Guidelines detailing the range and distribution of atmospheric dispersion model input parameter uncertainties

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Confidence
Coping with uncertainty for improved modelling and decision making in nuclear emergencies

EJP-CONCERT

European Joint Programme for the Integration of Radiation Protection Research

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D 9.1 - Guidelines ranking uncertainties for atmospheric dispersion

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Abstract

In the event of an accidental release of radionuclides into the atmosphere, dispersion calculations would be used to model the consequences and to assist in determining appropriate countermeasures. Environmental contamination depends on the characteristics of the releases, the trajectory of the radioactive plumes and the deposition episodes. The weather conditions (wind, atmospheric stability, etc.) determine the transport of the radioactive plume in the atmosphere, as well as its vertical and horizontal extension. The plumes are depleted during transport by dilution in the atmosphere and deposition processes. Dry deposition occurs in the absence of precipitation, whereas wet deposition is the dominant process during rainfall or snowfall episodes. The behaviour of the radionuclides in the atmosphere depends on whether they are in gaseous or particulate form, their size and their reactivity. These elements also influence their behaviour in relation to the deposition processes, as well as their absorption and their harmfulness to the human body. The composition of the releases and the characteristics of the radionuclides vary during the release phase according to the facility events that caused them.

Simulations are subject to significant uncertainties related to the source, to the meteorological conditions, those due to the atmospheric dispersion models and radiological assessment models. The identification and description of source term and meteorological uncertainties associated with the atmospheric dispersion model-specific uncertainties will enable a comprehensive assessment of the nature and impact of the atmospheric dispersion model (ADM) output uncertainties. It is intended that such uncertainty ranges and distributions will be used subsequently in the propagation of uncertainties through the chain of atmospheric dispersion and radiological assessment models for both historical (for example the accident at the Fukushima Daiichi Nuclear Power Plant) and hypothetical scenarios, to better understand the effect on model output, and thereby appraise the impact on decision making in the context of an emergency response.

This document provides guidelines describing uncertainties related to the meteorological conditions, related to the source and related to the atmospheric dispersion models. The **first** chapter looks at meteorological ensembles as a source of information on meteorological uncertainty for dispersion models. The **second** chapter questions the use of meteorological measurements to reduce uncertainty. The **third** chapter provides guidelines describing uncertainties related to the source. The **fourth** chapter presents a literature review to evaluate the range and distribution of atmospheric dispersion model-specific input parameter uncertainties. The **last** chapter provides Guidelines for ranking uncertainties in atmospheric dispersion.

<End of abstract>

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D 9.1.1 - Using Ensemble Meteorological Forecasts to Represent Meteorological Uncertainty in Dispersion Models

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Abstract

There are a number of sources of uncertainty in the dispersion model prediction, including uncertainty about the source term information, intrinsic uncertainty in the dispersion model and uncertainty in the driving meteorology. Here, the focus is on the impact of the uncertainty in the driving meteorology on the uncertainty in the dispersion model prediction.

Part of the aim of work package 1 of the CONFIDENCE project is to provide an assessment of the ability of the ensemble weather prediction systems to provide sufficient uncertainty information for dispersion modelling.

The presented review looks at meteorological ensembles as a source of information on meteorological uncertainty for dispersion models. The construction of the ensembles, their verification and examples of their use with dispersion models are explored.

<End of abstract>

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Introduction

In the event of a release of radioactive material to the atmosphere, atmospheric dispersion models are used to model the dispersion and deposition of this radioactive material. To do this, atmospheric dispersion models rely on information about conditions under which the material was released (the so-called “source term”, consisting of, e.g., height, amount, nuclides, physicochemical forms and timing) as well as meteorological information. The accuracy of the dispersion predictions (i.e., the difference between the model-calculated and the observed values of quantities like concentration in air or deposition on ground) clearly depends (among other factors) on the accuracy of these inputs (i.e., how close these inputs are to their true values). Increasingly there is also pressure (e.g. from decision makers, the scientific community) to provide information on the uncertainty of the dispersion and deposition forecasts. The uncertainty of dispersion and deposition forecasts can be expressed quantitatively as, e.g., the range of values of the quantity of interest that is expected to occur at each location (minimum and maximum) with some confidence limits (e.g., 90% or 95%), or the probability that a quantity of interest exceeds a critical threshold at each location. The exact formulation for expressing the uncertainties in dispersion computations depends on the method used to calculate them.

There are a number of sources of uncertainty in the dispersion model prediction, including uncertainty about the source term information, intrinsic uncertainty in the dispersion model and uncertainty in the driving meteorology. A useful discussion on the types of uncertainties in dispersion models is given by Rao (2005). The uncertainty in the dispersion model results will be propagated into the dose and environmental models, a topic that will be covered later in the CONFIDENCE project. Here, the focus is on the impact of the uncertainty in the driving meteorology on the uncertainty in the dispersion model prediction.

Typically, meteorological information is provided to dispersion models from a single numerical weather prediction (NWP) model. However, the atmosphere is a chaotic system. This means that small perturbations in the initial atmospheric state can grow quickly. Deterministic weather forecasting starts from the best estimate of the atmospheric state and then models how that atmospheric state will evolve over time. Small errors in the initial conditions and in the model calculations can result in incorrect forecasts at later times. To overcome this, meteorological modellers have developed systems to model errors in the initial atmospheric state and in the model calculations themselves called ensemble systems. An ensemble system contains multiple realisations of these model calculations - hence the term 'ensemble' - based on the initial state with superimposed errors in the observations (Figure 1 contains a schematic of a meteorological ensemble). Operational ensemble forecasts were first used in the 1990s and now many national meteorological centres routinely produce ensemble forecasts. Starting with the work of Straume et al. (1998) meteorological ensemble forecasts have increasingly been used as input to dispersion models, with the aim to produce uncertainty information in the dispersion forecasts.

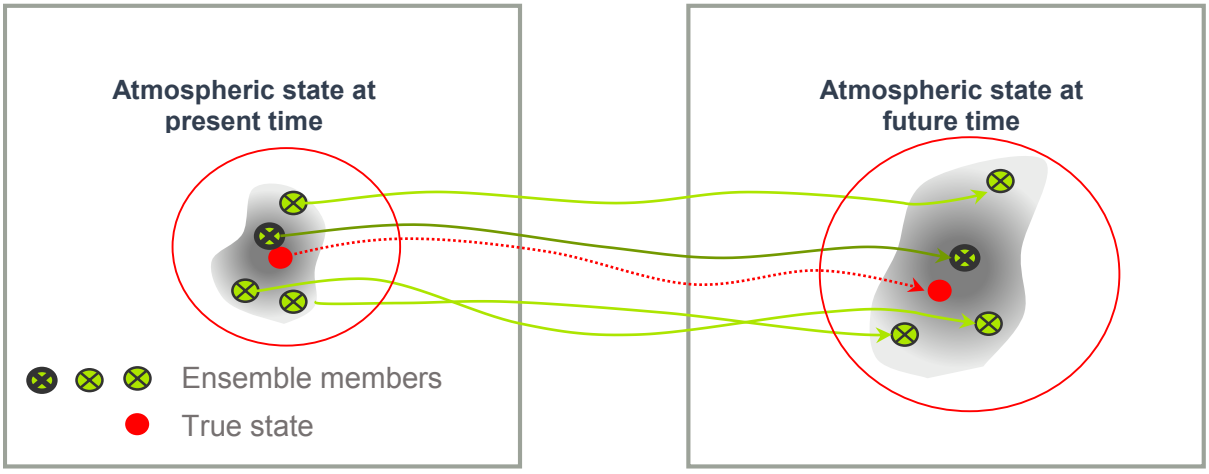


Figure 1 : Schematic of an ensemble meteorological forecast. The red circles and line represent the true state and the bold black member represents the control forecast.

Part of the aim of work package 1 of the CONFIDENCE project is to provide an assessment of the ability of the ensemble weather prediction systems to provide sufficient uncertainty information for dispersion modelling. The present review starts to address this by examining the current methods of producing an ensemble meteorological forecast and the techniques used to verify those forecasts against observations and analyses (analyses are best estimates of the atmospheric state constructed by combining models and observations). The review also considers the atmospheric variables most critical to dispersion modelling and how well they are represented in dispersion models. Next, the review discusses some studies that have used ensemble meteorology in dispersion models and some studies that have found it necessary to further perturb the meteorological variables in order to adequately represent meteorological uncertainty in dispersion models. Finally, the methods that are used to quantify and present uncertainties in dispersion forecasts are reviewed.

