Integrating the impact of rain into traffic management: online traffic state estimation using sequential Monte Carlo techniques

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ABSTRACT

This paper consists in a new step toward the integration of the effects of inclement weather into traffic management strategies. It is well recognized that adverse weather conditions are a critical factor impacting traffic operations and safety. In a previous work *(1)*, a methodology for the analysis of the rain impact has been put forward and this impact on key traffic indicators (*e.g.* free-flow speed, capacity) has been quantified. Thanks to these quantification studies, a first parameterization of the fundamental diagram according to the rain intensity is proposed. Next, since the fundamental diagram represents the basis of many simulation tools, the goal is to develop weather-responsive traffic state estimation tools, which can be useful for control applications and traffic management. More precisely, the online traffic state estimation takes place within a Bayesian framework with particle filtering techniques (*i.e.* sequential Monte Carlo simulations) in combination with a parameterized first-order macroscopic model. This approach has already been validated for sensor diagnosis and accident detection. Here, the goal is to show how the integration of the weather effects can improve this efficient tool. The approach is validated with real world data from the Lyon's ring road section (8 sensors from a homogeneous section). The results from different scenarios show the benefits of the integration of the rain impact for traffic state estimation. Strategies to detect a rain event in time and in space are also suggested.

INTRODUCTION

Effects of adverse weather on traffic, parameterization of traffic models.

Facing the growing complexity of road networks, road managers and road operators need proactive decision support systems (DSS) tools taking into account the critical factors impacting traffic operations. Among these factors, adverse weather events are of paramount importance: the literature about this subject is becoming more comprehensive not only from a safety point of view *(2, 3)* but also from a traffic one. At a macroscopic level, the impact of precipitation on the fundamental diagram and its parameters (capacity, free-flow speed, density) is well known, as recent studies confirmed (Rakha et al. *(4)*, Moons et al. (5), Unrau and Andrey (6), Billot et al. *(7)*, El Faouzi et. al *(8)*). In a previous work *(1)*, we proposed a multi-level approach (micro-, meso- and macroscopic-) and a methodology for such analyses. The empirical results have confirmed the general trend with a clear effect of precipitations on drivers' microscopic behaviours which reflect onto the macroscopic traffic variables *(1)*. Figure 1 summarizes some of the most relevant effects of precipitation at these two levels.

DRIVERS' BEHAVIOUR	Speed and acceleration	↘
	Time Headways	↗
	Spacing	↗
TRAFFIC OPERATIONS	Capacity	↘
	Traffic Volume	↘
	Speed	↘
	Speed Variation	↗
	Congestion Severity	↗

FIGURE 1: summary of precipitation effects on traffic and drivers' behaviors

Despite the fact that the effects of adverse weather conditions on traffic are well known, new studies are still needed since the heterogeneity of the sections, the lack of data as well as the regional differences prevent indeed from having a homogeneity in the results with a wide range of meteorological factors (heavy rain, snow). Nevertheless, the first basis of results, especially results focusing on interurban areas and freeways, enables a relevant parameterization of the macroscopic traffic models regarding the precipitation intensities. Traffic modelling is one of the main elements for the estimation and prediction of traffic. Therefore, the refinement of traffic models can lead to the improvement of the estimation tools, and, hence, the development of traffic management strategies.

Real-time traffic state estimation

In Active Traffic Management (ATM), traffic state estimation is often used for monitoring and control applications. Real-time traffic state estimation resides in the online estimation of the traffic state vector X along a road strech, knowing all the past measurements on the system. The vector X contains all relevant information describing the system (*i.e.* flows, speeds, densities). The measurement vector Y represents noisy observations related to the state vector. In signal processing, Kalman filters *(9)* have been widely used, providing an estimation of the state of a linear dynamic system from noisy measurements. Regarding traffic control applications, the non-linearity of the system has conducted researchers to apply alternatives from the Bayesian modelling framework which are not restricted by linearity hypotheses, among which extended Kalman filters, unscented Kalman filters and particle filters, as summarized in Arulampalam et al. *(10)*. Wang et. al. *(11)* applied extended Kalman filtering (EKF) in combination with a stochastic traffic model to carry out the traffic state estimation. The approach is validated with real-world data, eight-hour traffic measurement data collected from a freeway stretch of 4.1 km. The authors underlined the fact that appropriate and adaptative traffic parameters values are needed for such estimations. More recently, their work was extended with real-time traffic flow variables joint estimation *(12)*. However, in the extended Kalman filters, whereas the state transition and observation models do not need to be linear functions, the system is linearized at the estimated state (linearization around the current estimate). That is why unscented Kalman filters were proposed more recently *(13)*, aiming at predicting more accurately the system, without the linearization steps required by the EKF. In Hegiy et al. *(14)*, the authors deal with the comparison of extended and unscented Kalman filters for road traffic application. The performances of the two techniques were nearly equal.
In this paper, particle filtering will be used, which appears to be a sophisticated alternative to derive the traffic state estimation. Particle filters, also known as sequential Monte-Carlo methods, have been extensively described in *(10, 15)*. Regarding applications to traffic, particle filters have been applied in *(16, 17, 18, and 19)*. The promising results have demonstrated the accuracy of Sequential Monte Carlo Methods. Moreover, the constant increase of computing power leaves no doubt as to their relevance for traffic state estimations.

