M_d of day d as Boolean matrix of size "number of detectors" x "number of observations per day" composed of elements $x_l(t)$. First line of Figure 3 shows classical speed maps for the case study and the associated congestion maps M_d for 5 randomly selected days. Note that for the speed maps, the darker the color the lower the speed, whereas for the congestion maps, black color stands for $x_l(t) = 0$ (congestion) and white color for $x_l(t) = 1$ (free-flow).

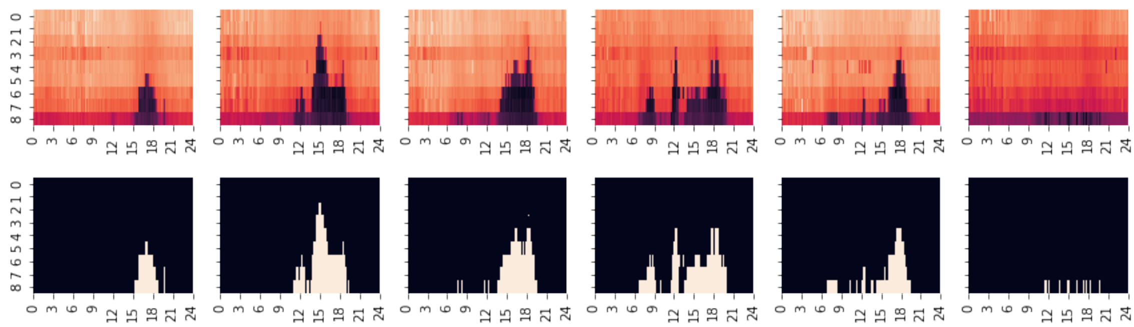

Figure 3: Top: speed maps for different days of the historical dataset (xlabel are for the time of the day whereas ylabel stand for the detector ID, traffic flows from 0 to 8). Bottom: associated binary congestion maps.

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3.2 Clustering historical data

As mentioned by [8], the regularity of traffic events makes very useful the information that we can obtained from historical data. Consequently, we classified the different observation days by using the method proposed in [8]. Because the size of the initial dataset is very large (12960 variables), the first step is to perform a Principal Component Analysis (PCA) to reduce the dimensions of the observations. Notice that we consider here speed $v_l(t)$ for $l \in [0, 8]$ and $t \in [0, 1440]$ as the vector of the PCA. Since PCA is a usual method, we do not study here the results in detail but only provide a short analysis based on Figure 4. The screeplot reveals that 12 components are sufficient to describe the historical dataset.

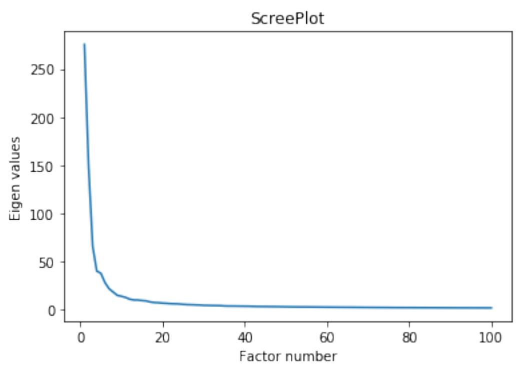

Figure 4: Scree plot of the PCA

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Then, the purpose of the second step of the method is to cluster similar days of the historical dataset. After reducing the dimensions of the observations with a PCA approach (here to 12 components), it is very convenient to use a Gaussian Mixture Model (GMM) to gather data. This kind of clustering method is based on the distribution of the data points and not only on the distance between them. Consequently, GMM is well adapted to our case because it provides clusters that may have different sizes and correlation within them. It is worth noticing that the optimal number of clusters have been determined by the use of Bayesian Information Criterion and fixed here to 30.

The different daily congestion maps of three random selected clusters are shown in Figure 5. First of all, it is easy to notice that clusters may have different sizes. Then, at a first glance, the shapes of the congestion maps within a cluster look very similar. For example, Cluster 1 clearly gathers days with a morning and an evening peak hours. Between these two peaks, the freeway remains congested but the queue is smaller. This cluster may correspond to regular week days. Days of cluster 2 are much more congested with a queue that is present all day long. Congestion maps of cluster 3 reveal a trend different from cluster 1 and 2 since the queue is longer in the evening than in the morning.

