

H14-203

THE “VOTRE AIR” PROJECT : DEVELOPMENT OF A MODELLING TOOL TO ASSESS THE REAL ATMOSPHERIC EXPOSURE IN PARIS

Frédéric Pradelle<sup>1</sup>, Fabien Brocheton<sup>1</sup>, Benjamin Chabanon<sup>1</sup>, Cécile Honoré<sup>2</sup>, Fabrice Dugay<sup>2</sup>, Karine Léger<sup>2</sup>, François Dambre<sup>2</sup>, Vivien Mallet<sup>3</sup> and Anne Tilloy<sup>3</sup>, R. Olesen<sup>1</sup> and Helen Higson<sup>2</sup>

<sup>1</sup> NUMTECH, Aubière, France

<sup>2</sup> AIRPARIF (Association in charge of air-quality monitoring in the Paris area), Paris, France

<sup>3</sup> Institut National de Recherche en Informatique et en Automatique (INRIA), Rocquencourt, France

**Key words:** Urban air-quality modelling, data assimilation

**INTRODUCTION**

Traffic generates about 60% of the Paris nitrogen dioxide and particles emissions, and the levels of these pollutants are a major concern, in particular near by the road traffic. Therefore, the realistic characterization of the population exposure draws special attention from the concerned actors. Nowadays, high resolution modelling tools like Urban’Air well reproduce the spatial distribution of atmospheric pollutants concentrations at the city scale. One limitation of these new modelling tools is that they are most of the time provided with “standard temporal profiles” of emissions data (weekly and monthly profiles), instead of real-time traffic data. Moreover, the pollution measured at the monitoring stations is not generally taken into account in the computations. The “Votre Air” project’s aim was to develop a numerical tool to provide realistic and real-time estimation of the air quality at the scale over Paris Center. In this paper, we especially detail how the real-time concentration observations are assimilated in order to better reproduce the chemical state of the atmosphere. The results are illustrated with nitrogen dioxide.

**GENERAL DESCRIPTION OF THE SYSTEM**

The “Votre Air” project has been designed to monitor the atmospheric pollution over Paris center on the basis of combining observations and simulations. The figure 1 presents a schematic view of the platform.

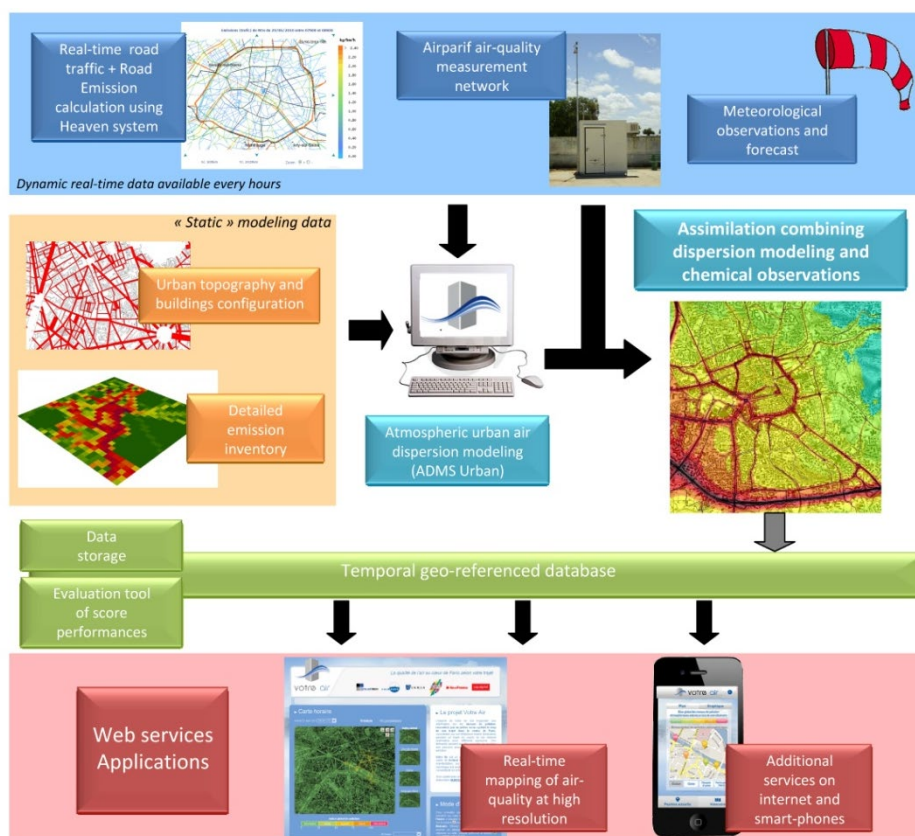


Fig. 17: Schematic illustration of “Votre Air” project’s principles.