Objectives of the work

The bottom line of this work is the integration of the weather effects into a traffic state estimation method, enabling the development of weather-responsive traffic management strategies. As mentioned before, sequential Monte Carlo (particle filters) will be used in combination with a macroscopic traffic model, parameterized by the rain intensity. The paper is organized as follows: the next section will describe the modelling framework: the LWR model (Lighthill, Whitham and Richards), the parameterization of the fundamental diagram and the sequential Monte Carlo techniques. Section 3 deals with the presentation of results from real-world data. The performances of the estimations will be demonstrated and the benefits of the integration of the rain effects will be highlighted. In this way, some scenarios with rain events in time and in space have been set up. Strategies to detect and react to these events are proposed. The last section discusses extensions of this work and further research about the weather impact on traffic and its integration into DSS.

MODEL FORMULATION AND BAYESIAN FRAMEWORK

Macroscopic traffic model

In the following study, the traffic model we are going to use is the Daganzo's sending-receiving cell version of the LWR model *(20)*. The model is classically written in a numerical discrete version (figure 2) at a section level. The motorway section is divided into n cells of length Δx_i. The cell contents are updated every Δt_N where the subscript *N* stands for numerical. Moreover, each cell is given a fundamental diagram, which may vary in time.

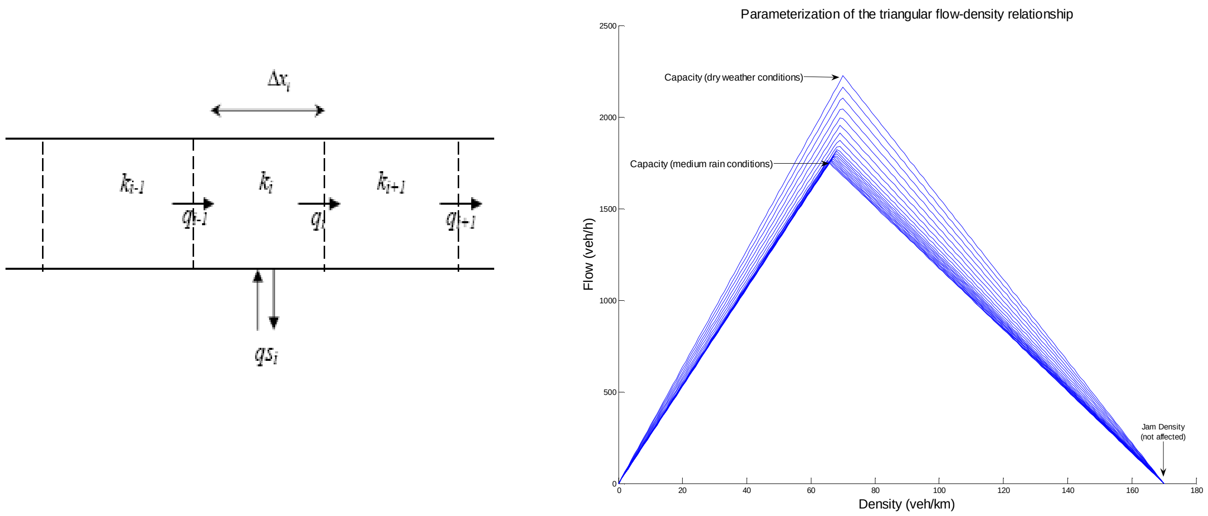

FIGURE 2: space discretization and parameterization of the fundamental diagram from empirical studies

From the space discretization, a classical Godunov scheme is applied, whose solution approximates the entropy solution *(21)*. The straightforward Godunov scheme consists of the two following equations:

$$\begin{cases} k_i(t+\Delta t_N) = k_i(t) + \dfrac{\Delta t_N}{\Delta x_i}\big(q_{i-1}(t) - q_i(t)\big)\ (conservation\ equation) \\ q_i(t) = \min\big(\Gamma_i(t), \Omega_{i+1}(t)\big)\ (flow\ equation) \end{cases}$$

The second equation simply traduces the fact that the resulting flow in cell i at time t will be the minimum between the cell $i+1$ supply $\Omega_{i+1}(t)$ and the cell i demand $\Gamma_i(t)$. The numerical time step is a sub-multiple of the observation time step (data are provided every 6min in our case) fulfilling numerical conditions (CFL).

In this paper, a triangular fundamental diagram is used. The originality of our approach lies in its parameterization (figure 2), which was carried out thanks to previous quantification studies of the rain impact on the fundamental diagram *(1)*. These studies have highlighted significant reductions of capacity, critical density and free-flow speed under light and medium rain conditions (up to 3 mm/h). These results are only valid with interurban areas or urban freeways, like the section we are going to study. Moreover, it must be precised that the jam density k_M was not affected by inclement weather conditions. This fact is in accordance with physical considerations since the maximum number of vehicles in a section still remains the same whatever the conditions are *(4,1)*.

