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# A generic framework for monitoring pollution plumes in emergencies using UAVs

Ichrak Mokhtari

Univ Lyon, INSA Lyon,

Inria, CITI,

EA3720, 69621 Villeurbanne, France

ichrak.mokhtari@insa-lyon.fr

Walid Bechkit

Univ Lyon, INSA Lyon,

Inria, CITI,

EA3720, 69621 Villeurbanne, France

walid.bechkit@insa-lyon.fr

Hervé Rivano

Univ Lyon, INSA Lyon,

Inria, CITI,

EA3720, 69621 Villeurbanne, France

herve.rivano@insa-lyon.fr

**Abstract**—Monitoring air pollution plumes in emergency situations (industrial accidents, natural disasters, deliberate terrorist releases, etc.) becomes an issue of utmost importance in our society given the dramatic effects that the released pollutants can cause. Considering these situations, the pollution plume is strongly dynamic leading to a fast dispersion of pollutants in the atmosphere. Thus, the need for real-time response is very strong and a solution to get precise mapping of pollution dispersion is required to mitigate risks. However, monitoring and forecasting air quality in real time in such situations remains a highly challenging endeavour. In this paper, we suggest a systemic approach for monitoring dynamic air pollution based on aerial sensing (sensors mounted on UAVs). The proposed framework consists of a cycle with feedback loop which will constantly combine a spatio-temporal forecasting model based on a convolutional long short term memory (ConvLSTM) network with a data assimilation technique to get accurate pollution maps, while adjusting at each time the trajectories of drones following uncertainty forecasts. Our solution was evaluated and validated using a highly dynamic real world data set namely Fusion Field Trial 2007 (FFT07). The proposed strategy, together with the obtained evaluation results, are presented, and carefully analyzed.

**Index Terms**—Dynamic air pollution, Deep Learning, Data Assimilation, Uncertainty, UAVs.

## I. INTRODUCTION

Monitoring the atmospheric dispersion of toxic, explosive or irradiating pollutants, following an anthropogenic accident (industrial, transportation of hazardous materials, etc.) or a natural one (volcanic eruption, etc.) is a major issue given the dramatic effects that these plumes can cause. In these emergency situations, very large amount of pollutants are released and quickly transported over the air, as was the case during the Fukushima explosion in Japan (March 2011), the Lubrizol accident in France (October 2019) or more recently the Beyrouth harbour explosion in Lebanon (August 2020). Besides contributing to the upliftment of the global warming, these dirty emissions constitute a prominent danger for the residents of the accident area, which can lose their lives, if no adequate actions are taken rapidly. Thereby, it is primordial to efficiently follow the pollution plume and predict its trajectory in real time to permit to decision makers to take the adequate actions at time and design evacuation schemes. In such emergency situations, the strong and unpredictable dynamics of the pollution plumes, the lack of knowledge of pollution sources

and emission rates, and the strong need for reactivity make the use of conventional approaches (air quality monitoring stations, wearable or portable sensors and detectors, dispersion models alone) difficult and generally inefficient.

In another side, the current progress in developing low-cost micro-scale sensing technology and the democratization of the Unmanned Aerial Vehicles (UAVs), also referred to "drones" is radically changing the traditional approaches to allow real-time air pollution monitoring in hardly accessible areas. Coupling the data collected by the UAVs with effective spatio-temporal forecasting models would enable precise mapping and efficient forecasting of plume dispersion, in the goal to provide valuable information to mitigate the risks encountered.

In air pollution field, great efforts were devoted to the study of chronic air pollution [1]. Historically, deep learning has been gaining ground since the significant advances in hardware. Many works have reviewed recent solutions using artificial neural networks (ANNs) for air pollution predictions and have claimed their ability to extract efficient representations of relevant functionalities and characteristics from large amounts of data [2] [3]. In another side, data assimilation techniques that combine numerical models to real observations have shown great potential to get accurate pollution maps [4]. However, most works in this field are focused on addressing temporal and spatio-temporal forecasting issues for chronic air quality. Nevertheless, the spatial and temporal resolution needed in emergency situations is much higher to efficiently cover the phenomenon in real time, due to the strong dynamic of the pollution plume.

In addition, considering the criticality of the risks during these situations, it is important to consider uncertainty quantification in the predictive modelling. However, this aspect has often been unheeded when designing pollution forecasting models. In fact, providing such information in an emergency situation, makes models more reliable and hence, permits better crisis management.

In this article, we introduce a novel real-time and fine-grained air quality monitoring system based on aerial sensing for dynamic air pollution in emergency situations. The general framework is based on the following components: efficient short-term forecasting and suitable path planning approach assuming a reliable communication between drones. This

paper offers a preliminary proposal of this framework.