In fact, such system has been already developed and deployed by NUMTECH over several cities in France, and is called Urban’air system (Pradelle et al., 2010). The innovations of “Votre Air” are:

- To apply an assimilation procedure at urban scale. The results of pollutants concentrations computed by the air dispersion model are immediately corrected by the assimilation of pollution measurements from Airparif fixed stations. The approach is detailed below.
- Contrary to previous applications of Urban'air, the objective was to obtain a near real-time survey (one hour of delay). This goal needs of course to gather chemical or meteorological observations in real-time. The key point is that a real-time emission system based on dynamic road traffic data is operated by AIRPARIF over Paris (Heaven system).
- To communicate pollution levels to the general public, in particular to pedestrians and cyclists, using air quality maps at spatial resolution around 10 meters and using tools such as smart-phones.

### ASSIMILATION APPROACH

In this project, the Gaussian model ADMS Urban provides the pollutant concentration at a number of receptors, these concentrations constitute the so-called forecast state vector. Model simulations and observations, like measurement from ground monitoring networks, are both uncertain and their error variances enable to determine the contribution of each source of information for assimilation in an improved state called the analysis vector. Because the model is not dynamical, the analysis state vector cannot be injected in the model for the next forecast. As a consequence assimilation methods like Kalman filters cannot be applied in this context. The analysis is computed as the Best Linear Unbiased Estimator (BLUE), based on prescribed error covariance matrices. The computations are carried out using the generic data assimilation library Verdandi (<http://verdandi.gforge.inria.fr/>), developed at INRIA.

The analysis state vector  $c^a$  is equal to the forecast state vector  $c^b$  plus a correction depending linearly on the innovation  $o - Hc^b$  where  $o$  is the observation vector and  $H$  the observation operator, as it is expressed in the equation 1. Under certain assumptions on the errors, the analysis is computed so that its error should have the minimum variance (more precisely, minimum trace of covariance matrix). This constraint leads to expression 2 of gain matrix  $K$ , where  $B$  is the state error covariance matrix and  $R$  the observational error covariance matrix.

$$c^a = c^b + K(o - Hc^b) \quad (\text{eq. 1})$$

$$K = B H^T (H B H^T + R)^{-1} \quad (\text{eq. 2})$$

At regional scale, the state error covariance matrices are often parameterized as a function of the geographical distance, e.g., with a decreasing exponential. At urban scale, the form of the state error variance is difficult to determine. Indeed, an observation located close to the road network does not provide information in isotropic way since it provides little information about the background concentrations.

### MODELING OF THE STATE ERROR COVARIANCE MATRIX

For nitrogen dioxide, we assume that an important part of the state errors originates from the traffic emissions. As a consequence, we assume high error correlations between receptors on the same road or on connected roads. Also, the error correlation between a receptor on a road and a receptor in the background should be lower than the error correlation between two (equally close) receptors on the road.

We introduce the distance  $d_{ij}$  along the road between two receptors indexed by  $i$  and  $j$ . The distance along the road is defined as the smallest distance it takes to travel on the road network between the two receptors. Because the two receptors  $i$  and  $j$  may not be located on a road, they are first projected on the road network, and  $d_{ij}$  is taken as the distance along the road between the projections. We also introduce the distance  $P_i$  of the receptor  $i$  to the road network, that is the geographic distance to the closest road.

Let  $B_{ij}$  be the coefficient ( $i, j$ ) of  $B$ , representing the covariance between the state errors at receptors  $i$  and  $j$ . The value  $B_{ij}$  is defined as

$$B_{ij} = v_s \exp\left(-\frac{d_{ij}}{L_d}\right) \exp\left(-\frac{|P_i - P_j|}{L_p + \alpha \min(P_i, P_j)}\right)$$

where  $L_d$  and  $L_p$  are characteristic distances respectively along the road network and transverse to the road network,  $\alpha$  a scaling coefficient without dimension and  $v_s$  a variance. The covariance is assumed to decrease exponentially against the distance along the road and to decrease almost exponentially in the direction transverse to the road. The correction  $\alpha \min(P_i, P_j)$  is added so that the decorrelation length is increased with the distance to the network: while the error correlation is assumed to decrease fast in the vicinity of the road, the error correlation between background receptors should remain significant across a wider scope.

Between two receptors on the road network ( $|P_i - P_j| = 0$ ), the state error covariance equals  $\frac{1}{2}v_s$  when the distance between the receptors is  $0.7 L_d$ .

### MODELING OF OBSERVATION ERROR COVARIANCE MATRIX

The observation error covariance matrix is diagonal, so that  $R = v_o I$ , where  $v_o$  is the observational error variance.