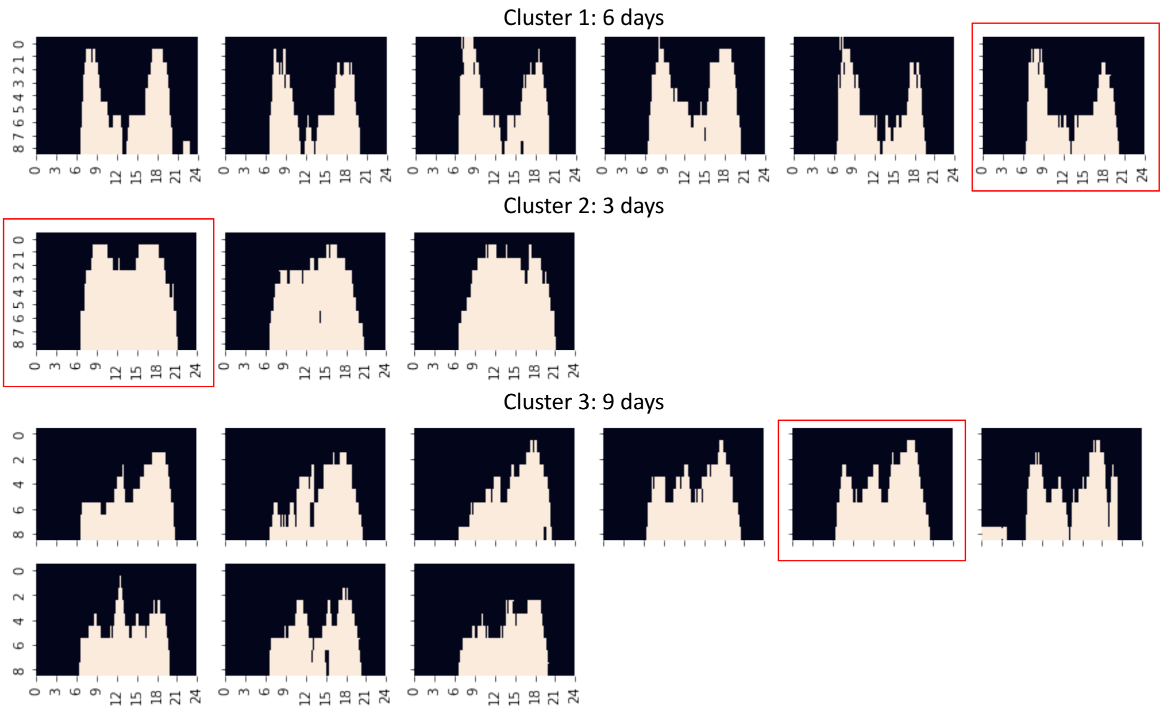

Figure 5: Congestion maps of 3 randomly selected clusters

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3.3 Identifying consensual days

Now our method clearly differs from the one proposed by [8]. The idea is to determine which day of a cluster is the most representative of the group. The motivation is to use these representative days as the prediction for the future days as explained in Figure 1. To this end, we have adapted the consensual learning method used in [9] to our specific case. Thus, the representative day of a cluster is identified according to a distance based on the Rand index, i.e. the accuracy, between congestion maps. The Rand index between two maps M_d and M_p of days d and p is defined as the number of concomitant results among the total number of observations. Here, we consider two observations as concomitant when, at a given detector l and time t both observations for day d and p are in the same state (free-flow / free-flow or congested / congested), i.e. $M_d(i,j) = M_p(i,j)$. This can be formulated as:

$$R(d,p) = \frac{a}{a+b+c} \tag{1}$$

where:

- a is the size of $\{x_l(t), M_d(l,t) - M_p(l,t) = 0\}$ (free-flow / free-flow or congested / congested);
- $b = |\{x_l(t), M_d(l,t) - M_p(l,t) = 1\}|$ (free-flow / congested);
- $c = |\{x_l(t), M_d(l,t) - M_p(l,t) = -1\}|$ (congested / free-flow);

Then, we define the consensual day d_k of a given cluster C_k as the one that maximizes the sum of the Rand indices within a cluster:

$$d_k = \arg\max_{d \in C_k} \{ \sum_{p \in C_k} R(d,p) \} \tag{2}$$

Consequently, the set of consensual days D_k can be determined for the whole historical dataset. Notice that the consensual days of the clusters displayed in Figure 5 are highlighted by red boxes.

