

# Uncertainty propagation in a model for the estimation of the ground level concentration of dioxin/furans emitted from a waste gasification plant

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1 Uncertainty propagation in a model for the estimation of the  
2 ground level concentration of dioxin/furans emitted from a waste  
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13  
14 **ABSTRACT:** In this paper we compare two approaches for uncertainty propagation in a model for  
15 Environmental Impact Assessment (EIA). A purely Probabilistic (PMC) and a Hybrid probabilistic-  
16 possibilistic Monte Carlo (HMC) method are considered in their application for the estimation of  
17 the ground levels concentration of dioxin/furans emitted from a waste gasification plant. Under the  
18 condition of insufficient information for calibrating the estimation model parameters, HMC is  
19 shown to be a valid way for properly propagating parameters uncertainty to the model output, with-  
20 out adopting arbitrary and subjective assumptions on the input probability distribution functions. In  
21 this sense, HMC could improve the transparency of the EIA procedures with positive effects on the  
22 communicability and credibility of its findings.

23 **Keywords:** Uncertainty propagation, Hybrid probabilistic-possibilistic Monte Carlo, waste gasifica-  
24 tion plant, Environmental Impact Assessment.

25 **1. INTRODUCTION**

26 According to the current EU regulations (Directive 85/337/EEC as amended by Directives  
27 97/11/EC and 2003/35/EC), an Environmental Impact Assessment (EIA) is required for public and  
28 private projects likely to have significant impacts on the environment by virtue *inter alia* of their  
29 nature, size or location. The scope of an EIA is the identification, description and assessment of a  
30 project's direct and indirect effects on human beings, fauna and flora, soil, water, air, climate, land-  
31 scape, material assets and cultural heritage. The EIA is a part of the decisional process for the ap-  
32 proval of a proposed project. The outcomes of the EIA help orient decision makers to the priorities,  
33 thus ensuring that environmental considerations are taken into account in an effective way. Fur-  
34 thermore, the EIA serves an important procedural role in the overall decision-making process by  
35 promoting public information and facilitating participation. This entails that an EIA be carried out  
36 taking into account that its findings will be handled not only by technical experts, but also commu-  
37 nicated to decision makers and stakeholders of various nature, including the local population. Since

1 in most common settings the proposed project does not meet popular consensus *a priori*, communi-  
2 cability of EIA results to the involved stakeholders plays a major and challenging role. To this pur-  
3 pose the EIA procedure must be open and transparent, reviewable and leading to robust and repro-  
4 ducible outcomes for informed decision-making and confident public awareness.

5 With reference to the proposal of new facilities responsible of atmospheric emissions (in the present  
6 work we consider a waste thermal treatment plant as an example), the EIA procedure consists of  
7 three main steps (Figure 1):

- 8 a) the characterization of the source: estimation of the atmospheric emissions resulting from the  
9 operation of the plant, in terms of both the nature and the quantities of pollutants;
- 10 b) the estimation of the atmospheric pollutant concentration levels in the area close to the proposed  
11 new installation, by means of proper atmospheric dispersion models;
- 12 c) the assessment of the pollutant concentration levels at the receptors, resulting from the superpo-  
13 sition of the estimated concentration to the existing background concentration levels.

14 The first objective of the EIA is then the demonstration that the resulting concentration levels at the  
15 receptors comply with both long-term (i.e.: annual average) and short-term (i.e.: hourly and daily  
16 averages) air quality limits for regulated pollutants. Secondly, as those facilities can be also respon-  
17 sible for the emission of both carcinogenic and non-carcinogenic trace pollutants, as metals or diox-  
18 ins and furans (PCDD/Fs) in the case of waste thermal treatment plants, additional evaluations may  
19 also include human health risk assessment. This latter assessment is characterized by two main fea-  
20 tures: i) a considerable complexity of the mechanisms involved and hence large related uncertain-  
21 ties, ii) a general attitude of “aversion to risk”, with implications on the way uncertainties are  
22 treated (Guyonnet et al., 2008).

23 The uncertainties that affect all the three steps of the EIA procedure may be originated from ran-  
24 domness of the physical processes involved or from lack of precise knowledge of them. In the end,  
25 regardless of the approaches and models adopted to estimate the plant emissions and their disper-  
26 sion in the atmosphere, the final ambient concentrations estimates can be seriously affected by the  
27 uncertainty of the values of the source term parameters and by the variability of meteorological pa-  
28 rameters.