Thus, based on quantification studies results, a weather-responsive macroscopic traffic model is proposed in such a way that our estimations could be adapted online to the prevailing weather conditions.
The state vector (length $2n+1$) to be estimated consists of the flows and densities in the n cells of the section:

$$x_t = (k_1(t), \dots, k_n(t), q_0(t), \dots, q_n(t))^T$$

The inputs u_t on the system are the demand upstream and the supply downstream of the considered section and other perturbations (incidents, work zones).
The state equation is then written as follows:

$$\mathrm{x_{t+1} = f(x_t, u_t)}$$

Sequential Monte Carlo technique for traffic state estimation

This simulation will be placed in a Bayesian Framework and more precisely deals with a Sequential Monte Carlo (SMC) filtering *(15)*. In the Bayesian framework, the dynamic state estimation is carried out through the construction of the posterior probability density (PDF) of the state based on all available information and new measurements. In order to make this estimation in time, recursive filtering is a convenient solution. The traffic model described before is viewed as a Markov Process of initial distribution $P(x_0)$ and transition equation $P(x_t|x_{t-1}, u_{t-1})$. The observations y_t depend on the state vector x_t and have then the conditional distribution $P(y_t|x_t)$. The goal is to recursively estimate in time the probability to have the distribution $x_{0:t}$ knowing the measurements and the inputs. Within the Bayesian framework, a classical straightforward recursive formula is obtained:

$$P(x_{0:t+1}|y_{0:t+1}, u_{0:t}) = P(x_{0:t}|y_{0:t}, u_{0:t-1}) \times \frac{P(y_{t+1}|x_{t+1})P(x_{t+1}|x_t, u_{0:t})}{P(y_{t+1}|y_{0:t}, u_{0:t-1})}$$

Since this theoretical solution cannot be determined analytically, the sequential Monte-Carlo approach is a technique for implementing the sequential Bayesian relations by Monte Carlo simulations, the required posterior density being represented by a set of random samples with associated weights. The main ingredients of the application of the SMC techniques to traffic flow estimation are also described in Sau *et. al. (18)*.
In this work, a partial Gaussian state space case approximation is carried out, the Markov model being written as follows:

$$\begin{cases} x_t = f(x_{t-1}, u_{t-1}) + \varsigma_t \;\; with\; \varsigma_t \sim N(0, Q_t) \\ \quad y_t = Cx_t + \varrho_t \; with\; \varrho_t \sim N(0, R_t) \end{cases}$$

Where C is a real $N \times N$ matrix and the diagonal matrices Q_t and R_t are made of respective state and observation vectors noise standard deviations.
In this case, the updates of the samples and weights are simplified. We refer the reader to *(15)* or *(18)* for the exact expressions of these updates.

RESULTS FROM REAL WORLD DATA AND ADVERSE WEATHER SCENARIOS

Data and pilot section

The study concerns the Eastern part of Lyon's ring road, an urban motorway of the third biggest city in France (Figure 3). Six-minute aggregated traffic data were provided by the French road manager CORALY. More precisely, the data were collected by 8 sensors located all along a section between the 4.5 km and the 10.1 km points in the North-South direction
For setting up the simulation scenario, a typical day's upstream demand and downstream supply and balances of ramp movements was generated. The profiles of these external actions on the motorway system are derived from the real data. Smoothed means from highway flow measurements in March 2007, on two similar weekdays (Tuesday and Thursday) were performed.

The motorway section under consideration is the most frequently congested part. The upstream flow comprises the flow from North-West Lyon and the on-ramp from the Geneva highway. Therefore, the upstream demand presents high values on classical peak hours in the morning and at the end of the afternoon.

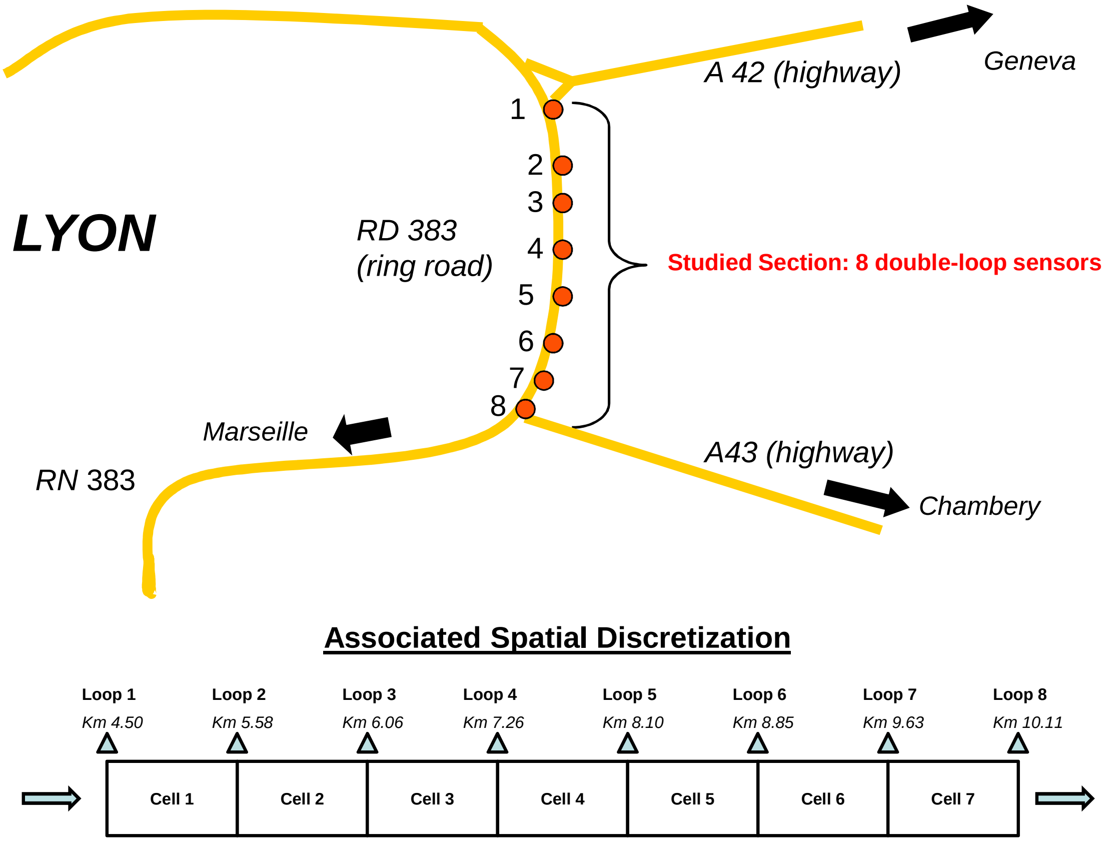

FIGURE 3: Test site and associated spatial discretization

According to the section configuration, the space discretization of our traffic model has been carried out in such a way that the discretized cells are the segments between two consecutive sensors (figure 3). Hence, we have 7 cells and 8 sensors. In this highway section, three on and off-ramps are located on cells 3, 4 and 6. Therefore, in the traffic model, source terms have to be considered in these cells (terms qs_i in figure 2).