### VALIDATION OF ERROR COVARIANCE MATRICES

Since the error covariance matrices are empirically chosen, their parameters should be adjusted. We rely on the  $\chi^2$  diagnosis to choose appropriate parameters. The diagnosis enables to check the consistency between the available innovations,  $o_n - H_n c_n^b$ , and their variances,  $S_n = R_n + H_n B_n H_n^T$ , where  $n$  represents the time step.

The scalar  $\chi_n^2 = (o_n - H_n c_n^b)^T S_n^{-1} (o_n - H_n c_n^b)$  is expected to be equal to the number  $F_n$  of observations.

And therefore, we should have  $\sum_{n=0}^T \frac{\chi_n^2}{F_n} \approx T$ .

### COMPUTATION OF THE DISTANCE TO THE ROAD NETWORK AND ALONG THE ROAD

The road network is modeled by an ensemble of road segments. A receptor is projected to every road segment (orthogonal projection when possible; projection to an extremity, otherwise) and the closest projection to the receptor is selected as the projection on the road network.

The road network is seen as a non-oriented graph. A road network is in fact an association of road segments whose extremities are seen as nodes. The projections of the receptors on the road network are also seen as nodes. The road segments are seen as edges; so are the road sub-segments between the projections and the extremities of the road segments. The weight of an edge is the distance between its two nodes. The shortest paths between all nodes are computed with Johnson's algorithm, whose complexity is  $N E \log(N)$ , if  $N$  is the total number of nodes and  $E$  the total number of edges

### RESULTS ON PARIS

The  $\text{NO}_2$  concentrations in Paris center, at 1.5m altitude, have been simulated with the dispersion model at urban scale ADMS Urban, during a test period from May 2010 the 15<sup>th</sup> to June 2010 the 21<sup>st</sup>. During this period, the observation network of Airparif provided every hour measurements of  $\text{NO}_2$  at 8 stations, which are described in Table 1.

Table 2. Characteristics of the stations

Location	Name	Type	Altitude in m
Luxembourg park	PA06	Urban	12.6
Eiffel tower	PA07	Urban	4
Flocon street	PA18	Urban	16.1
Neuilly	NEUI	Urban	2.6
Elysée	ELYS	Traffic	2.1
Bonaparte	BONA	Traffic	1.7
Célestins	CELE	Traffic	1.6
Hausmann	HAUS	Traffic	3.7

The characteristic distances respectively along the road network and transverse to the road network are set to  $L_d = 1$  km and  $L_p = 50$  m. The scaling coefficient  $\alpha$  is equal to 1. Considering that the stations measure at an altitude higher than 1.5 m, there can be a non-negligible representativeness error in the observations, in addition to the measurement errors. We chose an observation error variance of  $v_o = 100 \mu\text{g}^2\text{m}^{-6}$ , which is supposed to correspond to upper bound on the uncertainty. The forecast error variance of  $v_s = 650 \mu\text{g}^2\text{m}^{-6}$  is deduced from the  $\chi^2$  diagnostic once the observation error variance is set.

Table 2. Scores of the model.

Stations	Observed mean concentrations ( $\mu\text{g}\text{m}^{-3}$ )	Bias ( $\mu\text{g}\text{m}^{-3}$ )	Correlation	RMSE ( $\mu\text{g}\text{m}^{-3}$ )	Relative RMSE
PA06	28.8	1.8	0.72	12.3	0.45
PA07	30.6	-9.7	0.69	18.0	0.44
PA18	26.2	-12.0	0.76	17.4	0.46
NEUI	31.0	2.7	0.74	14.2	0.50
ELYS	34.2	-25.2	0.61	33.5	0.56
BONA	37.6	-25.8	0.57	35.4	0.56
CELE	38.3	-38.0	0.54	47.8	0.63
HAUS	34.6	-22.0	0.54	36.6	0.61

Before assimilation, the correlation over all the stations is of 0.60 and the root mean square error, equal to  $29.2 \mu\text{g}\text{m}^{-3}$ , represents 60% of the mean observed concentration. The model better reproduces the  $\text{NO}_2$  concentrations in background areas than close to the traffic. Over the roads, the  $\text{NO}_2$  concentrations are often underestimated. See Table 2

The improvements by data assimilation at places without observation are quantified by a crossed validation. On principle, 8 stations provide observations each hour. We carry out 8 experiments, each with one station excluded from the assimilation procedure. For each experiment, the performance of the analysis at the excluded station is reported. The bias at traffic

stations, strongly negative before data assimilation, is reduced most of the time. Scores are written in Table 3. No trend predominates in case of urban stations. The correlations and the root mean square errors are always improved. The root mean square error, calculated at each station successively ignored by data assimilation, is equal to  $22.0 \mu\text{g m}^{-3}$ , which approximately corresponds to a 25% decrease. At the station Bonaparte, the root mean square error decreases by 41%.