The main contributions of our work can be listed as follows:

- We propose a real-time and fine-grained general framework for dynamic air pollution monitoring based on aerial sensing, in the aim to follow pollution plumes. The system's architecture is designed to address air pollution monitoring issues in emergencies.
- Our proposal combines a multi-point deep learning model based on ConvLSTM network to a data assimilation technique to provide better estimations of the pollution map, while constantly update the trajectories of the UAVs with the goal to minimize the predictions uncertainty.
- We validate our general framework using a simple path planning heuristic and we apply our proposal on a highly dynamic real world data set namely Fusion Field Trials 2007 (FFT07). Several experiments have been conducted to demonstrate the effectiveness of our framework, where the impact of the number of drones deployed have been carefully investigated.
- Our results highlight the following engineering insights: using a small fleet of drones coupled with data assimilation instead of forecasts alone gives satisfactory results. In addition, our study suggests that it may be a good strategy to deploy many drones at the beginning and keep a smaller fleet on the long term. This would allow a better management of drones autonomy.

The remainder of the paper is organized as follows. Section II describes the context of the considered problem, the different hypothesis taken and our objectives. Then, section III formulates the dynamic air pollution monitoring problem based on aerial sensing. Section IV introduces our proposed approach to address the considered problem with details of its different parts. Section V presents the experimental settings, elaborates the evaluation results and show the effectiveness of our framework. Further, in section VI, we present the prior works while section VII concludes this paper and draws future work.

## II. CONTEXT, HYPOTHESIS AND OBJECTIVES

In this work, we consider the case where a pollutant plume is released following an accident or a deliberate action. We focus on monitoring outdoor plumes and without loss of generality, we consider gaseous air pollutants. Initially, we assume that we have little or no knowledge of the pollutant dispersion (plume size, plume contour, release source, emission rate, etc.). We envisage the use of connected UAVs that should be deployed as soon as the alert is given and should coordinate in order to timely monitor, characterize and follow the pollutant plume. We consider to that end the case of a fleet of UAVs equipped with adequate on-board environmental sensors, GPS, processing capabilities and wireless communication interfaces. For this study, we assume the use of rotary wing UAVs capable of performing hovering flight. In addition, We assume that the sensors are calibrated properly as recommended by manufacturer to reduce the sensor's errors. Regarding communication, we assume that drones remain connected to a central point (a

station on the ground or a leader UAV) when travelling within the area of interest.

Taking the aforementioned assumptions into consideration, our goal is to design an air pollution monitoring system for emergency situations based on a cooperative fleet of drones, in order to efficiently follow the pollution plume and mitigate the different risks. More precisely, the objectives of this study are dual: we aim to provide a best guess of the pollution plume while optimizing the path planning of the UAVs. These objectives are intrinsically dependent. Indeed, the pollution concentrations estimates impact the deployment strategy of the drones (e.g. push the drones to measure more in certain locations depending on the prediction results) and conversely, the deployment of the aerial sensors influence the effectiveness of the short-term prediction model.

To achieve these targets, we introduce a general framework designed to perform real-time monitoring of dynamic pollution plumes. Fig 1 presents a high level view of our framework. As can be shown, our approach is comprised of three major parts including: reliable communication between UAVs, spatio-temporal prediction and anticipatory path planning. The envisaged general approach consists in a cycle with feedback loop that may start with a short setup phase of regular or random navigation of the UAVs. After that, at each step the UAVs perform environmental measurements thanks to their different sensors. Then, all UAVs communicate their data to a central point (station on the ground or a leader UAV). The latter performs spatio-temporal prediction based on current and past data and computes short-term forecasted pollutant concentrations as well as the corresponding uncertainties. The pollution forecasts are then corrected using an appropriate chosen method (e.g. data assimilation technique). Afterwards, the central point computes optimal path planning based on these precedent predictions as well as current UAV positions, it then communicates the new suitable positions to each UAV. After moving to the next positions, all UAVs perform again the sensing process and so on. The proposed approach will continuously combine prediction of the plume evolution to optimized path planning algorithms in order to ensure the best plume characterization. Note that the power consumption as well as communication issues are out of the scope of this article and will be considered in future work.

## III. PROBLEM FORMULATION

In this section, we present the mathematical formulation that describes our dynamic air pollution monitoring problem. Let's consider a map of a given area that we call the monitoring region. The latter is discretized to get a set of points  $\mathcal{P}$  that approximate our region of interest with a high spatial granularity  $|\mathcal{P}| = n$ . We consider an aerial sensing system consisting of  $m$  drones that move between the  $n$  potential positions within the monitoring region in order to collect air pollution measurements  $z$ . Our objective is to be able to provide high quality forecasts of the concentration values at each point  $p \in \mathcal{P}$  in the near future, while considering at each time  $t$  an optimal redeployment scheme of the drones with

