Investigation of different methodologies to characterize and propagate uncertainties in atmospheric dispersion modelling: application to long-term impact assessment

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Introduction

The concentration of a pollutant in the atmosphere is a random variable that can not be modelled deterministically with certainty. Therefore there is a growing demand from regulatory institutions to provide uncertainties regarding the results of environmental impact assessment studies. This paper discusses a probabilistic framework to estimate the impact of various sources of uncertainties on simulation outputs used for environmental impact assessment studies. Using the common framework designed for the treatment of uncertainties in industrial practice, a complete chain for the quantification of uncertainties for environmental impact assessment studies has been developed.

Description of the chain for the quantification of uncertainties

Step 1: Problem

■ **Case-study:** unique source (50 m height and diameter of 1 m) located at the centre of a domain of 50 x 50 points ($\Delta x = \Delta y = 100$ m). The pollutant is a inert gas and the site of dispersion is flat.

■ **Input variables:** meteorology (5 years of observational data of wind speed and direction, temperature, cloud cover and precipitation, boundary layer height, Monin-Obukhov length), dispersion site rugosity, characteristics of the pollutant release (temperature, speed and quantity), grid and receptors height.

■ **Variables of interest:** Annual mean (CMEAN) and 100th hourly percentile (P100H) of ground-level concentrations.

■ **Dispersion model:** Gaussian plume model GANACHE developed at Central School of Lyon (France). Similitude theory used for the parameterization of atmospheric stability.

■ **Quantities of interest:** Dispersion of the results (mean values and standard deviation of the distribution of the variables of interest).

Step 2: Input uncertainties

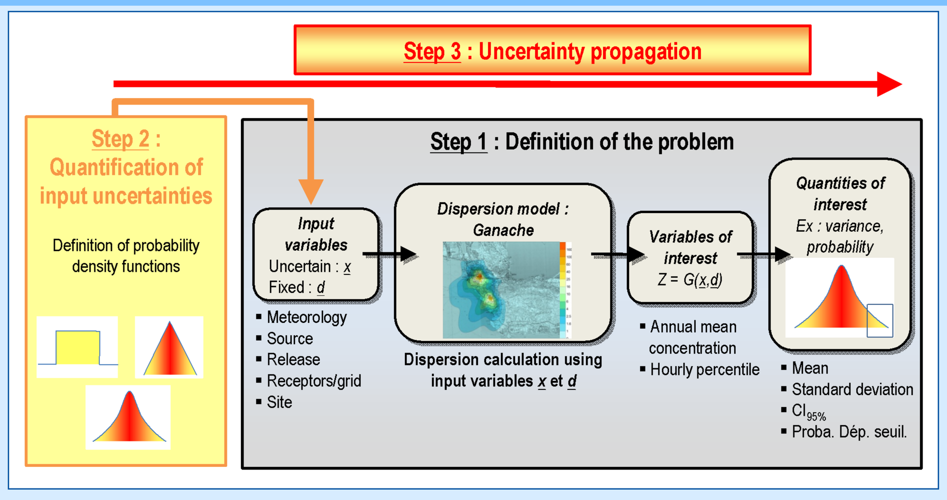
■ Two methods have been used to derive and propagate probability density functions (PDF) associated with meteorological variables :

■ ***Direct method***: consisted of adding uncertainties to each meteorological variable for every time step.

■ ***Indirect method***: consisted of generating a probabilistic model from statistical analysis of input data.

■ PDF of other input variables do not vary between direct and indirect approaches and were defined from expert judgment.

Variable	Direct approach	Indirect approach
Wind speed (m.s^{-1})	Normal (mean = 0; sigma = 0.15)	Weibull (α = 3.6026; β = 1.5086; γ = 0)
Wind direction (°)	Normal (mean = 0; sigma = 13.7[1])	Truncated mixture of normal laws
Temperature (°C)	Not used	Normal (mean = 12.19; sigma = 7.76)
Cloud cover (oktas)	Normal (mean = 0; sigma = 1)	Not used
Boundary layer height (m)	Normal (mean = 0; sigma = 25)	Weibull (α = 343.15; β = 0.92; γ = 0)
Inverse of the Monin-Obukhov length (m)	Derived from other input variables	Kernel Smoothing fitting
Dispersion site rugosity (m)	Uniform (min = 0.4; max = 0.7)	Uniform (min = 0.4; max = 0.7)
Temperature of the pollutant release	Normal (mean = 50; sigma = 1)	Normal (mean = 50; sigma = 1)
Speed of the pollutant release (m.s^{-1})	Normal (mean = 12; sigma = 1)	Normal (mean = 12; sigma = 1)
Quantity of pollutant released (g.s^{-1})	Uniform (min = 7; max = 13)	Uniform (min = 7; max = 13)
Grid and receptors height (m)	Triangular (min = 1; max = 2; mode = 1.5)	Triangular (min = 1; max = 2; mode = 1.5)