Introduction to Meteorological Ensembles

Uncertainty in Meteorological Forecasts

The aim of a numerical weather prediction model is to determine the future state of the atmosphere by modelling the evolution of the current state of the atmosphere. However, work by Lorenz (1963) pointed out that, for a non-linear system such as the atmosphere, small initial errors can grow rapidly thus resulting in incorrect long-range forecasts. Thus even with the best possible initial conditions and the most accurate NWP models, forecast errors are inevitable. To help overcome this problem Epstein (1969) suggested representing the initial conditions as a probability distribution. Models could then be used to predict the evolution of this probability density function. Unfortunately, there are many degrees of freedom in the atmosphere and the computations required to predict the evolution of the distribution are unsolvable. Instead, Leith (1974) suggested using a Monte Carlo approach, using an ensemble of randomly perturbed initial conditions to represent this probability density function. This is similar to the perturbation of initial conditions used in ensemble weather forecasting today although now perturbations are flow dependent and seek to maximise the perturbation growth in the time period of interest.

Errors in meteorological forecasting systems come from a number of sources. There can be errors in the initial conditions due to the sparseness in observations in uninhabited parts of the globe and the upper atmosphere. Satellite data have improved the spatial coverage of observations and these are used in estimating the initial conditions for meteorological forecasting systems. However, as the interpretation of the satellite data depends on models, this can also introduce errors. There are also errors in the observations due to limitations in the equipment used to take the measurements. There can also be errors due to observations not being representative of the region in which they are located. Errors are not limited to the initial conditions but also come from limitations and approximations in the numerical weather prediction models themselves. These errors may be the result of parameterising processes which are too small to resolve in the model (for example, turbulence, surface drag and convection), that are too complex to model, or for which there is a poor understanding of processes (for example, cloud microphysics and composition). Ensemble weather prediction systems take into account both initial condition errors and model errors. There are a number of ways in which to estimate initial condition errors and model errors and some of these are listed in the next two sections.

Initial Condition Perturbations

The number of perturbed members it is possible to include in an ensemble is small relative to the number of possible atmospheric states. Therefore, the aim in an ensemble prediction system is to focus on the initial conditions that will result in the largest forecast perturbations. There are a number of different ways to select the fastest growing perturbations. The first ensembles constructed at ECMWF (European Centre for Medium-range Weather Forecasts) used singular vectors to estimate the fastest growing perturbations. These singular vectors target perturbations that will grow quickly over the next few days (Molteni, 1996). In contrast, the first ensembles constructed at NCEP (National Centers for Environmental Prediction) focussed on perturbations that had grown fast recently, by using the 'error breeding' method (Toth and Kalnay, 1993). Other methods for generating an ensemble of initial conditions include the ensemble data assimilation approach now used, for example, by ECMWF, and the Ensemble Transform Kalman Filter or ETKF approach used, for example, by the Met Office (Bowler, 2008).

Model Perturbations

Early meteorological ensembles only used perturbations in the initial conditions, ignoring any model error. However, this strategy was shown to produce inadequate spread particularly in the short-range (see for example, Buizza, 1997). Errors can be introduced by simplifications within numerical weather prediction models and this means that even with perfect initial conditions there will be some error in the forecast due to model error. A few studies have compared ensembles constructed from initial condition perturbations only and model perturbations only. For example, in a study of convective rainfall in the US, Stensrud et al. (2000) showed that ensembles that include model error can increase the ensemble spread in the first 12-hours of a forecast. However, these studies are limited to only a few ensembles and a few case studies and most ensemble systems now consider both initial condition perturbations and model perturbations. A number of different approaches are used to account for model errors in an ensemble framework.

Multi-model approach: In this approach, each forecast is made using a different weather prediction model. This approach is, for example, used as part of the GLAMEPS (Grand Limited Area Modeling Ensemble Prediction System) where ensembles of two models HIRLAM (High Resolution Limited Area Model) and Alaro are combined to form a larger ensemble (Iversen at al., 2011). The use of a multi-model approach can increase ensemble spread and each member is physically consistent. However, the models have different biases and some models may be more skilful, on average, than others (Leutbecher, 2017). The multi-model approach is good for leveraging effort at a number of institutes but harder for a single institute to maintain.

Multi-physics approach: In this approach, each forecast uses a different set of parameterisations. The Danish Meteorological Institute-Ensemble Prediction System (DMI-EPS) uses two different parameterisation schemes for convection and condensation (Feddersen, 2009). PEARP (Prévision d'Ensemble ARPEGE), the global ensemble running at Météo France, uses 10 different sets of parameterisations (Descamps, 2015). The advantages and disadvantages of the multi-physics approach are similar to those of the multi-model approach.

Multi-parameter approach: In this approach, the parameters used in each parameterisation are perturbed. The key advantage of the multi-parameter approach is that parameterisations with more uncertainty can be given more weight. However, the uncertainty is usually based on data assimilation rather than a physical understanding of the processes. This approach takes more effort to maintain than the stochastic physics approach but less effort than the multi-model and multi-parameter approaches.

Stochastic-physics approach: In this final approach the tendency of atmospheric variables such as temperature are perturbed. This approach is used, for example, in the ECMWF, and Met Office ensembles.

A Note on Perturbations in Local Area Ensembles

Many meteorological centres now also run their own limited area ensemble system at higher resolution than the global ensemble systems. These limited area ensemble systems are focussed on perturbations within a smaller area of interest and usually over a shorter timescale than for the global ensembles.

In addition to an initial atmospheric state, these models also require boundary conditions. These boundary conditions may also be perturbed. A number of different approaches to perturbing the initial conditions, boundary conditions and model physics are adopted. For example:

- GLAMEPS takes lateral boundary conditions and initial perturbations from EuroTEPS, a version of the ECMWF ensemble with a focus on initial perturbations that grow fastest in Europe within 24-hours (Iversen et al., 2011).
- MOGREPS-UK takes initial and boundary conditions from MOGREPS-G (Tennant, 2015).
- The DMI-EPS and the NMI-MEPS (**Norwegian Meteorological Institute** Perturbation MetCoOp Ensemble Prediction System (Andrae, 2017) uses scaled-lagged average forecasts (called SLAF) a simplified form of the error breeding method used at NCEP. SLAF are constructed by taking perturbations from the difference between an old forecast and a more recent forecast and multiplying them by a scaling factor to provide an initial perturbation that can be added or subtracted.

Time-Lagged Ensembles

Time-lagged (or lagged average forecasts) provide an alternative method of generating a meteorological ensemble (Hoffman and Kalnay, 2000). They are computationally much less expensive than meteorological ensembles because they take advantage of the fact that single meteorological model runs are carried out every few hours. In addition, because they are initialised at different times they capture some of the error growth. However, the ensemble members with earlier start times have no knowledge of later observations so may be considered less accurate. Despite this, all members in a time-lagged ensemble are usually assumed to be equally likely.

To construct a dispersion model ensemble from a time-lagged meteorological ensemble the dispersion model is driven using successive meteorological model runs which overlap for the period of interest (see Figure 2).