29 On the contrary, the above mentioned attitude of “aversion to risk” often leads to answering to the  
30 question whether a given “acceptable” threshold may be exceeded, based on limited scenario calcu-  
31 lations. In common practice, this translates in ignoring input parameter uncertainties to adopt a di-  
32 rect, deterministic approach in which conservative assumptions on the scenarios and parameter val-  
33 ues are made, e.g.: i) full-load plant operation and ii) concentrations of the emitted pollutants equal  
34 to the regulatory limits. This approach leads to often excessively conservative results, not providing

1 a realistic and objective description of the plant impact on the environment (Lonati and Zanoni,  
2 2012)

3 To overcome this problem, the EIA procedure can be framed within a probabilistic approach for i)  
4 describing the uncertainties of the input parameters and ii) propagating them to the models outputs,  
5 i.e.: the atmospheric pollutant concentrations. In the probabilistic approach, the uncertain variables  
6 are described by means of probability distribution functions (PDFs), which are then propagated  
7 through the impact assessment model by Monte-Carlo (MC) simulation according to a pure Prob-  
8 abilistic Monte Carlo (PMC) method (Schuhmacher et al. 2001, Sonnemann et al. 2002, Lonati et  
9 al. 2007). Nevertheless, even in the PMC approach uncertainty and variability in the atmospheric  
10 dispersion model are usually neglected.

11 In general, the construction by statistical analysis of the empirical PDFs representing the uncertainty  
12 in the input parameters may not be an easy task due to the scarce availability of data (Ferson and  
13 Ginzburg 1996, Baudrit et al. 2006). Within a probabilistic framework, the analyst traditionally  
14 solves this task forcing a subjective PDF on the scarce available data, within a Bayesian (subjective)  
15 view of probabilities. This presents two major drawbacks:

- 16 - doubts may be raised on the consistency and even conservativeness of the forced PDFs, in light  
17 of the incomplete/imprecise information at hand. The risk is to introduce artificial information that  
18 is in fact not there;
- 19 - the subjectivity in the analysis is often neither declared nor justified, causing a loss of transpar-  
20 ency in the procedure.

21 These drawbacks are of particular relevance, considering the EIA role as decision aiding and infor-  
22 mative tool. A lack of transparency in the procedure can lead to a loss of credibility by the decision  
23 makers and public.

24 To cope with this situation of limited information, while avoiding to introduce subjective assump-  
25 tions, a number of alternative representations of uncertainty have been proposed (e.g.: fuzzy set  
26 theory, evidence theory, possibility theory and interval analysis) and applied in different fields of  
27 risk assessment (Klir and Yuan 1995; Aven and Zio 2011). Among them, possibility theory has re-  
28 ceived growing attention because of its representation power and its relative mathematical simplic-  
29 ity. In recent past years some applications of these alternative approaches have been exploited also  
30 in the environmental risk assessment field (Guyonnet et al. 2003, Kentel and Aral 2005, Li et al.  
31 2007, Kumar et al. 2009).

32 In practice, different input parameters of the same model may be characterized by different amounts  
33 of information availability, thus possibly giving rise to both probabilistic and possibilistic uncer-  
34 tainty representations. In this regard, Hybrid probabilistic-possibilistic Monte Carlo methods

1 (HMC) have been recently proposed for combining both representation frameworks in the same un-  
2 certainty propagation analysis (Baudrit et al. 2006, Baraldi and Zio, 2008, Flage et al. 2010).

3 In this work, the uncertainty representation and propagation problems are considered with reference  
4 to the first two steps of the EIA procedure (i.e.: emission estimation and atmospheric dispersion).

5 For ease of illustration, we make reference to a case study concerning the project of a new waste  
6 gasification plant. The plant, designed for a daily waste throughput of 900 metric tons, has been re-  
7 cently proposed for realization in the South-East of the city of Milan, Italy and is subject to the re-  
8 quirement of EIA for its potential impact on air quality.

9 The focus of the analysis is on dioxins and furans (PCDD/Fs) since the thermal treatment of waste  
10 is a well-known source of PCDD/Fs to the atmosphere (Domingo et al. 2002, Schuhmacher and  
11 Domingo 2006) and these pollutants have a relevant role in health risk assessment due to their car-  
12 cinogenic potential and to their persistency in the environment, once released into the atmosphere  
13 (Travis and Hattemer-Frey 1991, Mukerjee 1998).

14 The final objective of the work is the assessment of the contribution to PCDD/Fs long-term concen-  
15 tration (i.e.: annual average) in the ambient air in the surroundings of the proposed plant due to the  
16 flue gas emissions released at the stack of the plant. This information, other than a direct informa-  
17 tion on the environmental impact of plant emissions, is also the basic input for the subsequent  
18 health risk assessment step.

19 The results obtained through a HMC method for the assessment of PCDD/Fs ground-level concen-  
20 trations are compared to those obtained by a standard PMC approach, and both the transparency of  
21 the EIA procedure and the communicability of results are discussed.