Schematic diagram representing the approach which has been developed

Step 3: Uncertainty propagation

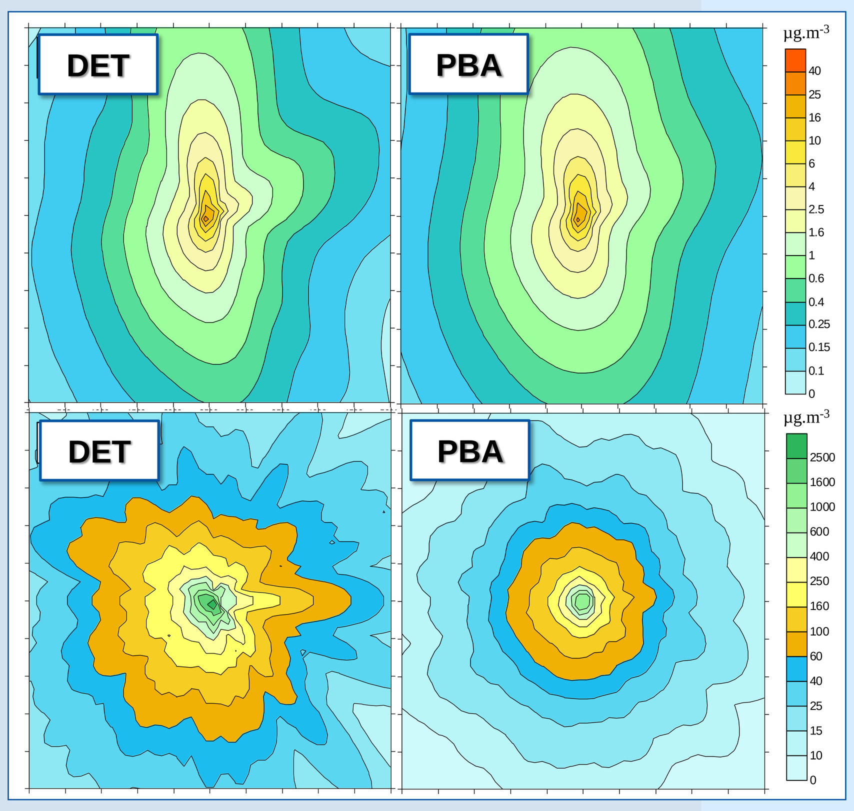
Monte Carlo (MC) simulations were used to propagate input uncertainties. Considering a simulation period of 1 year (8760 hourly time steps), we proceeded as follows:

■ ***Direct method***: 100 runs per time step were conducted.

■ ***Indirect method***: this approach does not account for the temporal dimension so that we can run a restricted number of MC simulations, here 8000. Note that we did not take into account possible dependencies between input variables.

Preliminary results

Deterministic versus probabilistic modelling



(Upper panel) CMEAN and (lower panel) P100H (µg.m^{-3}) derived from the deterministic run (DET) and the direct probabilistic approach (PBA).