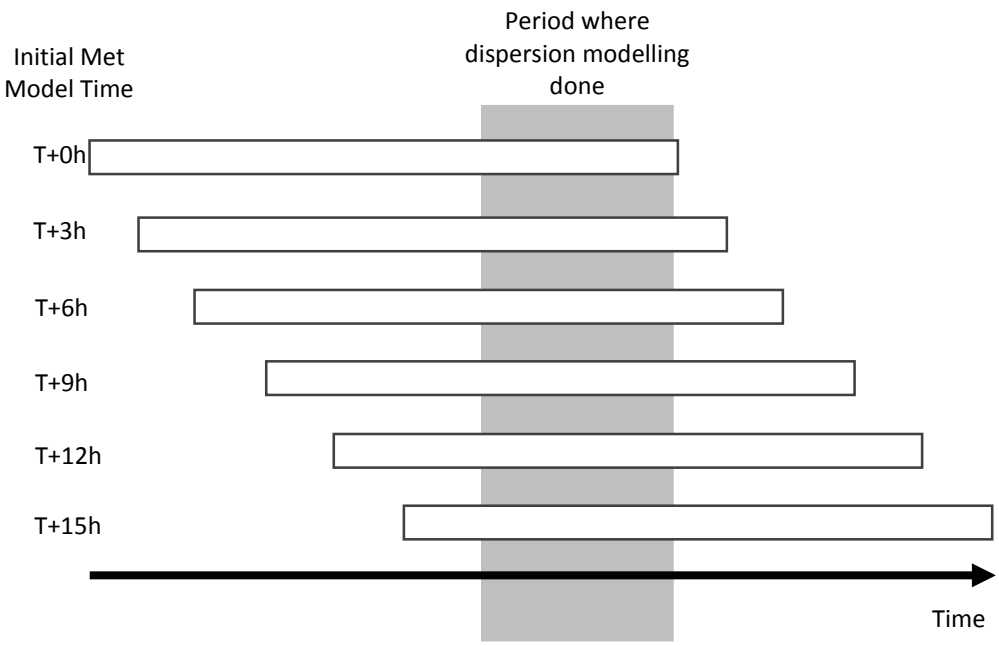


Figure 2 : Schematic of time-lagged ensemble use for dispersion modelling. The white horizontal bars represent the meteorological model started at 3-hourly intervals and the grey shaded region represents the period where dispersion modelling was carried out.

Verification of Meteorological Ensembles

Verification Techniques

The purpose of ensemble forecasting is to increase average forecast accuracy, provide an indication of forecast skill and to estimate event likelihood. Ensemble modellers carry out verification to determine whether ensembles are fit for purpose. Since national met services are interested in variables associated with general weather and with high impact events (for example strong winds or extreme temperatures) these are the variables which are most commonly verified. The subject of verification is well-studied and there are a large number of techniques used for verification. In the interest of brevity this section considers the most commonly used techniques.

First, station-based techniques are used to assess accuracy, where the predicted probability of the occurrence of an event is compared to the observed frequency of that event at a number of observing sites. To be considered accurate, an ensemble is required to be reliable; in that the frequency of occurrence agrees, on average, with the probability of occurrence. So if on 100 days an event was predicted with a probability of 70% we would, on average, expect that event to occur on 70 of those 100 days. A good ensemble is also expected to have resolution; in that it is possible to distinguish between the probabilities of events that occur with different frequencies. A number of other statistical techniques including the Brier score and the continuous ranked probability score are used to assess the reliability and resolution of ensemble meteorological forecasts (Wilks, 2006). The Brier score compares the probability of a variable exceeding a threshold to the observation (or not) of that exceedance and the continuous ranked probability score is the sum of Brier scores over a number of thresholds.

Second, station-based techniques are used to assess the ensemble spread by comparing the spread of ensemble members to the error at a number of observing sites. There is an expectation that averaged over time and space the spread of the ensemble should be similar to the root mean square error (RMSE) of the ensemble mean. If the ensemble spread is greater (less) than the RMSE then the ensemble is said to be over-dispersive (under-dispersive). The spread of an ensemble can be assessed by constructing a rank histogram where observations are scored according to the rank of the ensemble member they mostly closely match (see Figure 3 below). For an under-dispersive ensemble the histogram will be u-shaped as the observations are more often smaller than the smallest ensemble member and larger than the largest ensemble member. In addition, high spread is typically indicative of low confidence. Papers show that links between spread and error in any particular forecast are weak, even for a perfect ensemble (Houtekamer, 1993). However, when data are grouped into distinct bins based on ensemble spread and the ensemble spread is compared to the error within each bin the correlation between spread and skill is clearer (Wang and Bishop, 2003).

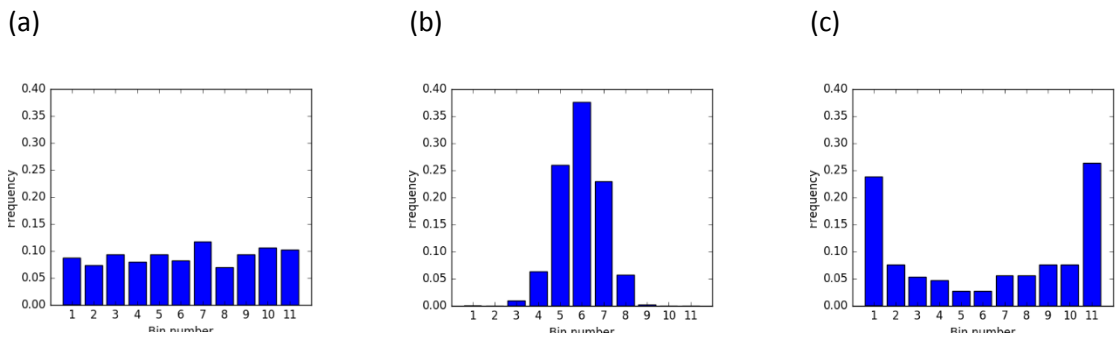


Figure 3 : Schematic showing rank histograms for a 10 member ensemble. In (a) the ensemble spread is on average good, in (b) the ensemble is overspread and the observations are more frequently ranked in the middle of the ensemble range and in (c) the ensemble is underspread and the observations are more frequently ranked at the extremes of the ensemble range.

As mentioned previously, station data are sparse, particularly in uninhabited parts of the globe, compared to the grid size of operational NWP models. For example, there are approximately 130 observing sites in the UK, but the high resolution (1.5km by 1.5km) NWP model run at the Met Office contains more than 500,000 grid points. Carrying out station-based verification only would verify less than 0.03% of the grid points in the model. To overcome this problem, meteorological ensembles are routinely verified against analysis meteorology. Meteorological analyses are constructed by assimilating large amounts of observational data and are considered to be the best estimate of the atmospheric state. They can also be used for the verification of variables for which there is no or very little observational data.

There are a number of limitations to the methods of verification described above. Firstly, as described the methods do not take into account deficiencies in the observations. The deficiencies in the observations used for verification may include incomplete coverage of observations, stations which do not represent the region surrounding them and errors in the measurements or processing of the measurements. A number of the verification techniques described above rely on the ability to state whether or not an event has occurred or not. For example, was the precipitation observed to be greater than 16mm in 24 hours, or was the wind speed observed to be greater than 10mph? If the observation is in error then the event may have observed to occur when it did not happen or vice versa. This may mean that forecasts are performing better than the verification scores suggest (Bowler, 2006).

Second, high-resolution (resolutions of a few kilometres or less) models are not expected to be accurate at the grid-scale meaning that when verified using traditional grid-point techniques features can appear mis-located. This results in the 'double penalty' effect where the model is penalised once for the predicted occurrence of an event that is not observed, and again for the non-occurrence of the observed event. To counter this, neighbourhood statistics consider several grid-points around the observation point and can provide a scale at which the model shows skill. However, care should be taken when comparing dispersion model performance to meteorological models verified in this way because dispersion models which use raw meteorological model output and which are compared to observations at a grid point implicitly assume grid-point accuracy

Verification of ensembles focuses on variables of interest to weather forecasting (temperature, wind, rain) and may have a particular focus on extreme events (storms, high/low temperatures, or heavy precipitation). The station-based verification also focuses on parameters that are routinely measured at weather observation stations including above surface observations from radiosondes. Verification against meteorological analyses can be carried out for a wider range of meteorological variables.

How well do ensembles verify?

National meteorological services routinely verify their ensemble forecasting systems against observations. However, much of this verification is not published in peer-reviewed journals. This section contains a discussion of results that are available in the published literature but it is possible that more information could be gained by approaching the meteorological services directly. Some meteorological centres, such as ECMWF, do produce an annual verification report (see for example, Haiden et al., 2016), although these often focus on large-area, longer-term averages and high impact weather such as tropical cyclones. Verification covers a wide-range of variables both at the surface and higher up in the atmosphere. For the short-range modelling of a surface release of a radioactive material the verification of surface variables is likely to be of greater interest. However, it may be useful to consider variables above the boundary layer for transport over longer distances and longer periods of time. This section focusses on the verification of wind and precipitation as these are the most easily verified surface variables of interest to dispersion modelling. A discussion of other variables of interest to dispersion modelling is discussed in the next two subsections.