22 The manuscript is organized as follows: in Section 2 the equations used to model plant emissions  
23 and ambient air concentrations are presented; the characterization of the input parameters uncer-  
24 tainty for the development of HMC and PMC methods is illustrated in Section 3; Section 4 shows  
25 the output of the two propagation methods and discusses their methodological implications; finally,  
26 the advantages of the HMC method are drawn in the Conclusions. For completeness, the Appendix  
27 Section A1 provides the basics of possibility theory and Section A2 presents the pure PMC method  
28 for uncertainty propagation and its evolution to the Hybrid probabilistic-possibilistic Monte Carlo  
29 method under conditions of scarce data availability.

30

31

## 32 **2. POLLUTANT AIR CONCENTRATIONS MODEL**

33 The contribution to the ambient air concentration  $C_{\text{air}}$  ( $\text{fg m}^{-3}$ ) on an annual average basis can be  
34 computed by multiplying an emission term  $Q$  ( $\text{ng s}^{-1}$ ), which quantifies the mass flow rate of

1 PCDD/Fs released into the atmosphere, and an atmospheric dispersion factor DF ( $\text{fg m}^{-3}/\text{ng s}^{-1}$ ),  
2 which quantifies the ambient concentration per unit of mass flow rate:

3

$$4 \quad C_{\text{air}} = Q \cdot DF \quad (1)$$

5

6 Since the atmospheric dilution of the emission occurs at different extents depending on the distance  
7 from the plant stack,  $C_{\text{air}}$  and DF are actually space-dependent and take different values,  $C_{\text{air}}(x,y)$   
8  $DF(x,y)$ , at the receptors points located in the study domain, usually described by a Cartesian grid  
9 centered on the plant stack.

10 Equation (1) follows a simplified approach for the assessment of  $C_{\text{air}}$  since it assumes that the  
11 PCDD/Fs are emitted in the gas-phase only: this approach, although still providing realistic results,  
12 reduces the complexity of the calculation model thus enabling the application of the uncertainty  
13 propagation methods.

14 The emitted PCDD/Fs mass flow rate  $Q$  in equation (1) has been computed on the basis of the plant  
15 daily throughput of waste,  $P$  ( $\text{Mg}_{\text{waste}} \text{ day}^{-1}$ ), the PCDD/Fs concentration in the emitted flue gas,  $C_D$   
16 ( $\text{ng m}^{-3}$ ), and the specific gas production  $V_F$  ( $\text{m}^3 \text{ Mg}_{\text{waste}}^{-1}$ ):

17

$$18 \quad Q = \frac{P \cdot C_D \cdot V_F}{3600 \cdot 24} \quad (2)$$

19

20 As usual for this kind of evaluations (Van den Berg et al. 1998, US EPA 2005), the PCDD/Fs con-  
21 centration is expressed in terms of equivalent toxicity mass per unit gas volume at normal condi-  
22 tions ( $0^\circ \text{ C}$ ,  $101.3 \text{ kPa}$ ); coherently, the specific gas production refers to the same temperature and  
23 pressure conditions.

24 The dispersion term DF in equation (1) has been computed by simulating the atmospheric transport  
25 and dispersion of the emitted PCDD/Fs in the surroundings of the plant by means of the ISCST3  
26 model (Industrial Source Complex – Short-term version 3). Formerly a US EPA regulatory model  
27 for air dispersion modeling, this model is still regarded as a screening model for the assessment of  
28 the impact on air quality of atmospheric emissions from industrial sources (US EPA, 1995).

29 Local meteorological conditions (wind speed and direction, ambient air temperature, atmospheric  
30 stability), source features (stack height, flue gas speed and temperature, pollutant mass flow rate)  
31 and geographical features of the area (terrain elevation, land use) are the basic input data for the  
32 dispersion model. Output of the ISCST3 model is the 2D field of the contribution to the ground-  
33 level concentration data in the study domain around the plant. Since in this model the output con-

1 concentrations are linearly proportional to the emitted flow rate, the dispersion term DF can be eva-  
2 luated running the model for a unit mass flow rate ( $1 \text{ ng s}^{-1}$ ).  
3 The DF values to be used in equation (1) for the estimation of the PCDD/Fs annual average concen-  
4 tration have been obtained for the 1681 nodes of a Cartesian grid centered on the plant (250 m cell  
5 spacing) through one-year long model simulations based on the hourly time series of locally meas-  
6 ured meteorological data.

7  
8

### 9 **3. UNCERTAINTY REPRESENTATION AND PROPAGATION**

10 The input parameters of the emission model (equation (2)) have been characterized as follows:

- 11 – the plant daily throughput  $P$  is a constant parameter whose value is assigned during project de-  
12 sign; for the plant of this case study,  $P$  has been set to the value of  $900 \text{ Mg}_{\text{waste}} \text{ day}^{-1}$ ;
- 13 – the PCDD/Fs concentration  $C_D$  is an uncertain parameter whose value varies during normal gasi-  
14 fication operation due to the fluctuations of the process parameters and to the heterogeneous and  
15 variable composition of the fed waste;
- 16 – the specific gas production  $V_F$  is an uncertain parameter. Although its value is usually set in the  
17 plant design phase, actually  $V_F$  can present variations during plant operation caused by fluctuations  
18 of the energy content of the fed waste as a consequence of its heterogeneous and variable composi-  
19 tion.