We are now going to take advantage of the consensual days to predict in real time both congestion and travel times evolution. Consider a new day of observation d^*. At time t, we try to determine which consensual day $d_k \in D_k$ is the closest one to this new day d^*. To this end, we only consider the last Δt observations and build a partial congestion map m_d^* composed of $x_l(t)$ for $t \in [t - \Delta t, t]$ and $l \in [0, 8]$. This map is compared to the partial maps extracted from the congestion maps of the consensual days M_{d_k} for $d_k \in D_k$. The consensual day d_k^* that has the maximal Rand index with the observation d^* is selected: $d_k^* = \arg\max_{d \in d_k}\{R(d^*, d_k)\}$ Now that d_k^* has been identified, we used the historical data $x_l(t)$ and $v_l(t)$ of d_k^* to predict variables of day d^* for the next time step δt. This process is iterated at each time t and congestion and speeds maps can be built by gathering the data. Notice that the optimal consensual day d_k^* can change with time t.

4 Results

The prediction method is now tested for our case study. We mainly focus on two metrics: the predicted congestion maps and the travel times series. Data has been divided into two sets: 8 months of data from year 2018 have been randomly selected as the historical data whereas the remainder is used to validate the prediction.

4.1 Congestion propagation

The ability of the proposed method to anticipate on congestion propagation is appraised by comparing the predicted congestion maps with the real observations. Figure 6 shows the real maps, the predicted congestion maps (for a $\delta t = 12$ minutes horizon) and the difference between these maps for 6 randomly selected days. The visual inspection reveals that the differences are very low between prediction and reality and this for different shapes of congestion propagation. This qualitative analysis is very encouraging.

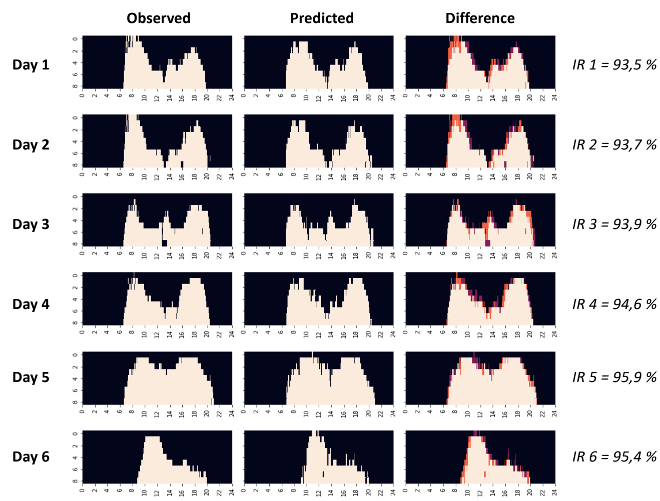

Figure 6: Comparison of observed and predicted congestion maps

To go further, we decided to calculate the accuracy of the prevision. The values are particularly good since they are very close to 100%. There is a small bias introduced in the comparison because the free-flow situations are easy to predict and strongly present in the congestion map. However, the travel times evolution analysis will confirm that the results of the method are encouraging.

4.2 Travel times estimation

As already mentioned, the proposed method is able to predict travel times by using the observed speeds of the consensual days. The main benefit of this approach is to produce realistic travel times because predictions come from past observations. Figure 7 shows travel times series for a randomly selected day. The blue curves correspond to the prediction whereas the orange ones are the observations. The horizontal black line is the moment where the prediction is made. For this example, we start the prevision at 6 in the morning and compute the method every hour. Without any surprise, the predictions become better when the number of observations of the current day increase. We can also observe that the optimal consensual day changes with time, see the different blues curves between graphs. What is also notable is that, even if the first selected consensual day is not appropriate for the second part of the day, the predictions are very good for the morning peak hours. Once the decrease of travel times is observed, then the method switches to a second consensual day. Fort this particular day, it is remarkable to observe that the evening peak hours are already accurately captured from 10 : 00.