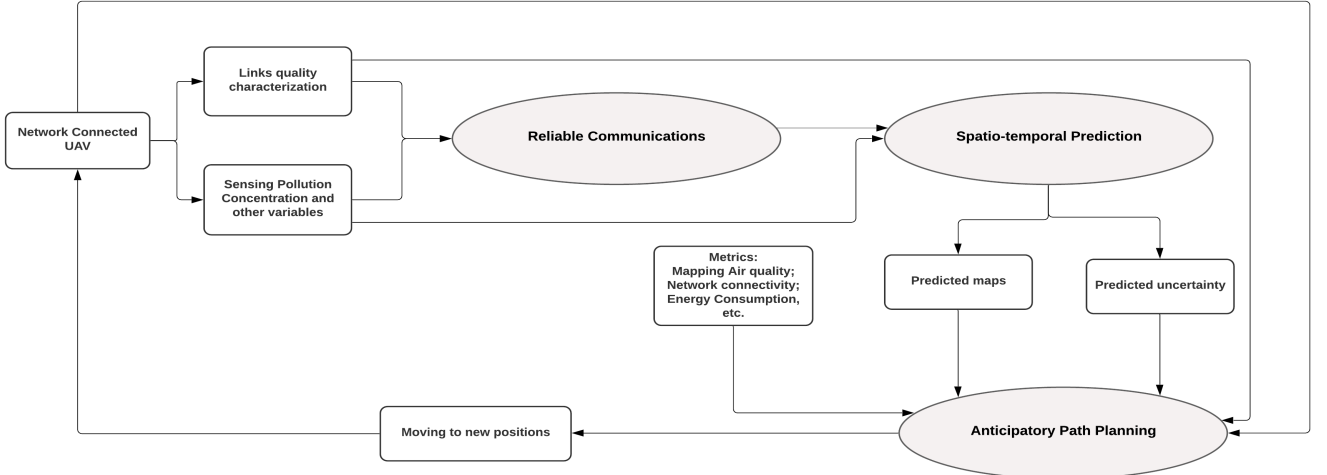


Fig. 1. High level view of the system's architecture

the goal behind to improve the estimated pollution maps. The measurements collected by the drones are used to forecast future pollution maps while at the same time the optimal drones path planning is performed based on the prediction results. In other words, our goal is to estimate at best the future concentrations map ( $\chi_{t+1}$ ) based on the  $J$  last partial measurements maps ( $\hat{\chi}_{t-J+1}, \dots, \hat{\chi}_t$ ), that are updated each time following the optimal drones path planning algorithm. Mathematically, the final pollution map of the next timestamp is inferred by calculating the maximum possible probability.

$$\tilde{\chi}_{t+1}(Y_{t+1}) = \arg \max_{\chi_{t+1}(Y_{t+1})} p(\chi_{t+1}(Y_{t+1}) | \hat{\chi}_{t-J+1}(Y_{t-J+1}), \dots, \hat{\chi}_t(Y_t)) \quad (1)$$

$$Y = (y_{ij}) \in \{0, 1\}^{m \times n} \quad (2)$$

$$\sum_{j=1}^n y_{ij} = 1 \quad i \in [1, m] \quad (3)$$

$$\sum_{i=1}^m y_{ij} \leq 1 \quad j \in [1, n] \quad (4)$$

where  $Y_t$  (we omit the time argument in formulas for simplicity sake) is an  $m \times n$  matrix depending on time, representing the positions of drones in the monitoring region at time  $t$  ( $y_{ij} = 1$  if the drone  $i$  is deployed at the position  $j$  and  $y_{ij} = 0$  otherwise). In general case, we ensure that for each potential position  $p \in \mathcal{P}$ , one drone at most is positioned (equation 4) and we ensure that a drone is deployed in one position at a time (equation 3).

#### IV. PROPOSED APPROACH

The problem we are considering in this work is pretty complex to solve, since it requires mixing up two intrinsically dependent problems : an optimal discrete path planning

scheme of UAVs and a continuous forecasting of pollution maps, and besides, these tasks should be performed in real time. We tackle this issue by breaking it down into separate parts namely: short-term forecasting, spatial fitting and drones path planning, which makes it more affordable to solve. In what follows, we present the core concept of our approach and thereafter we introduce its parts with detail of the different techniques investigated.

Our proposal consists in a cycle with feedback loop that starts with a short setup phase of regular navigation of the UAVs. This phase is considered as an initialization phase that permits to perform uniform measurements within the monitoring region. The objective behind this step is to characterize the different structures used in spatial fitting in one hand and in another hand to feed the prediction model with the collected measurements for training purpose.

Based on the current observations and the previous ones, our forecasting model performs short-term prediction of future pollution map as well as the corresponding uncertainties. Following the highest uncertainties, the UAVs are moved to new positions and perform air pollution measurements. The collected measurements are then forwarded to a central point (ground station or a leader UAV) to be preprocessed. Then, the central point uses the newly collected observations to perform spatial fitting. In this work, we propose a data assimilation technique for spatial fitting to correct the estimated pollution maps generated by the forecasting model. Afterwards, the corrected map is fed to the forecasting model to compute again short-term forecasted pollutant concentrations and so on. The general overview of the proposed framework is depicted in Fig 2.