20 Due to the rather limited applications of the waste gasification process, extended time series data-  
21 sets containing  $C_D$  and  $V_F$  values collected during operation of similar plants are not available.

22 However, different studies have recently investigated the pollutant emission from waste gasification  
23 plants (Klein 2002, Yamada et al. 2004, Porteous 2005, Arena 2012, University of California 2009).

24 From these studies, 35  $C_D$  and four  $V_F$  values have been derived.

25 The availability of a statistically significant set of  $C_D$  average values, has allowed to represent the  
26 uncertainty on this model parameter by means of a probability distribution. A Kolmogorov–  
27 Smirnov’s test considering lognormal, Weibull, Beta, logistic PDFs has been performed in order to  
28 properly choose the PDF best representative of the literature data. Figure 2 shows the selected Beta-  
29 PDF of parameters  $\alpha = 0.36$  and  $\beta = 1.32$  and maximum value  $0.07 \text{ ng m}^{-3}$ , that is 30% less than the  
30 regulatory limit of  $0.1 \text{ ng m}^{-3}$  (European Union, 2000).

31 Conversely, for  $V_F$  the available information (four literature values and the case study design value)  
32 is very scarce. Thus, two different alternative representations of the uncertainty affecting  $V_F$  have  
33 been considered:

1 – a subjective triangular PDF based on analyst judgment. The PDF range has been chosen to be  
2 [3360, 6670] ( $\text{m}^3 \text{Mg}_{\text{waste}}^{-1}$ ), which corresponds to the minimum and maximum values of the four  
3 literature values, and its mode has been chosen to be  $5420 \text{m}^3 \text{Mg}_{\text{waste}}^{-1}$ , which corresponds to the  
4 current case study design value (Figure 3);

5 – a triangular possibility distribution with the same range of the subjective PDF and most likely  
6 value set equal to the case study design value (Figure 3).

7 Notice that, although the possibility and probability distributions used to represent the uncertainty  
8 on  $V_F$  have similar shapes, they convey very different information: the possibility distribution  
9 summarizes a set of cumulative distributions, bounded by the so-called Necessity and Possibility  
10 functions (see Appendix a.1), whereas the subjective PDF defines just one specific cumulative dis-  
11 tribution of that set.

12 On the other hand, model predictions of the DF values in equation (1) are also uncertain quantities  
13 affected by i) the natural variability in the input parameters (such as meteorological variables and  
14 source features), ii) measurement errors and iii) modeling errors due to the difficulties in capturing  
15 the atmospheric behaviors (Sax and Isakov 2003, Rao 2005). Neglecting for simplicity the model  
16 uncertainties, it turns out that the DF values are mainly affected by the variability in the meteoro-  
17 logical input parameters, which largely exceeds the effect of the variability of flue gas temperature  
18 and speed. In fact, the temperature is typically kept at a rather constant value during plant operation,  
19 whereas the flue gas speed plays a negligible role on the atmospheric behavior of the emitted  
20 plume. Here, the DF uncertainty has been estimated indirectly, by taking into account 10 different  
21 years of local meteorological data and by separately running the dispersion model for each input da-  
22 ta set: thus, 10 yearly DF values have been estimated for each grid node in the computation domain.  
23 An example of the different wind conditions observed in the study area is given by the annual wind  
24 roses reported in Figure 4 for four years out of the ten considered.

25 For illustration purposes, only one grid point has been considered for the uncertainty propagation,  
26 chosen as the receptor most impacted by the plant emission ( $x_M, y_M$ ), i.e. the grid node characterized  
27 by the highest average of the 10 yearly DF values.

28 Due to the small dataset available, two alternative representations of the  $DF(x_M, y_M)$  uncertainty  
29 have been considered:

30 – a trapezoidal PDF based on analyst judgement with its minimum equal to 0, its core ranging be-  
31 tween  $5.69 \cdot 10^{-3}$  and  $4.19 \cdot 10^{-2} \text{fg m}^{-3}/\text{ng s}^{-1}$ , which corresponds to the minimum and maximum  
32 values of the ten estimated DF values, and its maximum equal to  $0.21 \text{fg m}^{-3}/\text{ng s}^{-1}$ , which is the  
33 DF obtained for the receptor point assuming the worst day conditions observed during the 10-  
34 year period for atmospheric dispersion all year long (Figure 5);



1 – a trapezoidal possibility distribution with the same features of the subjective PDF (Figure 5).