Although some ensembles now demonstrate good agreement between ensemble spread and RMS error for spatial 500hPa height (see Figure 4), many ensembles show a tendency to be under-dispersive when predicting surface variables (i.e. the spread of the ensemble members is less than the spread of the error of the ensemble mean). For example, Descamps et al. (2015) demonstrates that the PEARP model and the ECMWF ensemble are under-dispersive in their prediction of 10 m wind-speed and 24-hour accumulated precipitation over the European region at all lead times. Under-dispersion is also demonstrated for wind speed, 6-hour accumulated precipitation and 2 m temperature in the GLAMEPS and ECMWF models by Iversen et al. (2011) (see Figure 5). Both studies show that the ensembles are more reliable at predicting wind speeds than precipitation. This may be because precipitation is particularly sensitive to model scale. For instance a study by Flowerdew (2012) showed that higher resolution ensemble models are more reliable at predicting precipitation than lower resolution ensemble models.

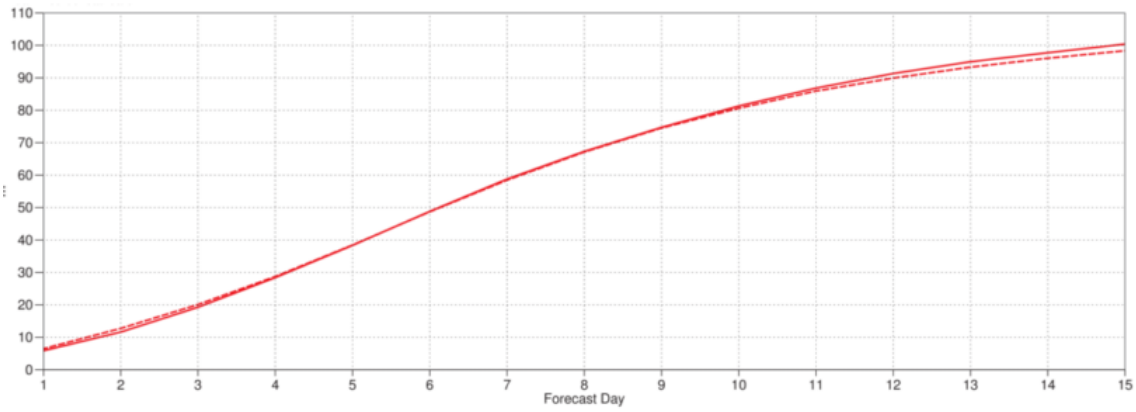


Figure 4 : Ensemble spread (standard deviation, dashed lines) and RMS error of ensemble- mean (solid lines) for winter 2015–2016; verification is against analysis, plot is for 500 hPa geopotential (top) over the extratropical northern hemisphere for forecast days 1 to 15. From Haiden et al. (2016)

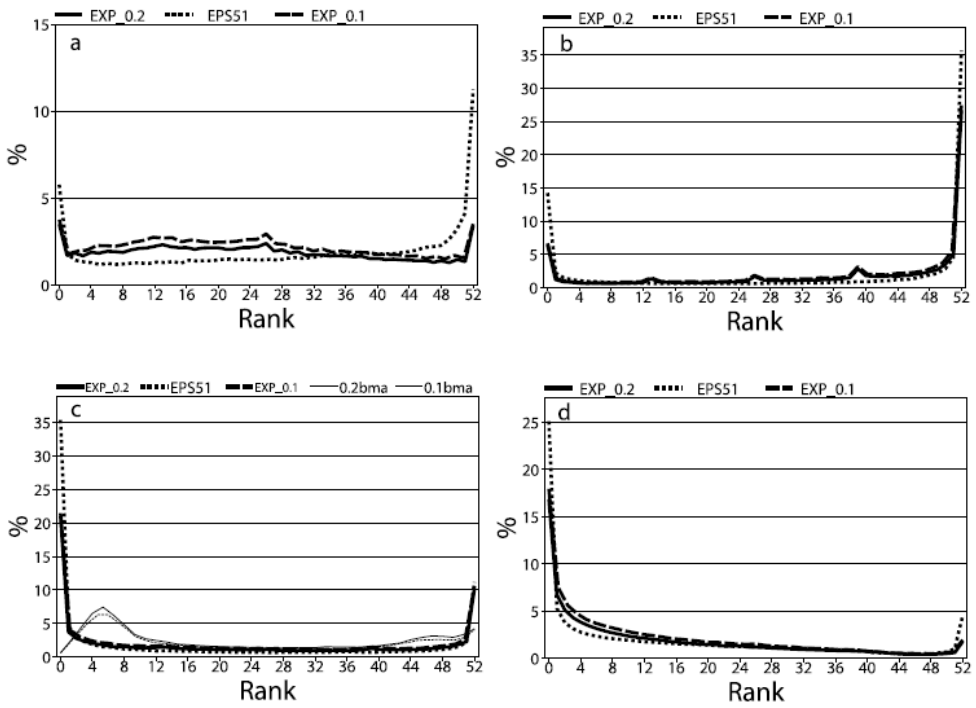


Figure 5 : Rank histograms (see previous section for a description of rank histograms) for +42 h predicted mean sea level pressure (a), 2 m temperature (b), 10 m wind speed (c) and +18 to +24 h predicted 6-hourly precipitation (d). Thick lines: continuous: 52-member GLAMEPS (EXP_0.2); dotted: 51 member operational EPS; dashed: 44-member GLAMEPS (EXP_0.1). Thin lines in (c) are BMA-calibrated wind speed for EXP_0.2 (continuous) and EXP_0.1 (dotted). From Iversen (2011).

High-resolution ensembles focused on the short-range and/or on a smaller region have been shown to perform better than long-range global ensembles when evaluated in the smaller region. For example, GLAMEPS shows up 25% improvement on ECMWF EPS for short forecasts of 10 m wind speed (Sørensen, 2013). Similarly, NAE MOGREPS, the regional modelling component of MOGREPS, focused on the North Atlantic-European area, performed better than its global counterpart, MOGREPS-G, and the ECMWF ensemble for forecasts of light rain and wind speed (Bowler et al., 2007)(see Figure 6). In Figure 6 it is also possible to see that MOGREPS-G and the ECMWF ensemble performed slightly better at lead times of 24 and 36 hours respectively. This is because the initial condition perturbations and model perturbations have been chosen to maximise ensemble spread at longer lead times than the NAE MOGREPS ensemble.

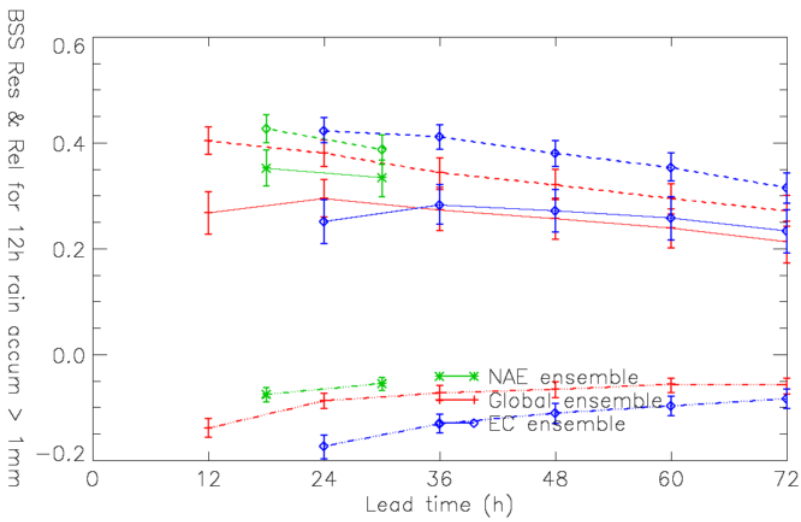


Figure 6 : Brier skill score (solid), and reliability (dash-dot) and resolution (dashed) components for the NAE, global and ECMWF ensembles for forecasts of 12h accumulated precipitation greater than 1 mm. The verification period is 1 July 2006 to 31 March 2007 (Bowler et al., 2007). The reliability component of the Brier skill score measures the ability of the ensemble forecast to predict the observed frequency and the resolution component measures the distance between the observed relative frequency and the climatological frequency (see Bowler et al. (2007) for calculation of components).