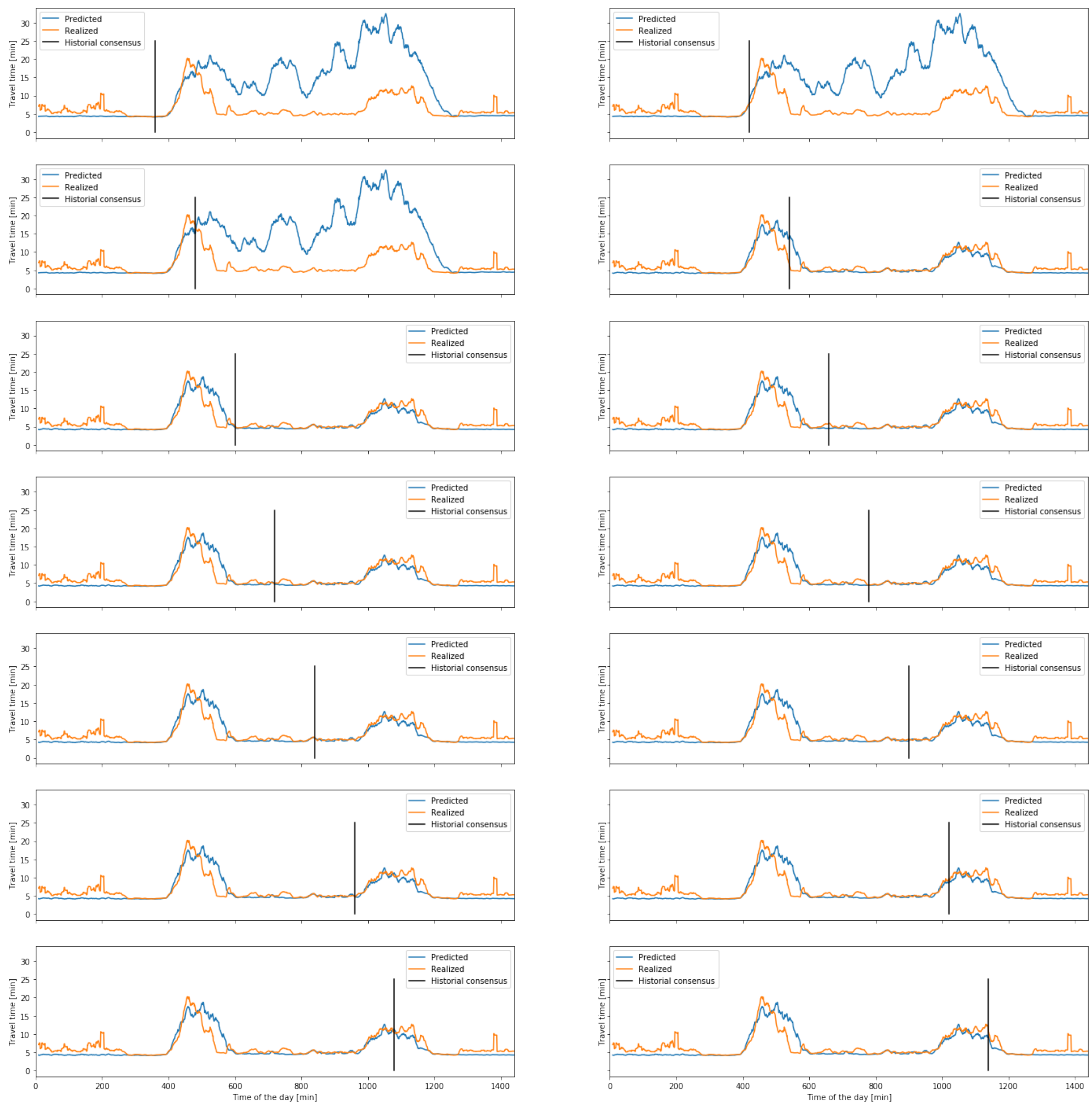

Figure 7: Comparison of observed and predicted travel times

Then, we decide to use only the last $\Delta t = 3$h in the observations as the real-time learning period. This real-time learning period is highlighted by the plain and dotted blacks lines in Figure 8. Here, we start the prediction at 6 in the morning, using a real-time learning period of Δt. Once again, the results are very encouraging since the peak hours can really be accurately captured by the proposed method. Without any surprise, in this case, the prediction of the variations of travel times are better since the calculated optimal consensual day is updated more frequently. For example, the change of optimal consensual day between Figure 8-5 and Figure 8-6 increases the prediction of the evening peak hours.