2

3

#### 4 **4. RESULTS**

5 With respect to the uncertainty propagation, the PMC method has been applied to the case in which  
6 the uncertainty on  $C_D$ ,  $V_F$  and  $DF(x_M, y_M)$  are represented by the PDFs, whereas the HMC method  
7 considers the PDF for  $C_D$  and the possibility distributions for  $V_F$  and  $DF(x_M, y_M)$ . The number  $m$  of  
8 MC realizations of the parameters  $C_D$ ,  $V_F$  and  $DF(x_M, y_M)$  used in the PMC method has been set to  
9 1000. The HMC procedure, instead, has been run considering  $m = 1000$  realizations of the parame-  
10 ter  $C_D$  and, for each of these realizations, 21  $\alpha$ -cut values (range 0-1, step 0.05) for the possibilistic  
11 variables  $V_F$  and  $DF(x_M, y_M)$ .

12 The cumulative distributions of the model output variable,  $C_{air}(x_M, y_M)$  obtained by applying the  
13 PMC and HMC uncertainty propagation methods are presented in Figure 6. The PMC method pro-  
14 vides a single cumulative distribution (continuous line), whereas the HMC model provides the be-  
15 lief (lower dotted curve) and the plausibility (upper dashed curve) of the set  $A = (-\infty, C_{air})$ , which can  
16 be interpreted as the boundary cumulative distributions of  $C_{air}$  at the receptor of coordinates  $(x_M,$   
17  $y_M)$ .

18 As expected, the cumulative distribution of the model output obtained by the PMC is within the be-  
19 lief and plausibility functions obtained by the hybrid approach.

20 Furthermore, the representation of the uncertainty on  $C_{air}$  provided by the PMC method appears to  
21 be more concise and easy to be interpreted than the one provided by the HMC method. This is a  
22 consequence of the different representation of the uncertainty on the input parameters  $V_F$  and  
23  $DF(x_M, y_M)$ : while the HMC method considers a set of cumulative distributions, the PMC forces all  
24 the uncertainty on  $V_F$  and  $DF(x_M, y_M)$  to be represented by single distributions. However, given the  
25 scarcity of information available for the two parameters in this case study, the use of a specific PDF  
26 seems unjustified.

27 Figure 6 also shows that the HMC method allows to process separately the uncertainty on  $C_D$ ,  
28 represented by a probability distribution, from the uncertainty on  $V_F$  and  $DF$ , represented by possi-  
29 bility distributions. These two contributions are explicitly visible in the results: in fact, the uncer-  
30 tainty on  $C_D$  affects the slope of the belief and plausibility functions, while the distance between the  
31 belief and plausibility functions reflects the lack of knowledge of the parameters  $V_F$  and  $DF$ . On the  
32 other hand, in the PMC method the contributions of the input parameters uncertainties on the model  
33 output are merged, giving rise to the slope of the output cumulative distribution.

1 Within the EIA procedure, for communication purposes, it is more effective to lump all the infor-  
2 mation contained in the obtained cumulative distribution of  $C_{\text{air}}$  into a single value, such as for ex-  
3 ample the  $\beta$  percentile. To this aim, setting a degree of confidence  $\beta = 0.95$ , the PMC method pro-  
4 vides a single value,  $C_{\text{air}}(x_M, y_M)^{95^{\text{th}}} = 2.80 \cdot 10^{-1} \text{ fg} \cdot \text{m}^{-3}$ , representative of the 95<sup>th</sup> percentile of the  
5 distribution of the PCDD/Fs annual average at the most impacted receptor point in the area. On the  
6 contrary, with the HMC the 95<sup>th</sup> percentile is an uncertain quantity itself, whose true value lies in  
7 the interval  $[1.15 \cdot 10^{-2}, 5.65 \cdot 10^{-1}] \text{ fg} \cdot \text{m}^{-3}$ , i.e. the 95<sup>th</sup> percentile of the Belief and Plausibility func-  
8 tions. Table 2 reports the values of different percentiles for both PMC and HMC methods: PMC  
9 values are always in the range of HMC values and the distance between the plausibility and belief  
10 functions increases from lower to higher percentiles. Notice that for any percentile considered the  
11 gap between the plausibility and the belief functions is in the range of one/two orders of magnitude:  
12 the uncertainty on the VF and DF parameters appears to significantly affect the estimated ground  
13 level concentrations. In this respect, the capability of the HMC method to separately process the  
14 contribution of the different uncertainties gives rise to results that clearly show the effects of the  
15 lack of knowledge on the input parameters. This is a desirable quality leading to more informative  
16 and transparent outputs, also in the light of the subsequent calculations for health risk assessment.  
17 It is worth noticing that the concentration estimates at the selected receptor for the most and the  
18 least favourable year for atmospheric dispersion obtained by means of the traditional deterministic  
19 approach are  $0.03 \text{ fg} \cdot \text{m}^{-3}$  and  $0.24 \text{ fg} \cdot \text{m}^{-3}$ , respectively, thus varying by almost one order of magni-  
20 tude. This means that the traditional deterministic approach based on just one single year simula-  
21 tion, as is done in the common practice, can lead to either too precautionary or non-conservative es-  
22 timates based on the arbitrary choice of the analyst about the reference year to be used in the model  
23 simulation. In this respect, a preliminary assessment of the representativeness of the year chosen for  
24 the weather model simulation or multi-year modelling are recommended for deterministic approach  
25 calculations.