Hypotheses and models parameters

Although Sequential Monte Carlo Methods can be very useful for sensor diagnosis *(18)*, we will rather consider during this simulation that no sensors failure occurred. Indeed, the estimation drifts will be just due to adverse weather conditions and the goal is to highlight the benefits of the knowledge about these effects from a traffic management point of view. In this way, we will also consider that the road operator can have an access to the weather information in general (amount of precipitation in mm/h) and is able to switch to the correct fundamental diagram (no search for the correct rain intensity).

Under dry weather conditions, the fundamental diagram of the LWR model presents the following parameters:

- Critical density: $k_c = 0.1 \text{ veh/m}$
- Maximum density: $k_M = 0.35 \text{ veh/m}$
- Maximum flow: $q_M = 167 \text{ veh/min}$

The variance-covariance matrices used in the sequential Monte Carlo treatment also have to be selected. For the flow measurement uncertainty we have chosen a standard deviation of $\sigma_R = 4.2$

veh/min (consistent with empirical analysis conducted on the raw data collected on this network). Hence, the variance-covariance matrix is then defined by: $R_t = diag(\sigma^2{}_R)$. Regarding the uncertainty of the state equation, the standard deviation was equal to 1/10 of the measurement one and assigned to the flow part of the state vector (σ_Q=0.42 veh/min). In other words, we assume the choice that the model is more robust than the measurements. The density magnitudes are much smaller than those giving the flow; therefore the standard deviation of the density part of the state vector is chosen to be

$$\sigma_k = \sigma_q \times \frac{k_c}{q_m} = 0.25 \times 10^{-3} \text{ veh/m}$$

Thus, the n first diagonal elements of the Q_t matrix are equal to $\sigma^2{}_k$ whereas the $(n+1)$ last ones are equal to $\sigma^2{}_q$.

Sequential Wald tests for estimations' drift detection

In order to set up an efficient alarm procedure for the detection of estimation errors, sequential Wald tests were implemented (Wald *(22))*. A Wald test is a statistical test usually used to detect whether a significant effect (*i.e.* difference between measurements and re-estimations) exists or not. Unlike classical tests, an essential feature of a sequential test is that the sample size is not predetermined but evaluated as it is collected, in contrary to classical t-test procedures. The test decision process is characterized by the existence of an indifference region in the decision rule. As in classical hypothesis testing, the sequential Wald test starts with a pair of hypotheses, H_0 and H_1, for the null and alternative hypothesis respectively. Regarding the presented study case, the goal is to detect a drift $\pm D$ which symbolizes the error between the measurements and the estimations, enabling a detection of the inclement weather conditions. In the following application, D was equal to 2 veh/min. Let us call p the drift parameter to be estimated. For each sensor, two tests were implemented with the classical H_0 and H_1 hypotheses:

Test T_1: $\begin{cases} H_0: p = 0 \\ H_1: p \geq D \end{cases}$ and Test T_2: $\begin{cases} H_0: p = 0 \\ H_1: p \leq -D \end{cases}$

In a Wald test, the next step is to calculate sequentially the sum of the log-likelihood ratio Λ_t (as a new data arrives):

$$Z_t = Z_{t-1} + \log \Lambda_t$$

Regarding the decision rule, two thresholds a and b are defined ($a < b$), according to the desired type 1 and type 2 errors (false positive and false negative errors) α and β:

$a = log\frac{\beta}{1-\alpha}$ and $b = log\frac{1-\beta}{\alpha}$

In our application, in order to generate few false alarms, α and β were equal to 0.01 and 0.05.
Based on this threshold, a simple stopping rule is defined: H_1 is rejected if $Z_t \leq a$, accepted if $Z_t \geq b$. In case of critical inequality, that is $a < Z_t < b$, we are in the indifference region, no decision is made, testing continues.
These sequential Wald tests, also known as sequential probability ratio tests, were implemented for each sensor during the next scenarios. The robustness and sensitivity of these tests should help to detect accurately estimation drifts, enabling a fundamental diagram's switching.

Scenario 1: rain over the whole section between 6 and 10am

For the first scenario, light rain conditions were simulated over the whole section between 6 and 10am, that is to say that all cells were concerned by the adverse weather conditions during this period (figure 4). The aim of this scenario is to show how this rain event can be detected in time by the sequential tests and how the change to a light rain fundamental diagram corrects the drifts.