##### A. Short-term forecasting

In this part, we consider the sequence spatio-temporal forecasting issue of dynamic air pollution. The purpose of this step is to determine the concentration values of the whole

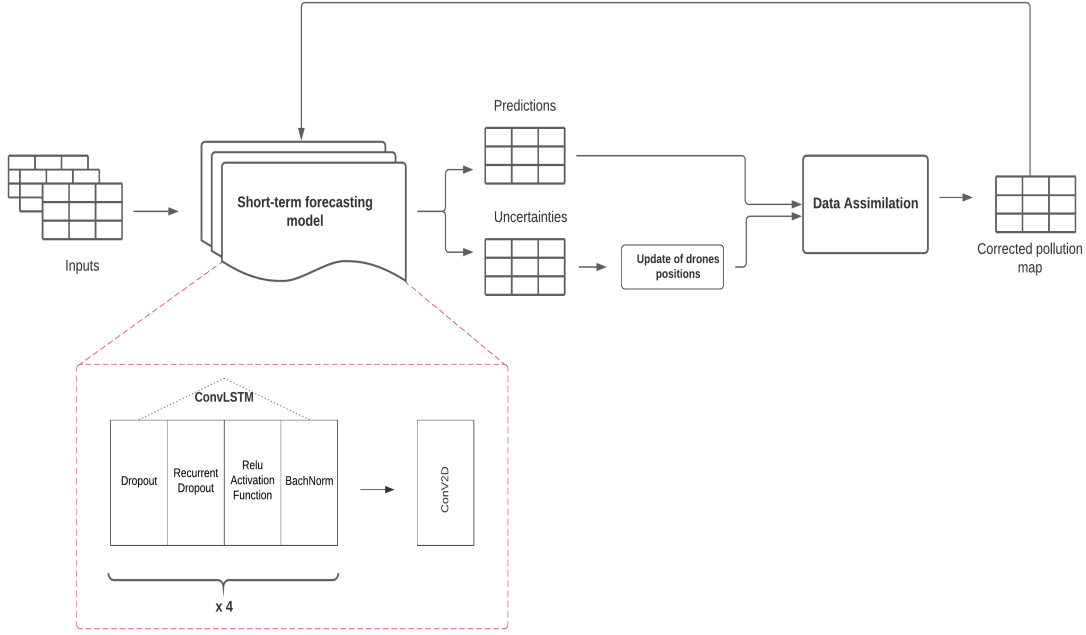


Fig. 2. Flow chart of the proposed framework. The enlarged diagram represents the forecasting architecture with 4 repeated ConvLSTM layers with skip connections

monitoring region  $\mathcal{P}$  in the near future assuming the historical pollution maps. Therefore, the system can provide the predicted air pollution at different locations before receiving the real measured values from the sensing devices.

In the view of the dynamic nature of air pollution and the spatio-temporal dependencies of the time series input data in emergency situations, a model combining the capability of recurrent neural networks (as LSTMs) and the feature extraction ability of convolutional neural networks (CNNs) is proposed. More concretely, the forecasting model consists of two components: a feature extractor module and a prediction module. The former is constructed by stacking multiple ConvLSTM layers. ConvLSTM is presented as an extension of LSTM to cope with spatial redundancy [5].

The output of the former module is fed to a Conv2D with  $1 \times 1$  filter to output the final estimation. Our model processes a sequence of grayscale pollution images as 2D input images and outputs the estimated pollution map of the monitoring region for the next timestamp. Hence, the input pollution data should be converted to images before feeding them to the forecasting model. This conversion could correspond to a simple projection if the data are uniformly distributed in space. Otherwise, more sophisticated conversion should be performed.

The performance of our deep learning model has been evaluated and compared to several state-of-the-art methods through extensive experiments in an anterior work [6] and the effectiveness of the proposed model has been demonstrated.

The same architecture described earlier is used to infer uncertainties of forecasts. More precisely, to quantify the

uncertainty of the forecasts, we consider prediction intervals (PIs) rather than point forecasts. This allows to get intervals that bracket the real values. To that end, we have compared the quantile regression method with Monte Carlo dropout technique on top of our forecasting architecture to generate PIs in [6]. In this work we consider uncertainty based on quantiles since the latter approach is not computationally expensive and generates good quality PIs.

The lower and upper bound of the PI are directly estimated through the forecasting network using the quantile loss described by the equation 5, where  $\tau$  is the considered quantile. Each time, two separate models are trained, one for the lower percentile and the other for the upper percentile to produce PIs following a considered confidence level (coverage level).

$$L_{\tau}(z, \hat{z}) = \sum_{i|z_i < \hat{z}_i} (\tau - 1)|z_i - \hat{z}_i| + \sum_{i|z_i \geq \hat{z}_i} \tau|z_i - \hat{z}_i| \quad (5)$$

## B. UAVs Path Planning

In the general case, the flight route of the UAVs could influence the effectiveness of the spatial fitting and the short-term forecasting. Indeed, the measurements collected by the drones after adjusting their positions are fed to the spatial fitting component to create a more precise and detailed distribution map of the air quality. The core idea of our proposal here is to guide drones based on the outputs of the short-term forecasting component. Concretely, we propose a simple path planning heuristic that has as a purpose to decrease the uncertainty of the air quality forecasting maps. Accordingly, we consider the uncertainties map generated by the precedent component

(short-term forecasting) to update the drones positions. More precisely, we consider high confidence level PIs and we choose their width to be our measure of uncertainty. Indeed, a PI is characterized by two parameters: its coverage (the percentage of real values inside the PI) and the width of the interval. Therefore, as a high coverage level (e.g. 80%) is sufficient to encompass the real observations within the PIs most of the time [6], the width could reflect the uncertainty.