26 Finally, notice that both PMC and HMC methods have been applied under the simplifying assump-  
27 tion of independence of the parameters  $C_D$  and  $V_F$ , although they are expected to be somehow cor-  
28 related. Future developments of this work may thus include investigating the effects of the depend-  
29 ence between these parameters on the uncertainty propagation results, for example resorting to the  
30 approach suggested in (Pedroni and Zio 2012).

31

32

## 1 **5. CONCLUSION**

2 In this work the uncertainties in the first steps for the atmospheric emission and dispersion estima-  
3 tion of an Environmental Impact Assessment (EIA) procedure have been treated by both a Hybrid  
4 probabilistic and possibilistic Monte Carlo method (HMC) and a pure Probabilistic Monte-Carlo  
5 method (PMC). Calculations have been performed for the case study of the project of a new waste  
6 gasification plant, focusing on dioxin/furan emissions that are a primary concern for human health  
7 due to their carcinogenic potential. The expected impact of the plant emissions has been quantified  
8 in terms of the contribution to the annual average concentration of dioxins and furans in ambient air  
9 at the most impacted receptor in the neighbourhood of the plant. The comparison between the re-  
10 sults obtained by the HMC and PMC methods points out that the former is more effective in propa-  
11 gating the input uncertainties through the model when little information is available for some input  
12 parameters. In particular, i) the information provided by the output of the HMC method is more  
13 consistent with that (little) available for the input parameters and ii) uncertainty is processed more  
14 “transparently” than with PMC methods, avoiding arbitrary and subjective assumptions by the ana-  
15 lyst on the input probability distribution functions and separating the contributions to the output un-  
16 certainty due to the probabilistic and possibilistic input parameters.

17 This research has been conceived as a preliminary study to assess the potential for the implementa-  
18 tion of HMC methods to the complete EIA procedure. In this regard, the satisfactory outcomes of  
19 this first analysis foster future works towards the extension of the HMC method to the remaining  
20 steps of an EIA procedure, i.e. the evaluation of the human exposure through the different impact  
21 pathways and the subsequent risk assessment.

22 Finally, it is worth noticing that the principal users of the EIA findings are decision-makers often  
23 responsible for communicating the results to the population living in the area of the planned instal-  
24 lation. With respect to environmental and health-related issues, there is in general social aversion to  
25 accept information expressed in terms of probability. Therefore, future studies will also have to in-  
26 vestigate the way of post-processing the results of a whole EIA procedure developed within an hy-  
27 brid probabilistic-possibilistic framework to make them communicable to the stakeholders and to  
28 make them more easily understandable. To this purpose, the abilities of the HMC method to avoid  
29 arbitrary assumptions and to provide results that explicitly report both probabilistic and possibilistic  
30 uncertainties could be useful for a transparent and clear post-process.

31

32

## 33 **APPENDIX**

### 34 **A.1. BASIC OF POSSIBILITY THEORY**

1 In possibility theory, uncertainty is represented by a possibility function  $\pi(y)$ . For each  $y$  in a set  
 2  $\Omega$ ,  $\pi(y)$  expresses the degree of possibility of  $y$ . When  $\pi(y) = 0$  for some  $y$ , it means that the  
 3 outcome  $y$  is considered an impossible situation. When  $\pi(y) = 1$  for some  $y$ , it means that the out-  
 4 come  $y$  is possible, i.e.: is just unsurprising, normal, usual (Dubois 2006). This is a much weaker  
 5 statement than when probability is 1.

6 The possibility function gives rise to probability bounds, upper and lower probabilities, referred to  
 7 as necessity and possibility measures ( $N, \Pi$ ). The possibility of an event  $A$ ,  $\Pi(A)$ , is defined by

$$\Pi(A) = \sup_{y \in A} \{\pi(y)\} \quad (\text{a.1})$$

8 and the necessity measure  $N(A)$  is defined by:

$$N(A) = 1 - \Pi(\text{not}A) = 1 - \sup_{y \notin A} \{\pi(y)\}$$

9 Let  $\mathcal{P}(\pi)$  be a family of probability distributions such that for all events  $A$ ,  $N(A) \leq P(A) \leq \Pi(A)$ .  
 10 Then,

$$N(A) = \inf P(A) \text{ and } \Pi(A) = \sup P(A) \quad (\text{a.2})$$

11 where *inf* and *sup* are with respect to all probability measures in  $\mathcal{P}$ . Hence the necessity measure is  
 12 interpreted as a lower level for the probability and the possibility measure is interpreted as an upper  
 13 limit. Referring to subjective probabilities, the bounds reflect that the analyst is not able or willing  
 14 to precisely assign his/her probability, and the bounds are the best he/she can do given the informa-  
 15 tion available; in other words, he or she can only describe a subset of  $\mathcal{P}$  which contains his/her  
 16 probability (Dubois 2006).  
 17