Variables of Interest to Dispersion Modelling

In order to understand whether a meteorological ensemble provides sufficient/suitable information on meteorological uncertainty for dispersion models, it is first necessary to understand which meteorological variables are important to dispersion modelling and which variables are important at the scale of interest. Here we focus on the meteorological variables that are important when considering a surface or near-surface release of radioactive material. This question is generally examined in relation to a single event. For example, Girard et al. (2016) used a statistical emulator of a complex 3D dispersion model —to reduce the number of model runs required to cover in detail the multidimensional space of input model variables and —to determine which dispersion model inputs provided the most uncertainty during the Fukushima accident. Their study looked at source term, dispersion model and meteorological variables. Their results showed that aggregated outputs were mainly influenced by uncertainties in the source term but the uncertainties at individual stations were also sensitive to wind perturbations, i.e. that the most sensitive variables depend on the result or outcome examined.

Considering a hypothetical release in 2007 or 2008, Haywood et al. (2008) showed that the regions in which sheltering and evacuation might be recommended were sensitive to small perturbations in wind direction and rainfall. In this case, the sheltering and evacuation regions were determined by scaling the dispersion model output to a single measurement point assumed to be in the centre of the plume. Wind direction can be particularly important where the proximity of the measurement point to the source is small and the plume is relatively narrow (and thus the concentration gradients orthogonal to the plume centre line are typically high).

The exact nature of an event (for example hot or buoyant source) or the weather conditions can also alter the sensitivity of a dispersion forecast to individual meteorological variables. For example, a study by Hamburger and Gering (2017) showed that the dispersion forecast is sensitive to small perturbations in atmospheric stability when the atmosphere is very stable but less sensitive to small perturbations in atmospheric stability when the stability of the atmosphere is more neutral.

Variables of interest to dispersion models was also a topic of discussion at the work package 1 workshop in Paris in June 2017. At the workshop participants ranked the meteorological variables used as inputs in dispersion models in order of the dispersion model sensitivity to each variable. The top 5 variables are shown in Table 1.

Parameter	Uncertainty/Effect	Rank
Wind direction	• Direction changes can result in large impacts on the dispersion results as a moderate change in direction can significantly alter air concentrations. • The timing of the wind direction change is important when combined with the timing of changes in the release rate. • The importance of wind direction to the response may depend on the phase of the response or the countermeasures taken. For example, if the countermeasures involve evacuating everybody within 5km of the nuclear power plant then wind direction will not impact this countermeasure.	1
Stability	The stability may be very important for certain types of release (e.g. an elevated release) and in the vicinity of the source. Stability may also be more important for some model configurations than others.	1 (early phase)
Precipitation		2
Wind speed	Wind speed is moderately important to dispersion calculations	3
Mixed layer depth	The importance of the mixed layer depth depends on the situation and the meteorology. For example, if the plume is entirely within the mixed-layer then the mixed-layer depth is not important but if the plume is likely to be fumigated into the mixed-layer then the timing of the mixed-layer depth change can be very important.	4

Table 1 Rank of the sensitivity of dispersion models to input meteorological variables discussed at the CONFIDENCE work package 1 workshop in Paris, June 2017.

Participants also discussed the sensitivity of dispersion model output to each input variable. The sensitivity of dispersion models to each input parameter is dependent on a number of factors:

a.) The nature of the release, the spread of a buoyant or elevated release may be less sensitive to surface parameters and more sensitive to variables such as the height of the boundary layer or mixed-layer.

b.) The radionuclides released. Radionuclides that are efficiently wet deposited will be more sensitive to the precipitation inputs than those that are not efficiently deposited.

c.) The meteorological conditions. In a particular scenario, the dispersion model may not be sensitive to a meteorological input. For example, work by Hamburg and Gering (2017) showed that their dispersion model was only sensitive to stability when the atmosphere was very stable.

d.) The dispersion model or modelling process. For example, if the dispersion model is to be used with a measurement to determine the source term then the dispersion model outputs are very sensitive to wind direction (Haywood, 2008). Also, a dispersion model which calculates the mixed-layer height from cloud cover, vertical temperature and wind profiles may be sensitive to changes in the vertical temperature profile but a dispersion model that takes the mixed-layer height directly from the NWP model may be more sensitive to the mixed-layer height input.

e.) The integration or averaging period of the outputs. For example, studies of Fukushima have shown that over longer integration periods, dispersion models are less sensitive to precipitation fields (Draxler, 2015).

f.) The countermeasure being taken. As mentioned in table 1 if the countermeasure involves evacuation out to 5km around a nuclear power plant, although the dispersion model output might be sensitive to wind direction it will have no impact on the countermeasure taken.

How are the variables of interest to dispersion modelling verified?

Variables of interest to weather forecasting are not necessarily the same as those of interest to dispersion modellers. As mentioned earlier the verification of ensemble weather forecasts typically targets variables of interest to weather forecasting, such as temperature, near-surface winds, precipitation and cloud cover. Although some of these variables are also relevant to dispersion problems, other parameters that have an influence on dispersion, such as surface fluxes of heat and momentum that are critical for determining atmospheric stability and boundary layer depth are not routinely verified. In addition to a lack of interest, these variables can also be difficult to verify due to a lack of suitable measurements, or a difficulty in obtaining a measured value that is equivalent to its modelled counterpart. For example, it is possible to measure boundary layer depth using radiosondes and ceilometers but radiosondes are typically only released from a small number of locations, once or twice a day, and ceilometers can struggle to detect and diagnose complex boundary layers (Selvaratnam et al., 2015). Sørensen et al. (2016) and Perillat et al. (2016), note that when meteorological ensembles are verified through local scale variables, such as wind speed at 10m above ground, they tend to be under-dispersive, probably because they mostly represent uncertainties in large-scale variables that are relevant to weather forecasting.

Ensemble Modelling with Dispersion Models

Use of Ensemble Meteorology with Dispersion Models

Ensemble forecasts have been available for a number of years. However, there have been concerns over their applicability to dispersion modelling and the ability to display output in a way that can be quickly interpreted. In addition, ensemble data sets can be very large making them difficult to store and making dispersion model runs computationally expensive to run. For these reasons, centres have only recently set up ensemble dispersion systems to run in real time. For example, Denmark has had an operational ensemble dispersion system since 2014 (Sørensen et al., 2017a). There have, however, been a number of studies that have explored the use of an ensemble meteorological forecast for a few real dispersion events and hypothetical case studies.

Real Incidents and experimental campaigns

Dispersion models have only been combined with ensemble meteorology for a few real incidents/live experiments. The first time ensemble meteorology was used to drive dispersion models was for ETEX (European Tracer Experiment) that took place in Europe in 1994. In this experiment, an inert tracer

was released in France and monitoring stations were set up to sample the tracer's spread over much of Europe. ECMWF ensemble meteorology, which at the time of ETEX was available at a resolution of approximately 210km by 210km, was used with a number of dispersion models to investigate the added information provided by an ensemble of outputs (Straume et al., 1998; Straume, 2001; Galmarini et al., 2010). Their work showed that in general the dispersion ensemble mean was closer to the observations than any individual member was. However, they also highlighted the issue of selecting an appropriate statistical measure of skill. No single ensemble member could be considered the 'best' for every statistical measure.

Straume et al. (1998) also investigated whether the ECMWF clusters were appropriate for use with dispersion models In order to create a limited set of weather scenarios that represent (most of) the ensemble distribution, ECWMF apply a clustering to their ensemble forecasts. The clustering consists of an empirical orthogonal function decomposition of the 500 hPa height field over a number of time windows starting from three days. ECMWF then select the first N clusters so that 80% of the variance in the 500 hPa field is explained. N can be any value between two and six where a large value suggests a greater spread in the ensemble. Straume et al. (1998) used clusters based on the the forecast between days 5 and 7. The lack of difference in the dispersion model forecasts for each of the clusters indicated that for ETEX the clusters did not represent the spread in the surface parameters in the first three days. Thus, it would not be sensible to use the current set of ECMWF clusters to represent the ensemble of dispersion model output. However, it may be possible to develop a set of clusters that is more appropriate for dispersion modelling.