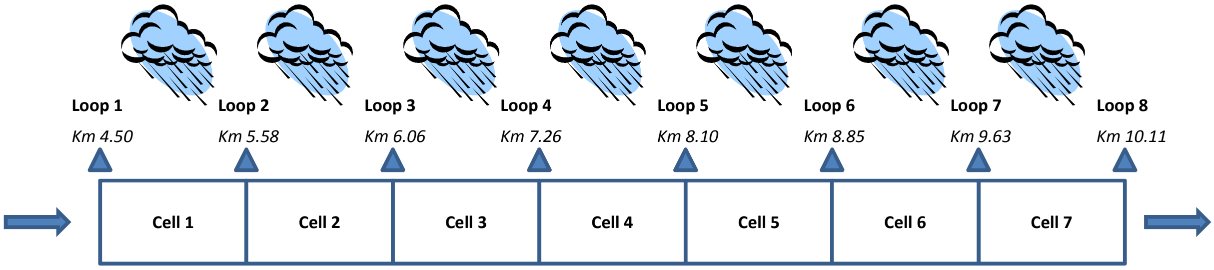

FIGURE 4: Scenario 1. Light rain over the whole section between 6 and 10am

During the light rain meteorological conditions, we know from previous studies *(1, 7)* that all traffic models parameters drop (*e.g.* capacity is reduced by 15% and free flow speed by 8%). In Figure 5, the flow estimations results and the flow measurements for the test day are reported. If a "dry weather" fundamental diagram is kept, estimation errors come on light during the rainy period (figure 5).

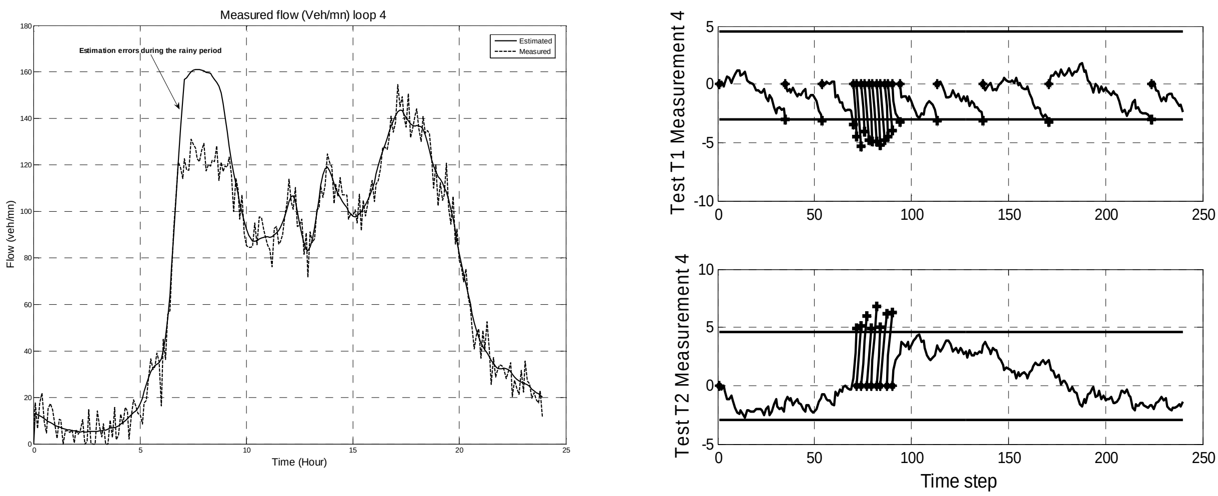

FIGURE 5: Estimation errors and Wald tests results for scenario 1(example with loop 4)

Figure 5 also indicates the sequential Wald test results, which confirm the graphical observations. Before time step 60, when dry weather conditions prevail, one can see that for test T_1, H_0 can always be accepted. If the results for test T2 are analyzed, it is observed that the lower boundary is always reached (H_0 accepted) before time step number 60, when we know that the weather conditions are normal. After this time step and until time step 100, light rain conditions lead to the upper boundary crossing, indicating that H_1 would be the correct decision, that is $d \leq -2veh/min$. These results show how the Wald tests can also help to detect in time inclement weather conditions. Thanks to this information, it is possible to switch to an adverse weather fundamental diagram. In this case, the estimations become correct (figure 6). In sequential tests, the upper boundary is never reached. In the lower part of figure 6, QQplots between estimations and measurements are more linear after this correction (right side), traducing a better similarity between the two quantities.