## 18 **A.2. PROBABILISTIC-POSSIBILISTIC UNCERTAINTY REPRESENTATION AND** 19 **PROPAGATION THROUGH A MODEL**

21 Let us consider a model whose output  $Z = f(Y_1, Y_2, \dots, Y_n)$  is a function of  $n$  uncertain variables  
 22  $Y_i, i = 1, \dots, n$ . The uncertainties of the first  $k$  variables can be represented by probability distribu-  
 23 tions  $p_{Y_i}(y)$  properly derived from data, whereas for the remaining  $n - k$  the scarcity of informa-  
 24 tion provide a weaker statistical base for a specific probability assignment, making the construction  
 25 of PDFs a critical operation. Two different approaches are here presented to represent and propa-  
 26 gate such uncertainties  
 27

### 28 **a. Pure probabilistic Monte-Carlo method (PMC)**

29 The uncertainties of all  $n$  input variables are treated in terms of probability distributions. Probabil-  
 30 ity representations of the  $n - k$  variables can be assigned i.e.: based on expert judgment. For exam-  
 31 ple, let us considered a typical case in which the available information on a model parameter  $x$  is  
 32 only that its values are located somewhere between a value  $x_{min}$  and a value  $x_{max}$ . In this case, a uni-  
 33 form probability distribution  $p(x) = 1/(x_{max} - x_{min}), \forall x \in [x_{min}, x_{max}]$  is typically assumed to repre-  
 34 sent the uncertainty on  $x$ . This approach appeals to: i) Laplace principle of insufficient reason ac-  
 35 cording to which all that is equally plausible is equally probable and to ii) the maximum entropy  
 36 approach (Baraldi et al. 2010). However, doubts on the consistency of this uncertainty representa-  
 37 tion have been raised (Baudrit et al. 2006) as it seems that the insufficient knowledge may justify  
 38 choices of specific functional probability distributions, like the uniform, but it should somehow ac-  
 39 count for the full set of possible probability distributions on  $X = [x_{min}, x_{max}]$ , so that the probability  
 40 of value  $x \in X$  is allowed to take any values in  $[0,1]$  (Baraldi et al. 2010).

1 The PMC method then applies a single loop Monte Carlo simulation to propagate the uncertainties  
2 of the  $n$  variables through the model. The operative steps of the propagation procedure are the fol-  
3 lowing:

4 1 Sample the  $i$ -th realization  $(y_1^i, \dots, y_n^i)$  of the uncertain variables  $(Y_1, \dots, Y_n)$  from their respec-  
5 tive PDFs  $p_{Y_1}(y_1), \dots, p_{Y_n}(y_n)$

6 2 Compute the output of the model corresponding to the  $i$ -th realization of the uncertain va-  
7 riables:  $Z_i = f(y_1^i, \dots, y_n^i)$

8 3 Repeat steps 1 and 2 for many times. Then, derive the cumulative distribution  $F(Z)$  from the  
9 outputs  $Z_i, i = 1, \dots, m$

10 The cumulative distribution  $F(Z)$  obtained gives information on the output uncertainty. Setting a  
11 percentile  $\beta$ , that corresponds to the desired degree of confidence, a concise output value of  $Z$  can  
12 be provided. The output realizations  $Z_i, i = 1, \dots, m$ , found in step 2 can be directly used to compute  
13 other lumped indicators of the output distribution, such as its mean and standard deviation values.

#### 14 **b. Hybrid probabilistic-possibilistic Monte-Carlo method (HMC)**

15 In the Hybrid probabilistic-possibilistic method, the uncertainties of the  $n - k$  variables are  
16 represented in terms of possibility distributions  $(\pi^{Y_{k+1}}, \dots, \pi^{Y_n})$ .

17 Different methods have been developed to derive possibility distributions from the available infor-  
18 mation (Baudrit & Dubois 2006, Dubois 1993). Often the analyst only knows that an uncertain vari-  
19 able can take values in a given range  $[a, b]$  wherein the most likely value is  $c$ . Triangular possibility  
20 function with the range  $|a, b|$  taken as base and  $c$  taken as vertex can be typically used to describe  
21 this information. It has been shown that the family of probability distributions defined by such pos-  
22 sibility distribution with contains all the probability distributions with support  $[a, b]$  and mode  $c$   
23 (Baudrit & Dubois 2006).