Ensemble meteorological data has also been used to explore the spread of radioactive material from the Fukushima accident. Périllat et al. (2016) used both a global meteorological ensemble (ECMWF), with a horizontal resolution of 0.25° (approximately 25km), and a limited area meteorological ensemble (designed by MRI, Sekiyama et al., 2013), with a horizontal resolution of 3km, to predict gamma dose rates at a number of monitoring locations in Japan. Their initial comparison of the meteorological data with observations of wind speed and direction at a couple of local stations showed the observations to be outside of the spread of forecast values for much of the time, suggesting that the ensembles were either under-dispersive or not capturing local effects such as sea breezes or orographic effects. Once the meteorological ensembles are propagated through the dispersion model, the dispersion results can be compared to radiological observations (deposition measurements, gamma dose rates on monitoring stations). This showed that despite the under-dispersion of weather prediction ensembles when compared to meteorological stations, the radiological results were more widespread, even without taking into account other sources of uncertainties. A hypothesis is that meteorological uncertainties accumulate along the plume trajectory. However, work still needs to be done to design dispersion ensembles that are able to reproduce the variability of environmental observations.

Sørensen et al. (2016) use meteorological ensembles to assess uncertainties in dispersion models applied for the Fukushima accident. They firstly evaluate the meteorological ensembles by comparison with 10m-wind data from a number of meteorological stations throughout Japan. They find a tendency for the ensembles to be under-dispersive, in agreement with other verification studies. Based on the meteorological ensembles they produce ensembles of dispersion forecasts, using a single source term. The results are presented as contour plots of ensemble average of instantaneous concentrations at different times (time-series of contour plots) and accumulated deposition of specific radionuclides. The quantities that are selected for showing the uncertainties are minimum-average-maximum values, 10th, 50th and 90th percentiles and probabilities of exceeding certain thresholds. For discussions with decision makers, thyroid dose contour plots are also considered: 10th, 50th, 90th percentiles and

probabilities of exceeding 10 and 50 mGys after 54 hours. Ensemble dispersion results are not compared to observations in this study.

The above cases studies show that ensemble meteorology is a useful tool for producing uncertainty information in dispersion forecasts, but care needs to be taken when comparing to observations. Although not directly comparable some work has been done modelling the transport of volcanic ash using ensemble forecasts and lessons may be learned from these studies. For example, Dare et al. (2016) used the ensemble model ACCESS, with the dispersion model HYSPLIT to predict the transport of volcanic ash following the eruption of Kelut, Indonesia in 2014. Their results showed that combining the ensemble members into an ensemble mean or median can mask the presence of small regions of high concentrations of volcanic ash that have a highly variable location

The studies considered so far in this section have all used meteorological ensembles from a single meteorological model with a single dispersion model. However, there are a number of other ways to generate a dispersion model ensemble (see Galmarini et al., 2004, for a comprehensive discussion):

- A meteorological model – dispersion model ensemble where the meteorological models are deterministic models from different meteorological centres. For example Galmarini et al. (2010) produced dispersion ensembles of ETEX1 using (a) a single dispersion model driven by ensemble weather data (b) multi weather prediction deterministic models combined with multi dispersion models. They note that the first method puts the emphasis on the variability in the weather prediction whereas the second on the dispersion models intrinsic uncertainty.
- A dispersion model ensemble using a number of different dispersion models with a single meteorological model (Draxler et al., 2015).

Hypothetical Case Studies

In addition to the real case studies, a number of hypothetical studies have been carried out to look at the value of using ensemble meteorology with a dispersion model. Scheele and Siegmund (2001) released a large number of trajectories into a trajectory model driven by ECMWF ensemble forecasts to examine whether the spread of the ensemble of trajectories could predict the error in the trajectory forecast. They showed that the spread had some skill in predicting the error when the error was calculated as the mean of the ensemble minus the trajectory based on analysis met data. They also showed that the trajectory driven by the control forecast was closer to the trajectory driven by analysis data in the first 48-hours but that beyond 48-hours the mean of the ensemble was likely to be closer to the trajectory driven by analysis data.

A number of case studies have also been carried out by Nordic Nuclear Safety Research. They used two sets of scenarios to examine the size of the uncertainties produced by driving a dispersion model with ensemble meteorology. Their first study, called Meteorological Uncertainty of atmospheric Dispersion model results (MUD, Sørensen et al., 2013) used ensemble meteorological forecasts from DMI EPS at a resolution of 0.05° (approximately 5.5km) and the dispersion models DERMA and EEMEP to model the dispersion of radionuclides from four nuclear power plants in four different meteorological scenarios. Their results showed that the uncertainties (expressed as the difference between dispersion model ensemble members) in time integrated air concentration and total deposition 54 hours after the start of the release could be as large as a factor of ten. The largest uncertainties were observed in the scenarios where convective precipitation was involved but the uncertainty could also be large for light-wind scenarios. Their second set of scenarios looked at the uncertainty in shorter-range forecasts out to a distance of approximately 200 km (Sørensen et al., 2017b). Here the uncertainties in the dispersion model output provided by the uncertainty within the meteorological ensemble were shown

to be smaller than those for the long-range study, although they could still be of the order of a factor of two or three.

Other Approaches to Meteorological Uncertainty

A number of other approaches have been used to include meteorological uncertainty in dispersion models. Draxler (2001) experimented by shifting the source location by one grid-point in each horizontal direction and by ±250m in the vertical with respect to the meteorological data. This resulted in an ensemble of 27 members that were compared to data from ANATEX (Across North America Tracer Experiment) in North America. Their results showed that for this case the trajectory ensemble accounted for between 41 and 47% of the variance in the measurement data.

Kolczynski et al. (2009) note that in an emergency situation there is probably not enough time to compute an ensemble of dispersion forecasts. Therefore, decisions have to be based on a single run of a dispersion model. They propose a method to estimate the uncertainty of the wind field present in the meteorological ensemble. Then they transfer this uncertainty, together with a single wind field to the dispersion model. Of course this presupposes that the dispersion model has the capability of receiving such uncertainty information as input and of producing from it uncertainty estimates in the dispersion forecasts.

Noting that many ensembles are under-dispersive, Perillat et al. (2016) added additional uncertainty to the meteorological data they used to model the Fukushima accident. They did this by adding a homogeneous time-dependent perturbation to wind and precipitation fields. The perturbation was chosen to reduce the under-dispersion of the meteorological ensemble. This additional perturbation did improve the dispersion models ability to model the dose rates at individual stations despite the unphysical nature of the perturbation. They recommend that in future it might be better to construct meteorological ensembles that better represent the uncertainties in boundary layer quantities such as 10-m wind-speed and direction.

Quantification and presentation of dispersion forecast uncertainties

This section concerns the methods used to quantify and display the ensemble dispersion forecasts that are generated with the aim to deduce uncertainty information. The forecasted quantities which are relevant for dispersion of hazardous substances and in particular radionuclides are:

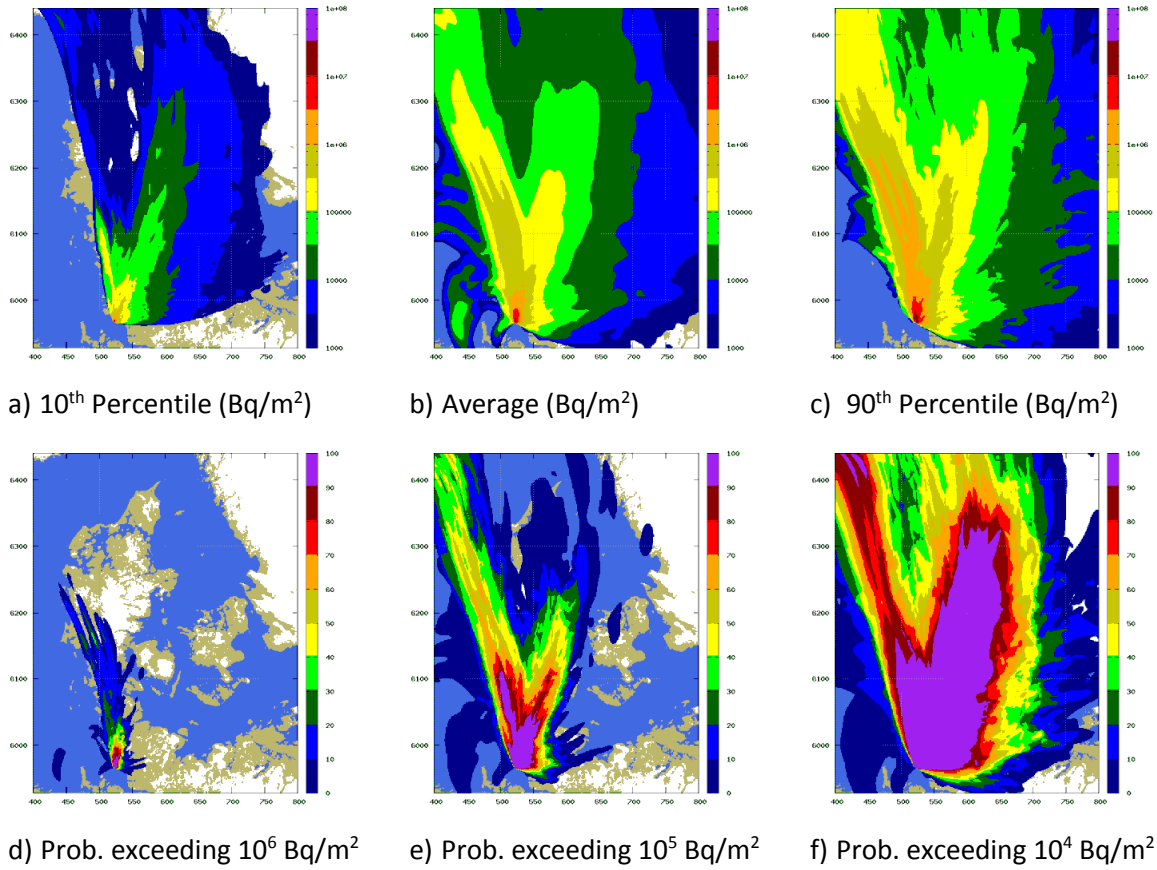
(a) instantaneous concentration in air, as function of space and time (Straume et al., 1998, Straume, 2001, Galmarini et al., 2010, Sørensen et al., 2016, Girard et al., 2016)
(b) time-integrated concentration in air at the end of a specific time period, as function of space (Haywood et al., 2010, Sørensen et al., 2013, Sørensen et al. 2017b)
(c) accumulated deposition on ground at the end of a specific time period, as function of space (Sørensen et al., 2013, 2016, 2017b), total and wet deposition
(d) gamma dose rate, as function of space and time (Girard et al., 2016, Perillat et al., 2016)
(e) organ dose (e.g., thyroid) at the end of a specific time period, as function of space (Sørensen et al., 2016)

To aggregate the results of dispersion ensembles and deduce uncertainty information regarding the above quantities from the dispersion ensembles, the most common methods encountered in the literature are the following (see Figure 7 for examples):

(a) Ensemble average (Galmarini et al., 2010, Sørensen et al., 2013, 2016, 2017)
(b) Percentiles (or quantiles), e.g., 10th, 50th, 90th (Dabberdt and Miller, 2000, Galmarini et al., 2010, Sørensen et al., 2013, 2016, 2017b). It is noted that the 50th percentile is the ensemble

median, while the 100th percentile is the ensemble maximum. The percentiles can be interpreted as probabilities that the quantity of interest lies below the specific value.

(c) Probabilities of exceeding a certain threshold value; this is also mentioned as "agreement in threshold level" (Straume, 2001, Sørensen et al., 2013, 2016, 2017b). If this threshold value is set to zero or to the detection limit, these probabilities represent the probabilities that the cloud or plume is present at the particular location.



a) 10th Percentile (Bq/m^2) b) Average (Bq/m^2) c) 90th Percentile (Bq/m^2)

d) Prob. exceeding 10^6 Bq/m^2 e) Prob. exceeding 10^5 Bq/m^2 f) Prob. exceeding 10^4 Bq/m^2

Figure 7 : Examples of methods for presenting uncertainty information produced from dispersion ensembles (from Sørensen et al., 2017b). Figure shows the 10th percentile, (a), average (b) and 90th percentile (c) of accumulated deposition of Cs-137 and the probability of the accumulated deposition of Cs-137 exceeding 10^6 Bq/m^2 (d), 10^5 Bq/m^2 (e) and 10^4 Bq/m^2 (f) for a hypothetical scenario. Contours for (a), (b) and (c) are a log-scale from 10^3 Bq/m^2 to 10^8 Bq/m^2 and contours for (e), (f) and (g) are percentages from 0 to 100.

The products that are used for presenting the above results are contour plots overlaid on geographical maps. Dabberdt and Miller (2000) have also used concentration histograms at specific geographic locations of interest (Figure 8). Ease of communication to and interpretation by the decision makers of the uncertainty-related information is very important.

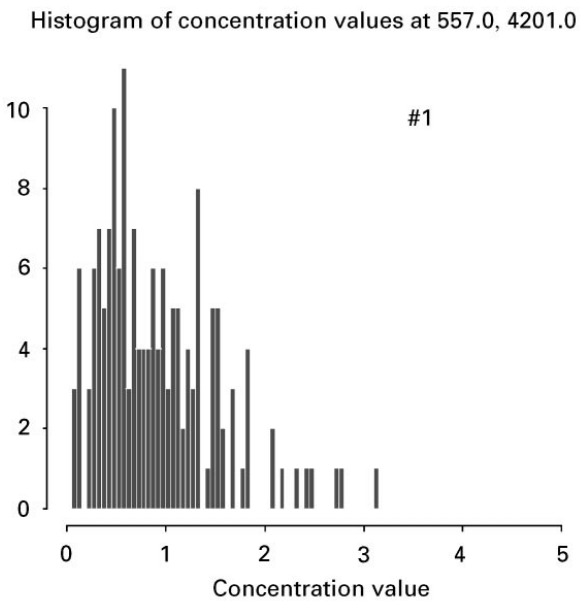


Figure 8 : Example of a histogram showing concentration values at a single location (from Dabberdt and Miller, 2000).

For purposes of dispersion ensembles validation in comparison to observations from real cases, various products have been used: ranked histograms (Perillat et al., 2016) (Figure 9a), time history plots, (Perillat et al., 2016) (Figure 9b), and a wealth of statistical performance indicators (Galmarini et al., 2010).

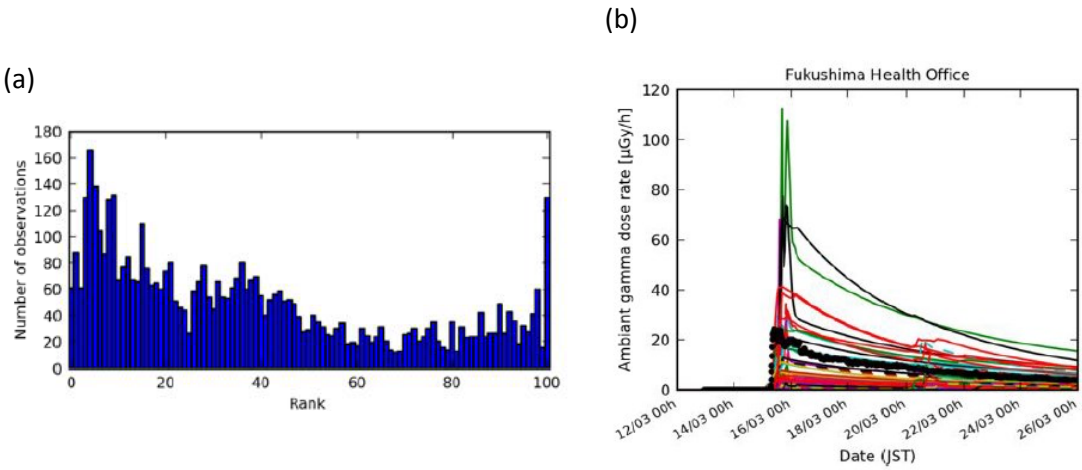


Figure 9 : (a) Rank histogram showing the rank of each gamma dose observation compared to the gamma dose rate computed using an ensemble dispersion model and (b) a time-history plot showing the gamma dose rate from each member of an ensemble dispersion model compared to observations (black dots) at a single location. (from Perillat et al., 2016)

Summary

This review looks at meteorological ensembles as a source of information on meteorological uncertainty for dispersion models. The construction of the ensembles, their verification and examples of their use with dispersion models are explored. At the CONFIDENCE work package one workshop in Paris in June, 2017 several questions about the ability of meteorological ensembles to provide meteorological uncertainty information to dispersion models were discussed:

- How well do ensembles represent the uncertainty in the meteorology?