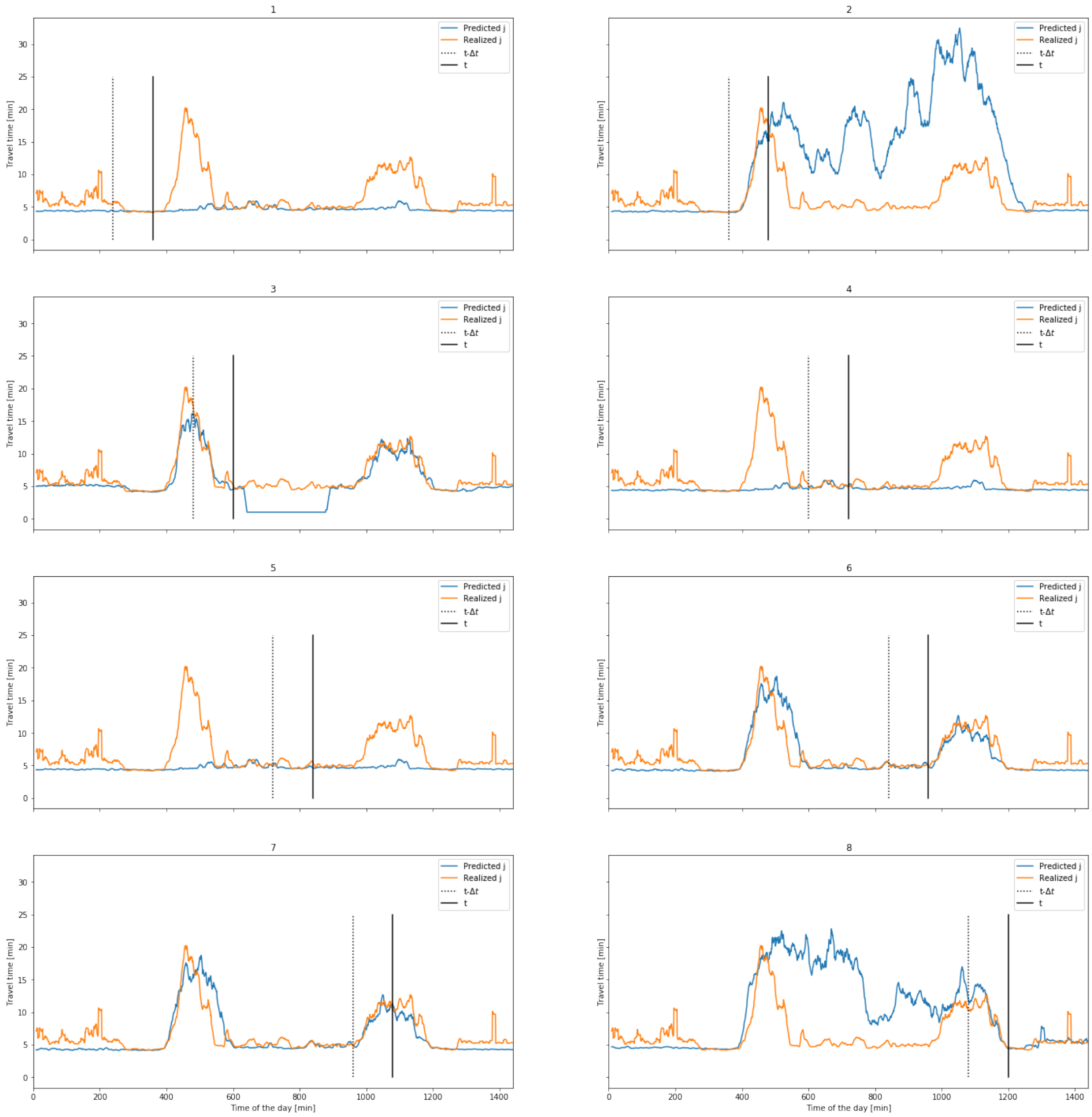

Figure 8: Travel times predictions using a $\Delta t = 3$h real-time learning period

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Finally, it is thus appealing to test a last and drastic implementation of the proposed method by considering only the last $\Delta t = 12$min in the observations. Thus, every Δt, the consensual day is updated and traffic conditions are predicted for the next $\delta t = 12$min horizon. Figure 9 shows the travel times series for the 6 days of Figure 6. Visually, the results are very good and the trends of the traffic evolution are well predicted. However, we have calculated the normalized RMSE between observations and predictions. They fall into the range of what can be noted in the literature [8] without being remarkably better. To complete the analysis, Figure 9 shows the distributions of the errors between predictions and observations. These results are more encouraging since the errors are mainly below one minute.