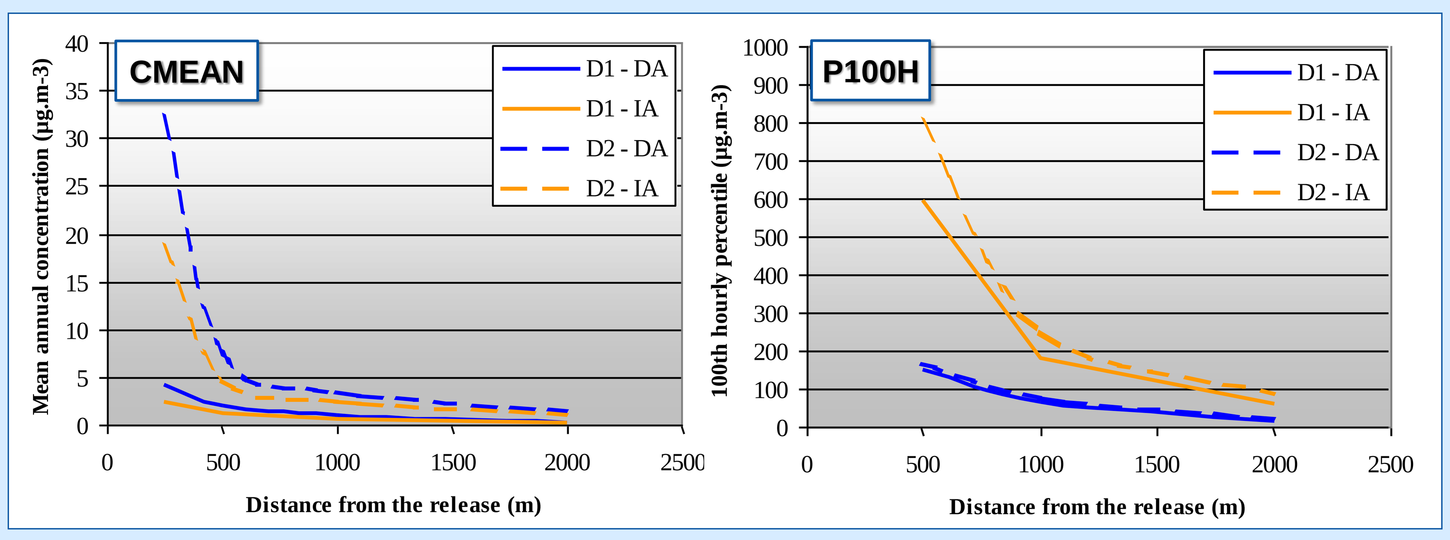
■ PBA results smoothed in comparison with DET ones.

■ **CMEAN:** PBA differs from DET by more or less 3 µg.m^{-3} in the vicinity of the release, that 10 % of the DET value.

P100H: DET produces higher values than PBA over the whole simulation domain (more than 2000 µg.m^{-3} and 250 µg.m^{-3} at 250 m and 1000 m of the release, respectively).

■ **Every variable:** this is not shown but the standard deviation of the ensemble results derived from PBA was very small (less than 1% of the ensemble mean), even at very short range of the release.

Direct versus indirect probabilistic approaches



Evolution of the variable of interest (µg.m^{-3}) as a function of the distance from the release. D1 (resp. D2) is used for the wind direction frequently (resp. rarely) observed and DA (resp. IA) for the direct (resp. indirect) approach

■ **Method:** comparisons were achieved performing numerical simulations considering fixed receptors that were placed according to two particular wind directions D1 (frequently observed) and D2 (rather infrequent) at various distances of the release (250, 500, 1000 and 2000 m).

■ **CMEAN:** values larger in direction D2 and decrease when the distance from the release increases. The indirect approach produces larger values than the direct one but the differences between the two methods become negligible for receptors located at 500 m or more from the source.

■ **P100H:** values derived from the indirect approach ranges between 2 to 4.5 times the results provided by the direct method.

Conclusions

■ A chain for the quantification of the impact of input uncertainties on ground level concentration simulations has been developed.

■ Considering input uncertainties may involve different results than those provided by simple deterministic approaches.

■ At this point of the study, the direct approach appeared to be more appropriate than the indirect one for probabilistic modelling applied to EIA studies.

■ (Not shown) The high uncertainty related to the definition of single receptors for specific establishments (schools, hospitals, etc.) has also been pointed out.

Future work

■ Finalizing the development of the chain by adding a step for uncertainty sources ranking (sensitivity analysis).

■ Validating the results provided by the complete chain for a specific case-study taking into account 5 years of meteorological observations.

■ Going further on applications considering the indirect approach.

■ Working with different propagation methods (for example, polynomial chaos expansion) and alternative approaches for the parameterization of atmospheric stability (Pas-Gifford and Doury classes).