Thence, we move the drones to new positions at each step according to the highest uncertainty locations i.e where the width of PIs are the highest. To that end, we first sort the  $n$  sites (nodes) within the monitoring region according to their uncertainties in a decreasing order. Then, following the considered order (from nodes where the uncertainty is the highest to the ones where the uncertainty is the smallest), every node will receive the nearest not yet treated drone and so on till we send all the drones to their new sites. Note that even if energy consumption is not explicitly taken into account in this work, our heuristic permits to reduce the routes length traveled by drones as a second criteria, which hence, reduces the movements of drones and their energy consumption.

Several extensions of this path planning heuristic can be proposed thereafter to take into account realistic constraints.

### C. Spatial fitting

Spatial fitting designates the usage of the current data i.e the limited number of collected observations from measured locations and sometimes historical data as well to provide a best estimate of the air quality at unmeasured locations and therefore establish a more fine-grained distribution of air pollution.

In this work, a data assimilation technique is used for spatial fitting. Data assimilation methods combine different sources of information to estimate at best the state of the system. These sources represent usually the real observations and the simulations of a numerical model. Without loss of generality, we opted for the best linear unbiased estimator (BLUE) technique following the satisfactory results that the latter showed in air pollution field when its parameters are well characterized [4]. The goal of using BLUE in our context is to correct at each time the estimated pollution map using the measurements collected by the drones. Mathematically, this method aims to estimate the true state of a system  $x^t \in \mathbb{R}^{n \times 1}$ , assuming an unbiased background estimate (prior knowledge)  $x^b \in \mathbb{R}^{n \times 1}$  and a partial observation  $u \in \mathbb{R}^{m \times 1}$ , ( $m < n$ ). The result of BLUE is given by :

$$x^a = x^b + K(u - Hx^b) \quad (6)$$

where  $x^a \in \mathbb{R}^{n \times 1}$  is the analyzed state which represents the estimate of a target variable after correction (the pollution concentrations here),  $K \in \mathbb{R}^{n \times m}$  is the Kalman gain and  $H \in \mathbb{R}^{m \times n}$  the observation operator. Concretely  $H$  is a binary matrix where  $h_{ij} = 1$  if the sensor (observation)  $i$  is deployed at position  $j$ , and  $h_{ij} = 0$  otherwise. As seen from expression 6, the analysed state is a correction of the background estimate with  $K(u - Hx^b)$ . BLUE determines the optimal Kalman gain,

by minimising the sum of the squares of the errors of the analyzed state, as follows:

$$K = BH^T(HBH^T + R)^{-1} \quad (7)$$

where  $B \in \mathbb{R}^{n \times n}$  is the co-variance matrix of the background estimate (prior knowledge) and  $R \in \mathbb{R}^{m \times m}$  is the co-variance matrix of the observations. The intuition behind using BLUE in our case study is to propagate the prediction errors to the whole pollution map in the view of correcting the forecasted concentration values using the real measurements. To that end, we consider the estimated pollution map generated by the forecasting model as our prior knowledge (background estimate)  $x^b$  while  $u$  represents the measurements collected by the drones at  $m$  potential locations within the monitoring region. We assume that pollution measurement errors are uncorrelated because of the fact that they mainly depend on the electronics of the sensing mechanism. Thus, the co-variance matrix of sensing errors  $R$ , is a diagonal matrix. The co-variance matrix of the prediction errors  $B$  is constructed in the initialization phase using the measurements collected by the drones and the outputs of the short-term forecasting model.

## V. VALIDATION

In this section, we provide the results of the experimental evaluation of our framework for dynamic air pollution. Before going deeper in experimentation, we present the data set used to validate our approach, the preprocessing made and we detail the experimentation setup.

### A. Data set and preprocessing

In this work, we use the Fusion Field Trial 2007 (FFT07) [7] real world data set to evaluate our general framework. FFT07 is a set of short range ( $\approx 500$  m) dispersion experiments conducted at the U.S Army's Dugway Proving Ground (DPG), Utah in September 2007. The experiments provide high spatial and temporal resolution dispersion of the pollutant considered (propylene  $C_3H_6$ ). It includes continuous and instantaneous releases from single and multiple sources (up to 4) where the gas is released continuously over a period of 10 min with a release rate of  $377.5 \text{ L min}^{-1}$ . The concentration measurements were recorded by a set of 100 sensors that were placed in a rectangular staggered grid of area  $475 \text{ m} \times 450 \text{ m}$  in 10 rows and 10 column at a height of 2 meters above the ground (see Fig 3).