Table 3. Scores of the model coupled with data assimilation, at the station ignored by data assimilation.

Stations	Observed mean concentrations ( $\mu\text{g m}^{-3}$ )	Bias ( $\mu\text{g m}^{-3}$ )	Correlation	RMSE ( $\mu\text{g m}^{-3}$ )	Relative RMSE
PA06	28.8	8.1	0.84	12.3	0.45
PA07	30.6	-7.8	0.79	14.8	0.37
PA18	26.2	-9.6	0.80	14.9	0.39
NEUI	31.0	5.0	0.79	13.6	0.48
ELYS	34.2	-17.4	0.81	23.9	0.40
BONA	37.6	-11.7	0.83	20.6	0.33
CELE	38.3	-30.1	0.65	39.8	0.52
HAUS	34.6	-9.4	0.77	22.6	0.40

The figure 2 represents two maps of  $\text{NO}_2$  concentrations in Paris center, before data assimilation and after data assimilation, in a case of large effects. The  $\text{NO}_2$  concentrations forecast by the model ADMS Urban are underestimated at traffic stations. The data assimilation at urban scale leads to a large increase of the concentrations along the road network. The effects on background areas are weaker since the model is more consistent with the observations.

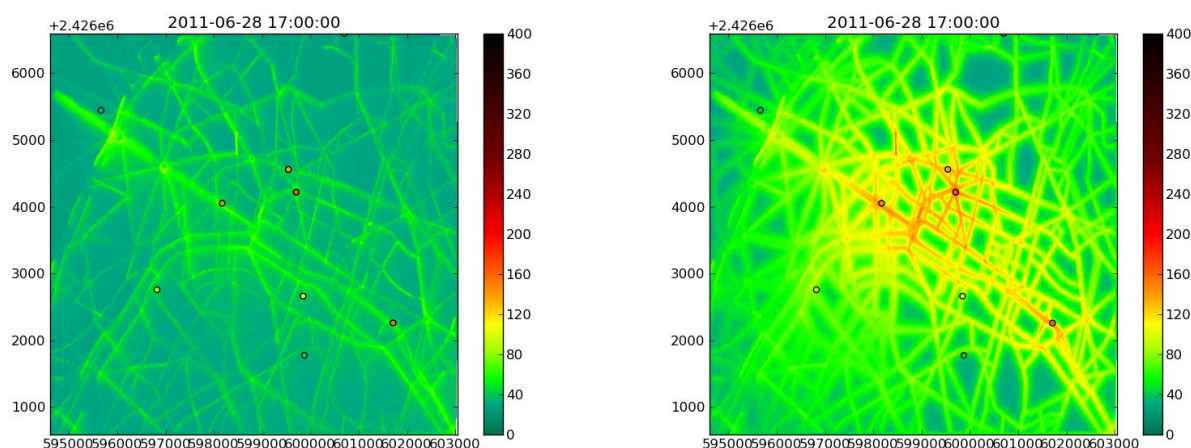


Fig. 2:  $\text{NO}_2$  concentrations forecasted by the model (on the left) and  $\text{NO}_2$  concentrations after data assimilation (on the right).

## COMMUNICATION TOOLS

In this project, in addition to the classic mapping of air-quality by a web-site, it was decided (i) to test the use of smart-phones (real-time information from geo-location), and (ii) to test a specific application for pedestrian and cyclist (possibility to compute exposure to pollution along specific itinerary in the city provided by the user). On web platform and smart-phones applications, concentrations of  $\text{O}_3$ ,  $\text{NO}_2$  and  $\text{PM}_{10}$  are shown using air quality indexes adapted to the general public. The Citeair index (<http://www.airqualitynow.eu/>, Common Information to European Air) has been selected. The “Votre Air” platform was tested in summertime 2011, during the event Festival Futur en Seine 2011 (Paris) which is dedicated to digital innovations. A questionnaire submitted to the general public showed a genuine interest in such a service.

## ACKNOWLEDGEMENTS

The authors are grateful to Cap Digital, competitiveness pole on numerical contents and services of Ile de France, for its financial support.

## REFERENCES

- Pradelle, F., A. Armengaud, C. Pesin, M.N. Rolland, J. Virga, G. Luneau, C. Schillinger, and D. Poulet, URBAN AIR System: an operational modeling system for survey and forecasting air Quality at Urban scale, proceedings of the 13th International Conference on Harmonisation within Atmospheric, Dispersion Modeling for Regulatory Purposes, Paris, France, 1-4 June 2010, p 688-692.
- Heaven system : <http://www.airparif.asso.fr/page.php?rubrique=modelisation&article=heaven>