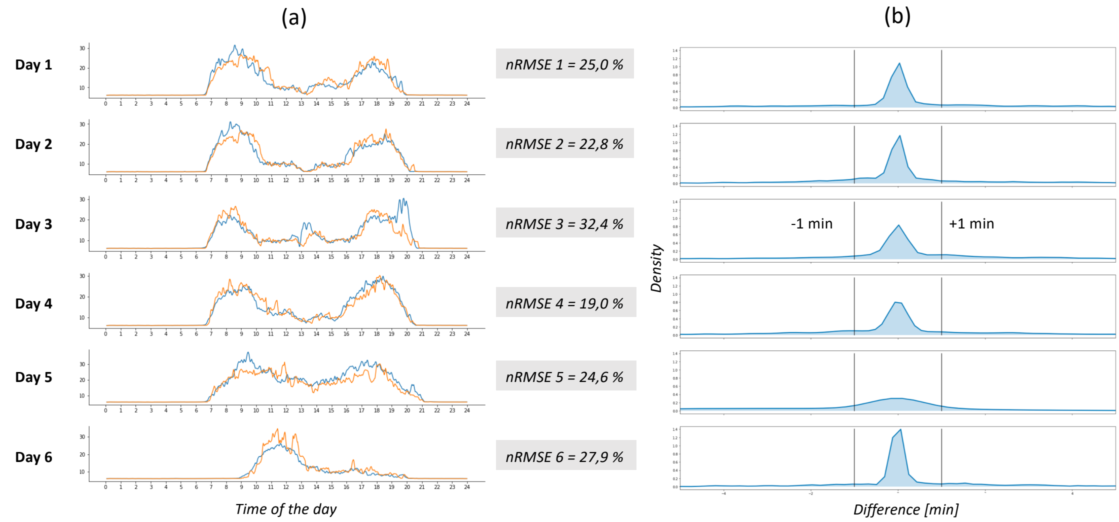

Figure 9: (a) Travel times predictions using a Δt = 12min real-time learning period for a δt = 12min horizon and associated normalized RMSE; (b) Distributions of the difference between predictions and observations of travel times.

5 Discussion

Prediction of congestion propagation and travel times evolution has been and still is a topic actively studied in the literature. This paper tries to make its contribution by proposing a very simple method, which has the main benefit to be fully explainable compared to recent approaches based on machine learning or artificial intelligence methods.

The key component is the concept of *congestion map*, which is binary observation metric of traffic states on a freeway. By using this proxy, it reinforces the importance of focusing on traffic dynamics that on the numeric values of observations variables. Thus, the historical dataset of a French 6 km long freeway is classified into groups of days presenting similar traffic states. The second innovation of the proposed method is to identify a *consensual day* for each cluster. According to a distance based on the Rand index, the objective is to determine the day that is the most representative of the cluster. It makes it possible to find almost the expected traffic situations of this freeway: morning and evening peak hours, only morning / evening peak hours, all day long congestion, free-flow day, holiday traffic, etc.

Once those consensual days have been determined, the method can be applied in real-time to predict congestion propagation and travel times evolution. According to a real-time learning period, observations of a new day are compared to the congestion maps of the consensual days. The closest one is identified and the congestion map and speeds, that have been observed for this specific day, are used to predict the behavior of the new day for a given horizon. This very simple method gives encouraging results for both congestion and travel times evolution.

There are various future directions that can be pursued. The methodology can be improved by identifying the best duration to compare congestion maps, the accurate prediction horizon and the congested speed threshold. To perform the study, we naively tested different values but a sensitivity analysis could be conducted. A second improvement could be to use congestion maps that are no more dependent to the time of the day. The idea is to focus only on the shape of the maps, i.e. shockwaves profiles. These claims still need to be researched and validated.

6 Acknowledgment

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