The present study utilizes the observations measured during multiple continuous releases (3 sources in trial 28). In total, the trial 28 contains 4910000 records and with it, several flags were provided to describe the status of the observations. Concerning the preprocessing made, we removed the dysfunctional sensors entirely (10 sensors). The corrupt and missing data were dropped and were not imputed. The reason is that we observed that the vast majority of these latter data were recorded towards the end of the experiment, and as the pollution plume at this point completely disappeared, the sensors logically measured zeros, which isn't of much interest for our study. Finally the concentrations data were aggregated

to a second scale and were normalized and scaled to [0,1] by the MinMaxScaler method and de-normalization were applied to the predicted data outputs.

To the best of our knowledge FFT07 is one of the rare highly dynamic real world data set where punctual releases were measured by dozens of sensors simultaneously, this makes this data set well suited to study dynamic air pollution plumes.

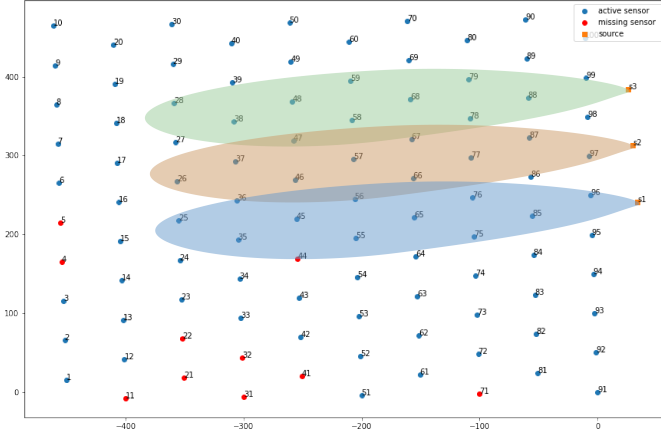


Fig. 3. FFT grid for trial 28

### B. Experimentation setup

In this section, we describe the details of the practical part of this work. The high level neural network library Keras [8] which runs on top of Tensorflow [9] is used to build our deep learning forecasting model. Adam [10] was used as optimizer with a learning rate of 0.00005. The weights were initialized according to the Xavier uniform initialization [11]. The batch size was set to three and the number of epoch to 60. The parameters were chosen following a grid search in the parameters space.

In all our evaluations, the time lag for the forecasting model was set to 5. Also, the time of the initialization phase was set to 10 minutes. The quality of the obtained results is measured using mean absolute error (MAE). Its corresponding formula is defined as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^n |z_i - \hat{z}_i| \quad (8)$$

Where  $z_i$ ,  $\hat{z}_i$  are the measured and predicted propylene concentration, respectively, and  $n$  is the number of measured values.

### C. Short-term prediction quality

This experiment is designed to verify the feasibility of our forecasting model and to show the estimated concentrations as well as the prediction intervals generated. To that end, we suppose having the historical data in all the nodes. The performance of our forecasting model on four nodes (sensors) taken at random are shown in Fig 4, where the first 80% of the data were used for training and the following 20% for

tests in this experiment. To generate the PIs of a coverage level of 80%, two models were trained with a percentile of 0.1 and 0.9 to infer the lower and upper bound, respectively. As can be observed from Fig 4, the model's predictions (in blue) follow the general trend of the real observations (in red) and are pretty close in terms of concentration values. We also observe that the generated prediction intervals with a coverage level of 80% surround the predictions made by the model and bracket the ground truth values most of the time. It can also be noticed that the PIs obtained are asymmetric and don't have the same width along the timestamps, which comforts us in our choice of considering the PIs width as our measure of uncertainty.

It's worth to mention that several coverage levels for the PIs were tested ranging from 10% to 90%, and a coverage level of 80% is chosen here as it generates PIs with a good compromise between percentage coverage and interval width [6].

### D. Evaluation of the general framework

In this part the global loop described in Fig 2 is considered i.e the short-term prediction, the path planning and the spatial fitting. The aim of this experiment is to demonstrate the effectiveness of our general framework and to assess the impact of the data assimilation technique "BLUE" in the loop. To that end, we considered three scenarios: 1) in the first scenario, at each step, we assume the lack of knowledge of the real observations within the whole monitoring region. Concretely, this scenario corresponds to the case where data assimilation is omitted and hence, the predictions made by the model are directly injected into the historical data to perform the upcoming predictions. 2) In the second case which corresponds to our global loop, at each step, we assume having partial observations collected by  $m$  drones in the study area, for example 5 drones. In this second scenario, the real measurements collected are fed to the data assimilation algorithm to correct the forecasting model's predictions. 3) In the last scenario, the real observations of the whole grid are at each time injected to obtain the predictions. In other words, this could be assimilated to the case where drones are deployed in each of the 90 nodes of the monitoring region. The resulting scores are plotted in Fig 5. Obviously, it can be seen that the third case scenario scores better. This is due to the use of the real observations to predict the next timestamp pollution map. In other hand, the first scenario corresponds to the worst case with no drone deployed, it produces the highest errors. Indeed, the system uses the precedent predictions to perform the upcoming ones without being fed by the ground truth. We observe also that using data assimilation greatly improves the results comparing to when no spatial fitting is used. Even deploying only 5 drones, permits to reduce the MAE from 4.8 to 3.7 where the highest pick is observed. Finally, we notice for the three scenarios that the MAE get lower over time. That can be explained by: 1) the fact that the sources emissions stopped. 2) The dispersion of the pollutants released in the