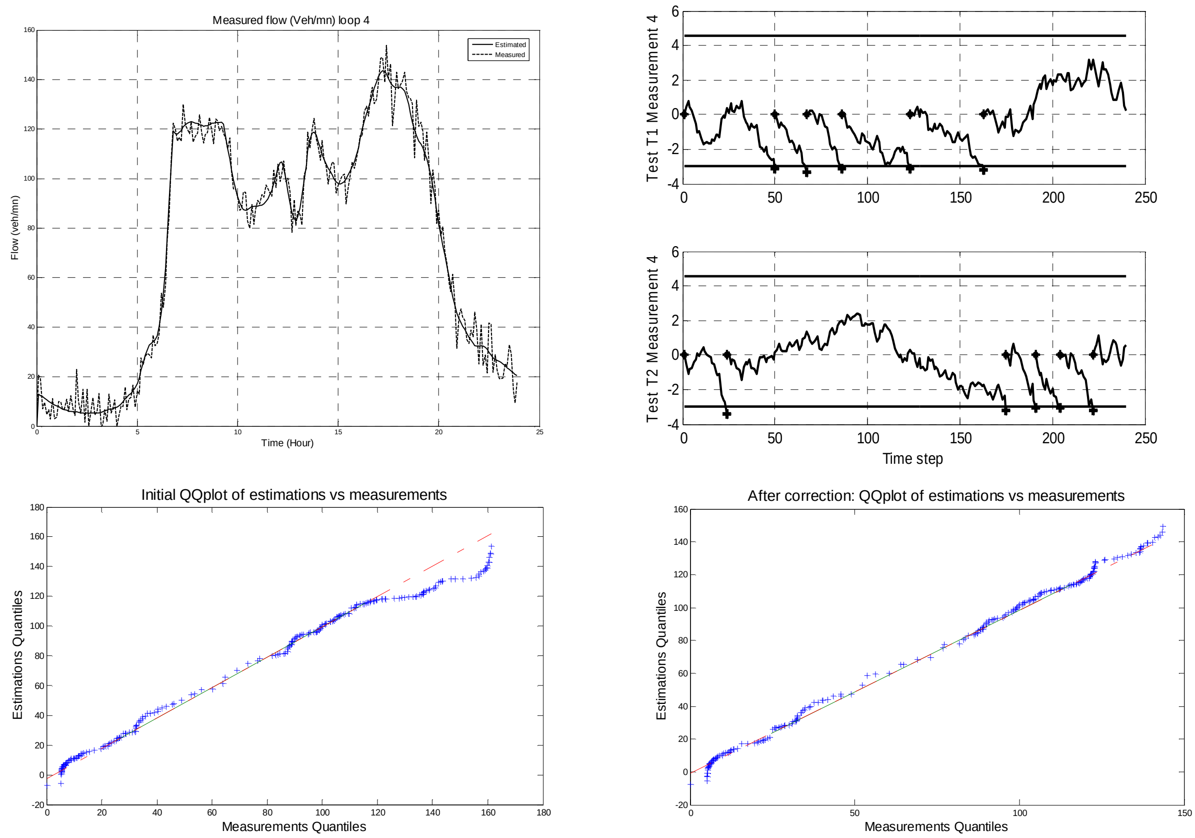

FIGURE 6: estimations after correction (top). QQplots of measurements vs. estimations before (left) and after (right) correction (bottom).

This first scenario dealt with a classical rain event which can perturb the estimations if the traffic model parameters are not weather-responsive. Thanks to the sequential probability ratio tests, it is possible to detect in time the errors made by the Monte Carlo estimations. The next scenario is more complex as it will concern a localized weather event to be detected in time and in space. We will see that this kind of events is more challenging.

Scenario 2: one sensor concerned by a localized medium rain event between 4 and 8pm

Especially during the summer period in France, weather events can be more localized (*e.g.* thunderstorms) and hence, represent a challenge for a road manager. Indeed, this type of events is usually heavy in terms of precipitation intensity and the resulting perturbations can propagate very quickly, leading to a degradation of the global level of service. In this second scenario, such a scenario has been simulated by introducing the effects of a medium rain event only onto cell 6 (figure 7).

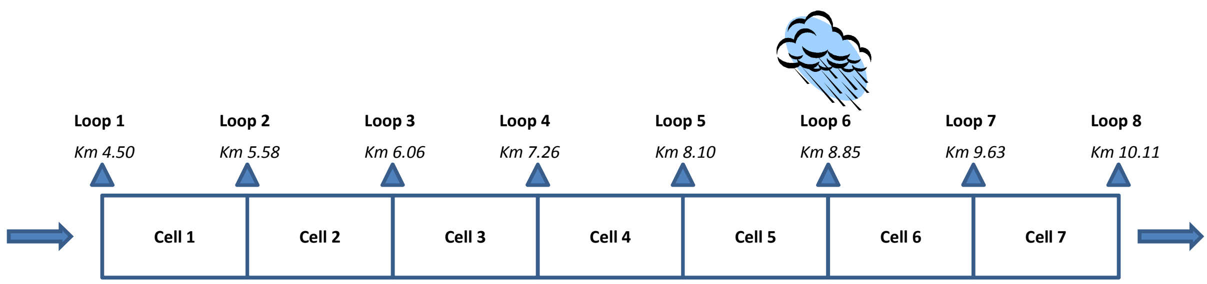

FIGURE 7: scenario 2. Localized rain event (loop and cell 6) between 4 and 8pm

Since localized events are more intense, models parameters reductions were stronger (capacity decreased by 20%). This perturbation was placed between 4 and 8pm. As the first scenario, this perturbation leads to a drift during the rainy period. However, although the event concerns just one cell, all the sensors are affected by estimation errors: the perturbation propagated onto the whole section and it is impossible to determine its precise location with a classical procedure. Figure 8 shows the errors for loop 6 and loop 2. It can be seen that the upper boundary is reached in the two cases for test T_2 during the rainy period