24 In the HMC method, the propagation of the uncertainties expressed in terms of both PDFs and pos-  
25 sibility curves is performed by combining the Monte Carlo technique with fuzzy interval analysis  
26 (Baudrit et al. 2006). The operative steps of the propagation procedure are the following:

27 1 sample the  $i$ -th realization  $(y_1^i, \dots, y_k^i)$  of the random variable vector  $(Y_1, \dots, Y_k)$

28 2 select a possibility value  $\alpha \in [0, 1]$  and the corresponding  $\alpha$ -cuts of the possibility distributions  
29  $(\pi^{Y_{k+1}}, \dots, \pi^{Y_n})$ , i.e.: the intervals of values of the possibilistic variables  $(Y_{k+1}, \dots, Y_n)$  with associated  
30 possibility distributions greater or equal to  $\alpha$ .

31 3 calculate the smallest and largest values of  $f(y_1^i, \dots, y_k^i, Y_{k+1}, \dots, Y_n)$ , denoted by  $\underline{f}_\alpha^i$  and  $\overline{f}_\alpha^i$  re-  
32 spectively, considering the fixed values  $(y_1^i, \dots, y_k^i)$  sampled in 1. for the random variables

33  $(Y_1, \dots, Y_k)$  and all values of the possibilistic variables  $(Y_{k+1}, \dots, Y_n)$  in the  $\alpha$ -cuts of their possibil-  
34 ity distributions  $(\pi^{Y_{k+1}}, \dots, \pi^{Y_n})$  found in 2. Then, consider the extreme values  $\underline{f}_\alpha^i$  and  $\overline{f}_\alpha^i$  found in

35 3. as the lower and upper limit of the  $\alpha$ -cut of  $f(y_1^i, \dots, y_k^i, Y_{k+1}, \dots, Y_n)$

36 4 return to step 2. and repeat for another  $\alpha$ -cut; the fuzzy random realization (fuzzy interval)  $\pi_i^f$   
37 of  $Z = f(Y)$  is obtained as the collection of the values  $\underline{f}_\alpha^i$  and  $\overline{f}_\alpha^i$  for each  $\alpha$ -cut

38 5 return to step 1. to generate a new realization of the random variables.

39 The procedure is repeated for  $i = 1, \dots, m$ : at the end of the procedure  $m$  realizations of fuzzy inter-  
40 vals are obtained, i.e.:  $(\pi_1^f, \dots, \pi_m^f)$ .

1 For each set  $A$  contained in the universe of discourse  $U_z$  of the output variable  $Z$ , it is possible to  
 2 obtain the possibility measure  $\Pi_i^f(A)$  and the necessity measure  $N_i^f(A)$  from the corresponding  
 3 possibility distribution  $\pi_i^f(z)$ , by:

$$\Pi_i^f(A) = \max_{z \in A} \{\pi_i^f(z)\} \quad (\text{a.3})$$

$$N_i^f(A) = \inf_{z \notin A} \{1 - \pi_i^f(z)\} = 1 - \Pi_i^f(\bar{A}) \quad (\text{a.4})$$

$$\forall A \subseteq U_z$$

5 Finally, the  $m$  different realizations of possibility and necessity measures can be combined to obtain  
 6 the belief  $Bel(A)$  and the plausibility  $Pl(A)$  for any set  $A$ , respectively (Baudrit et al. 2006):

$$Bel(A) = \sum_{i=1}^m \frac{N_i^f(A)}{m} \quad (\text{a.5})$$

$$Pl(A) = \sum_{i=1}^m \frac{\Pi_i^f(A)}{m} \quad (\text{a.6})$$

8 For each set  $A$ , this technique computes the belief and plausibility as the average of the possibility  
 9 measures associated with each output fuzzy interval.

10 The likelihood of the value  $f(Y)$  passing a given threshold  $z$  can then be computed by considering  
 11 the belief and the plausibility of the set  $A = (-\infty, z]$ ; in this respect,  $Bel(f(Y) \in (-\infty, z])$  and

12  $Pl(f(Y) \in (-\infty, z])$  can be interpreted as bounding, average cumulative distributions

13  $\underline{F}(z) = Bel(f(Y) \in (-\infty, z])$ ,  $\bar{F}(z) = Pl(f(Y) \in (-\infty, z])$  (Baudrit et al. 2006). Thus, one way to es-

14 timate the total uncertainty on  $f(Y)$  is to provide a confidence interval at a given level of confi-

15 dence, taking the lower and upper bounds from  $Pl(f(Y) \in (-\infty, z])$  and  $Bel(f(Y) \in (-\infty, z])$ , re-

16 spectively (Baudrit et al. 2006). Notice, however, that it is not possible to directly obtain

17 information on the mean and standard deviation of the output distribution from the plausibility and  
 18 belief distributions.

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