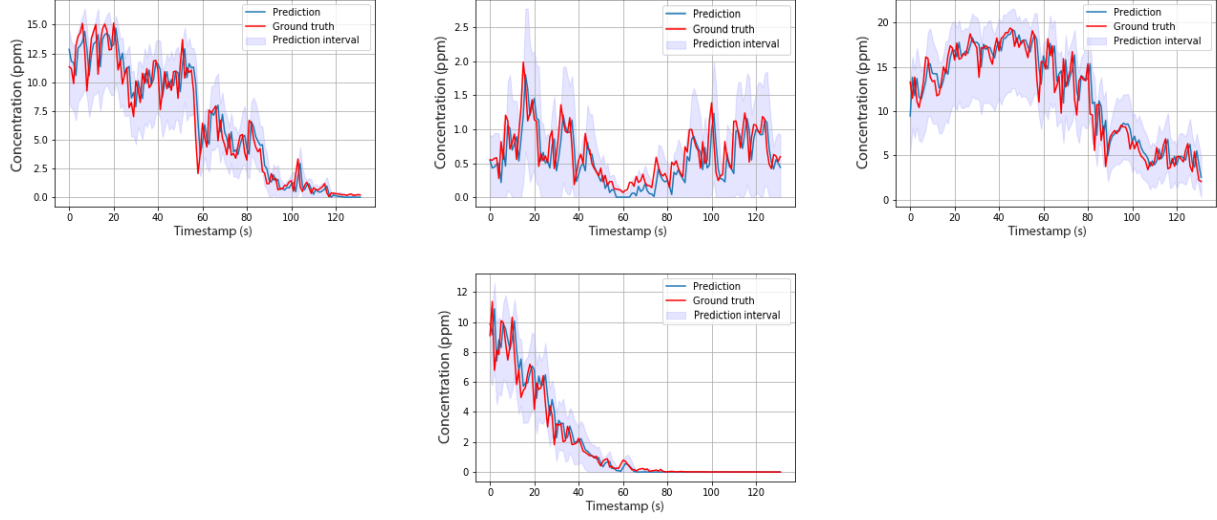


Fig. 4. Ground truth Vs predicted values as well as their prediction intervals for four sensors

atmosphere: the concentrations values become progressively lower, thus the mean absolute error decreases.

#### E. Impact of the training size on the mapping quality

We inspected here the effect of the training size on the mean absolute error while considering the three scenarios described earlier. To that end, we considered various training sizes ranging from 2 to 12 minutes and we set the number of drones to 10. The experience where repeated several times and the results where averaged and depicted in Fig 6. According to the resulting plot, we observe that increasing the training size results in smaller errors for the three scenarios considered. Moreover, the findings observed in the precedent test are confirmed. Indeed, the third case scenario (using observations) achieves the best score whatever the training size considered, followed by the case where data assimilation is used and then the one using only predictions. In addition, we notice that using data assimilation reduces significantly the errors comparing to the case where this latter is omitted, when considering small training sizes (for instance, it scores 64% better than the first case scenario for a training size of 2 min). Finally for large training sizes (over 10 min) the errors obtained with the scenario using real measurements and the one using data assimilation with partial observations are pretty close. This is due to the fact that the forecasting model is trained with enough data. Thus, it is able to provide accurate pollution forecasts even with few real measurements as input.

#### F. Impact of the number of drones on the mapping quality

To investigate further the impact of the number of drones deployed on the system performance. We variate the number of UAVs deployed considering these values  $m \in \{5, 10, 20, 30, 40\}$ . The MAE in each case is computed and depicted in Fig 7. Results confirm that the more drones you deploy, the lower the MAE is and hence better is the result.

Moreover, generally, considering more than 30 drones in our monitoring region is not of much practical value since as shown in this experiment, it doesn't provide any advantage as the performances stagnate. In addition, from a certain point of the experiment, decreasing the number of the deployed drones to 10-20 has a modest impact on the errors.