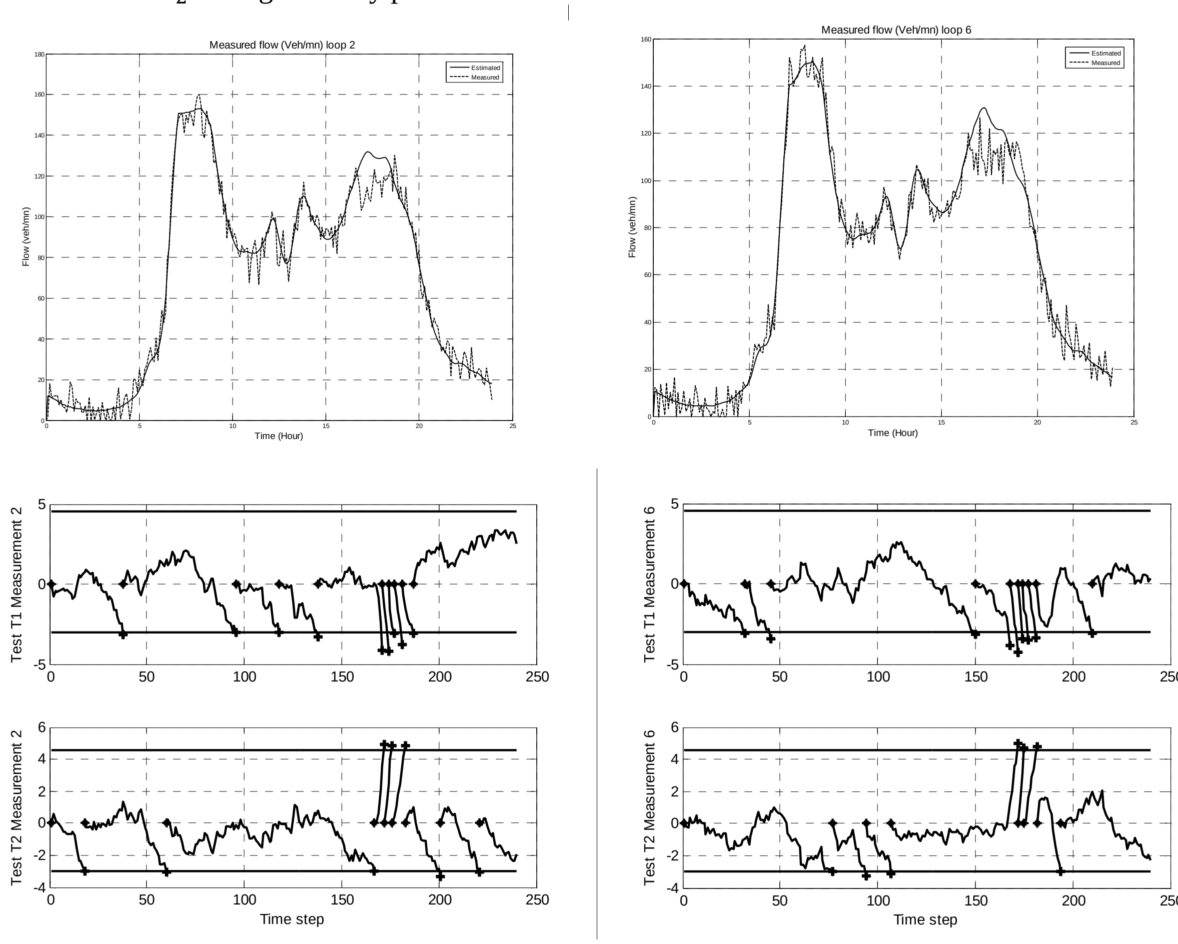

FIGURE 8: Scenario 2. The estimations errors reflect on all sensors (example with sensors 6 and 2)

In the light of this difficulty, it is necessary to implement a procedure in order to detect the location of the weather event. A space detection procedure is proposed here. The principle is to correct and test iteratively each cell by switching to a medium rain fundamental diagram. At the end of each iteration, a statistical test is carried out in order to compare *a posteriori* the final distributions of measurements and re-estimations for all sensors. At the end of the procedure, the global p-values and test statistics are compared to determine for which cell the modification of the parameters have produced the better results for the whole section. The sensor number maximizing these statistics is logically the number of the cell where the weather event occurred (loop 6 in our case). Before describing the algorithm, let us describe the statistical test used in the procedure. To test if two samples come from the same distribution, non-parametric Kolmogorov-Smirnov tests are often used. One weakness of a Kolmogorov test is that only the maximum difference between cumulative frequency distributions is taken into account. This drawback is corrected by Cramer Von Mises tests *(23)*, which compute a L_2 norm of the differences, taking better into account the whole distribution. Cramer Von Mises test has exactly the same application than a Kolmogorov test. In case of a two-sample test, this test is more powerful than a Kolmogorov test *(23)*.

The test statistic for two distributions F_1 and F_2 is similar to:

$$T = \int [F_1(x) - F_2(x)]^2 dx$$

Then, the test is classical with the two hypotheses H_0 and H_1:

$$\begin{cases} null\ hypothesis\ H_0: F_1(x) = F_2(x)\ for\ all\ x \\ alternative\ hypothesis\ H_1: F_1(x) \neq F_2(x) \end{cases}$$

Cramer Von Mises test were carried out at a significance level $\alpha = 0.05$ with associated p-values and test statistics.
Based on these tests, the pseudo-code of the space detection procedure is written as follows:

Begin
<u>Step 1: iterative test.</u>
For i in 1: number of cells do

1. **Correction** : switch to an adverse weather fundamental diagram for the cell i
2. **Estimation**: launch the estimations with the previous parameters.
3. **Evaluation**: Comparison of measurements and estimations for all sensors with Cramer Von Mises tests (CMV). Mean p-values and CMV statistics are recorded.

End For
<u>Step 2: detection</u>
The critical cell is detected as those who maximizes the mean p-value and minimizes the CMV statistic.
End

This procedure was successfully applied to Scenario 2. Figure 9 presents the distributions of p-values and CMV statistics. One can remark that sensor 6 correction (where the weather event was located) maximizes the probability that measurements and estimations come from the same distribution. The procedure enables the detection in space of the event and the readjustment of the estimations. If the estimations are rerun with a simple correction for cell 6, estimations become correct again for all sensors (lower part of figure 9).