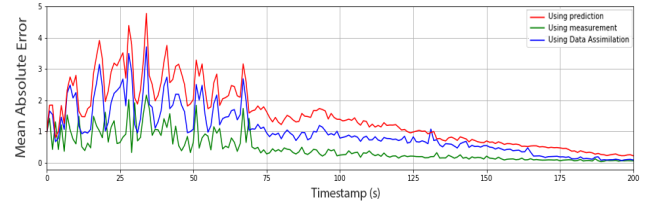


Fig. 5. Mean Absolute Error Vs timestamp, considering three cases: using real measurements, using data assimilation with 5 drones deployed and using the predicted values

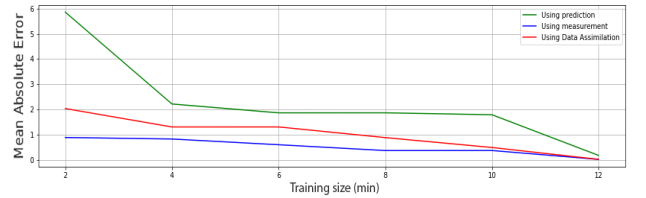


Fig. 6. Mean Absolute Error Vs training size considering three cases: using real measurements, using data assimilation with 10 drones and using the predicted values

## VI. RELATED WORKS

The problem considered in this paper has two main search axis that should be considered to design and evaluate our global systemic approach.



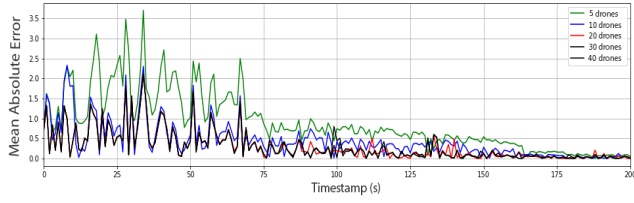


Fig. 7. Mean Absolute Error Vs timestamp, considering various number of drones  $m \in \{5, 10, 20, 30, 40\}$

The first axis covers works on the spatio-temporal air quality prediction. At this axis, a lot of machine and deep learning approaches were recently proposed [12] [13] as well as some data assimilation solutions that combine measurements with physical models [14]. A recent work of Du et al. propose a deep learning model named DAQFF for  $PM_{2.5}$  single step forward and multi-step forward forecasting. The framework is compromised of two components: a multiple one dimension convolution layers (CNN) and a bidirectional LSTM [15]. The first component is used to extract spatial features between stations and the second one to capture the temporal features in the time series input data. In Another work [16], a deep forecasting model combining an artificial neural network with CNN and LSTM is developed to extricate spatio-temporal relations and forecast air pollution for up to 48 h. In this work, different meteorological data as well as information related to the elevation space to extract terrain impact on air quality, were used. The evaluations carried out demonstrated the effectiveness of the proposed model compared to the state-of-the-art methods considered. In this axis, most of the approaches may be of interest in our case. However, they are focused on addressing the case of monitoring chronic pollution. Therefore, they don't consider the numerous challenges of emergency situations and none of them incorporate the uncertainty in their forecasting models.

The second axis considered concerns path planning of UAVs. Quite recently, considerable attention has been paid to the use of UAVs in several domains [17] [18] In [19], Wei and Zheng present an informative path planning algorithm based on a reinforcement learning approach using a single robot. In the formulated problem, the reward of a path is defined based on the information collected through it. The authors modeled the problem as a sequential decision process and proposed a solution based on the Q-learning algorithm. In another work [20], the authors propose a path planning algorithm for robot navigation while combining global planning and reinforcement learning. First, a path graph is built using an accepted-rejected sampling where points are generated randomly and deleted if located in obstacle regions. After random sampling, the paths collided with the obstacles are removed and the k nearest points from the collision-free paths are computed for each source point. Finally, a Q-learning algorithm is performed to find the next path point according to the current position. These general approaches are very interesting, however, to the best

of our knowledge, only few pollution-specific solutions were proposed in the literature [21] and the majority of approaches considered the use of a single UAV.

## VII. CONCLUSIONS AND FUTURE WORK

In this paper, a general framework designed to monitor real-time dynamic air pollution in emergency situations is introduced. The problem addressed involves predicting accurate pollution maps while at the same time considering a suitable drones path planning approach to improve the concentrations forecasting. The architecture of our framework includes the following components: short-term prediction, spatial fitting and drones path planning. The short-term prediction is performed using a spatio-temporal deep learning model based on ConvLSTM, which is an adequate choice to model high dynamic pollution map due to its capacity to capture the temporal and spatial dependency within a neighborhood. The spatial fitting is realized using a data assimilation technique named "BLUE", which has as objective to correct the estimated pollution map generated by the forecasting model when using the real observations collected by the drones. Finally, a simple path planning heuristic is proposed to validate our framework. This heuristic updates the drones positions at each time following the highest uncertainties. Our solution was validated and evaluated through several experiments using a real world dynamic data set (FFT07). The preliminary analysis and results point towards interesting potential of the proposed framework. We aim in our future work at extending our framework to incorporate more sophisticated path planning algorithms. For instance, the latter can be designed to take into account communication constraints as well as the limited power consumption of the drones. For example, we can decrease progressively the number of the drones deployed over time, which will enable a better autonomy management of the drones. Indeed, at the beginning of the plume dispersion, the uncertainties are the highest and the lack of knowledge is important, which justifies a deployment of larger number of drones at first. Another open direction is to envisage the consideration of an online learning model capable of a constant evolution (update of its parameters) with the possible evolution of the data arriving. The cost of this model in terms of forecasting accuracy and time processing will be carefully investigated.

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