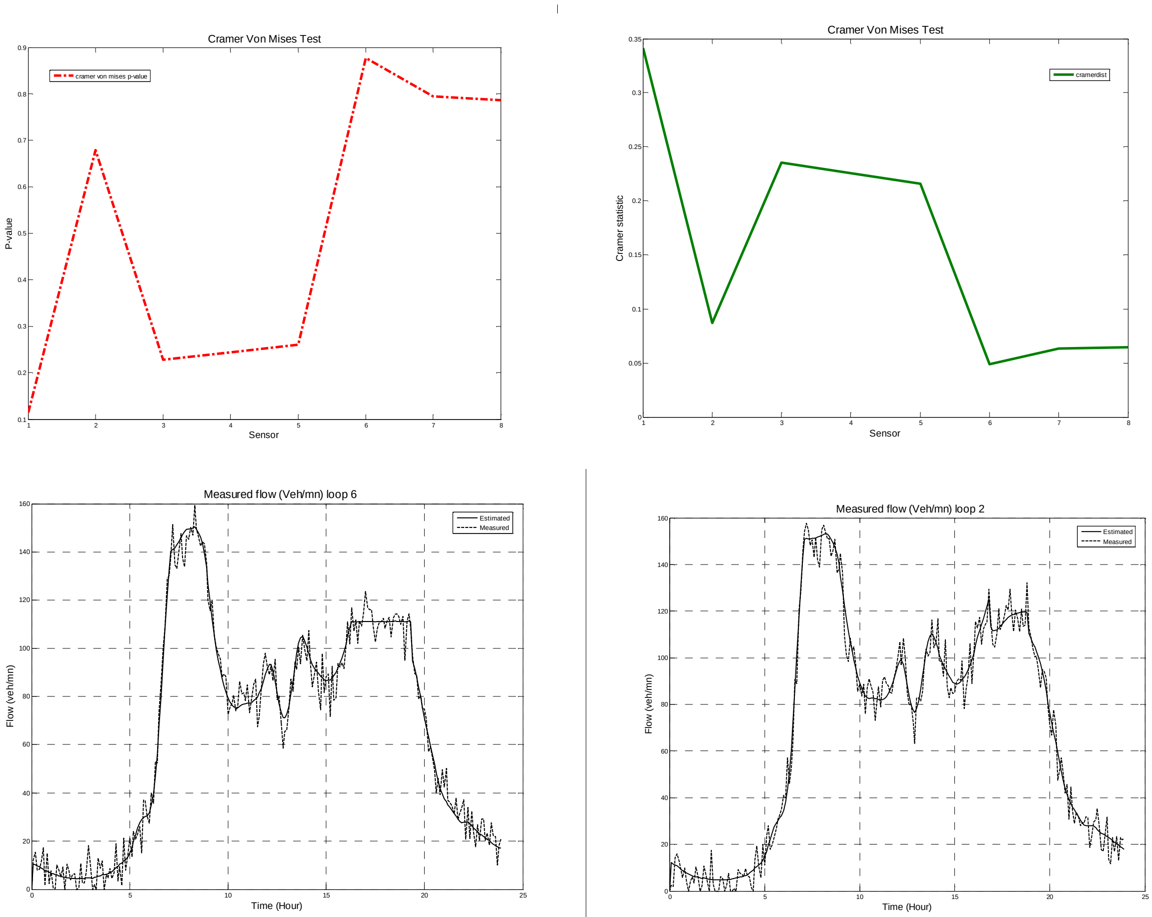

FIGURE 9: Scenario 2. Cramer Von Mises tests results for space detection (top). Corrected estimations for sensors 6 and 2 (bottom)

CONCLUSIONS AND PERSPECTIVES

In this paper, weather-responsive strategies for traffic state estimations have been proposed. Thanks to previous quantification studies about the rain impact on traffic models parameters, the purpose was to show how the new knowledge about this impact can be integrated into simulation tools. Traffic models are the basis of many decision support tools and their parameterization can help the road operators to respond to the meteorological changes. In this work, traffic state vector estimations were carried out through the use of sequential Monte Carlo methods, whose performances have been already demonstrated for control applications such as sensor diagnosis or accident detection. Sequential Wald tests are a key element of such an alert system which can be generalized to detect all the elements impacting the traffic operations and the level of service. Here, the uncertainty factor was the prevailing weather conditions and two scenarios were set up from real world data (one day data from the Lyon’s ring road). The first scenario was the basic case where a rainy period occurred over the whole section. The results prove that it is possible to detect the rain in time and correct the estimations by switching from a fundamental diagram to another one (adverse weather fundamental diagram).With regard to the detection in space (scenario 2), a localized weather event was simulated over one cell. Since the error can propagate over the other cells, a space detection procedure has been proposed to detect which cell is really concerned by the perturbation and to correct it. This scenario seems to be relevant as the meteorological information has not the granularity implied by such a section.

Regarding the perspectives, it appears logical to make the scenarios more complex *(e.g.* more localized and shorter events over several cells) and to observe the estimations results as well as the detection problems. As for the traffic model, the lack of data prevented from having a wide range of precipitation intensities. Quantification studies must be carried on to obtain a parameterization of the fundamental diagram from dry to heavy snow weather conditions.

With regard to the estimation tool, that is Sequential Monte Carlo methods, our ongoing research deals with a refinement of the tool with new features like online traffic parameters estimation and importance sampling.

To conclude, this paper was an attempt for the integration of the weather effects into decision support tools. The validation with real-world data proved that this approach can bring many benefits to the road operators, the promising results paving the way for weather-responsive traffic management.

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