- What are the advantages in using a short-range meteorological ensemble for dispersion modelling
- Can we determine how uncertain a single forecast is?
- Do ensembles represent the uncertainty in the variables of interest for dispersion models?
- How do uncertainties propagate along a trajectory?
- Should we add additional perturbations to ensemble meteorology to better capture the uncertainty in the variables of interest?
- Can we select ensembles that better represent the uncertainty of interest to dispersion models?

Ensembles can be used to drive dispersion models providing useful information about the influence of the meteorological uncertainty on the dispersion predictions. However, meteorological ensembles have been designed to improve weather forecasts, and especially severe weather events such as heavy rainfall and extreme temperatures. Some of the meteorological variables of interest for dispersion models are common to those of interest to weather forecast, for example, wind speed and precipitation. There are also meteorological parameters of interest to dispersion modelling which are of lower interest to weather modelling, such as boundary layer depth and ensembles may be less skilful at estimating the uncertainty in these parameters. Hence, it may be necessary to consider additional methods of adding meteorological uncertainty to these parameters. Dispersion modellers should also be aware that different meteorological ensembles can only be expected to capture uncertainties within their resolution. Local effects will not be captured in global ensembles and possibly only partially captured in high resolution ensembles. These effects, for example sea breezes and channelling by terrain, may be important and it may be here that additional uncertainties need to be added. Generally though, selecting the ensemble numerical weather prediction model that will provide the uncertainty information for the scale of interest will improve the estimate of uncertainty in the dispersion model prediction.

To help answer the above questions the next phase of work of work package one of the CONFIDENCE project will examine a number of dispersion scenarios. The work will compare high-resolution and coarse-resolution ensembles in different meteorological conditions as well as using the Fukushima incident to verify dispersion ensembles against radiological observations.

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D 9.1.2 - Using meteorological measurements to reduce uncertainty

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Abstract

This chapter presents computational methodologies for optimally combining numerical weather prediction data and meteorological observations to produce meteorological fields that can be used for atmospheric dispersion calculations. When meteorological data calculated through 3-Dimensional Data Assimilation methods are applied in modelling real cases of dispersion or air pollution, it appears that they improve the agreement between calculated and observed concentrations of air pollutants.

<End of abstract>

Contents

Introduction

Atmospheric dispersion simulations can be decoupled from wind flow (in general meteorological) computations if atmospheric pollutants are passive (i.e., if their density, mass, chemical properties and temperature do not affect the flow field). This is usually the case with radionuclides released following a nuclear or radiological incident (at least at some distance from thermal effects that might be influencing the flow near the source). Therefore a very common practice followed to produce prognoses of atmospheric dispersion by models operating in the framework of emergency response, is first to provide prognostic meteorological data by some Numerical Weather Prediction (NWP) model and then run the Atmospheric Dispersion Model (ADM) independently using as input the meteorological data. A common requirement in this setup is the possibility of driving the ADM by different NWP models operating on different meshes and providing different sets of outputs. Therefore the ADM should be independent from the NWP model.

Therefore, in the above modelling sequence a Meteorological Pre-Processing (MPP) model that acts as an interface between the NWP data and the ADM should be used. This is necessary primarily for two reasons:

a) the ADM operates on a different computational grid (e.g., finer or on a different coordinate system) than the NWP model; therefore the NWP data needs to be transformed to the ADM grid. This is accomplished by some kind of spatial interpolation by the MPP code. For the wind velocity components a divergence minimization procedure could be performed after the interpolation to ensure that the newly calculated wind fields are mass consistent, which is mainly important for ADMs that assume divergence-free wind fields (e.g., Eulerian ADMs)

b) the ADM might require input meteorological variables that are not included in the NWP data; these additional variables are calculated by the MPP code through empirical or semi-empirical relationships

The de-coupled meteorological field – dispersion calculation provides also the flexibility to run the ADM for the same case using NWP data from multiple forecast models, and therefore assess the related uncertainty.

It is possible that meteorological measurements could be available in emergency response scenarios. These can be used alone to calculate “diagnostic” atmospheric dispersion. In this case the MPP code

constructs the meteorological input data required by the ADM and based on the meteorological measurements.

If both NWP data and meteorological measurements exist in the same spatial and temporal context (e.g. Figure 1) the MPP can combine them to produce the meteorological fields that will drive the ADM, exploiting this way all the available information in the computational domain. Since the prognostic data have been produced by a model and provided to the MPP as snapshots of the atmosphere at successive time instants, the MPP calculations are diagnostic. Therefore the combination of the prognostic data with observations in the frame of the MPP is a problem of 3-Dimensional Data Assimilation (3DDA).

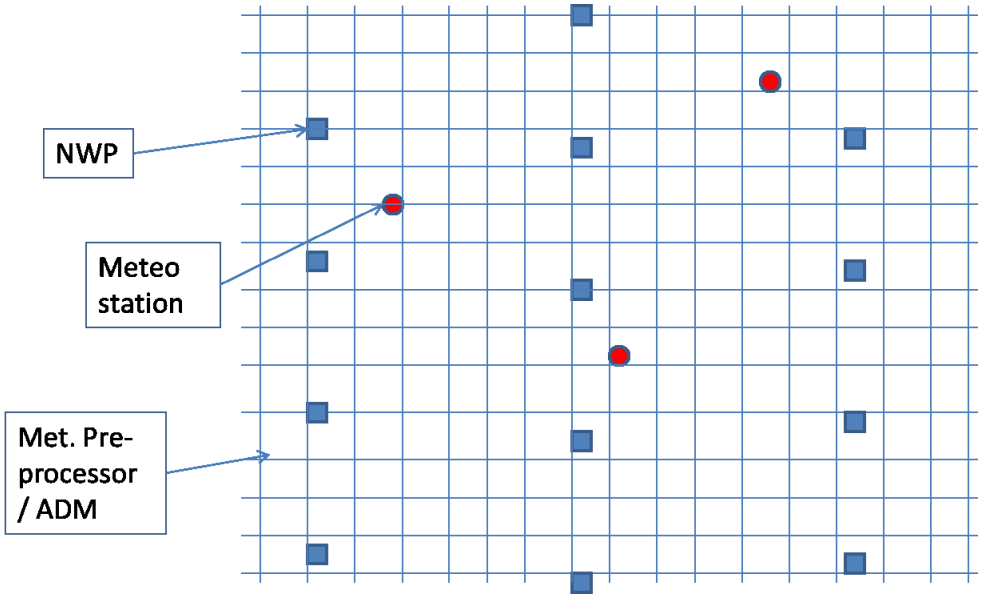


Figure 1 : Blue squares: nodes of the NWP grid; red circles: meteorological measurements locations; solid lines: MPP (and ADM) grid.

Here we mainly refer to meteorological measurements that have not already been assimilated in the NWP model computations. This may happen for data from weather stations that are not connected to National Weather Services (e.g., stations at Nuclear Power Plants). Also this may happen because of the time delay for delivery or the low update frequency of NWP data from National Weather Services to external Institutes that perform dispersion calculations in cases of emergencies. Although in several National Weather Services the delivery time for operational weather forecasts can be in the order of two hours and the cycle time may be three hours, there might be a considerable delay in delivery of NWP data to external organisations, especially of medium or long range forecasts. Therefore meteorological measurements may become available in the time interval between analysis and delivery times of NWP data.

In addition, as Kovalets et al. (2005) note, based on Scire et al. (2000), even if some meteorological observations were already used for the calculation of the NWP forecast, they should be used again if these forecasts are being pre-processed on a finer grid by the MPP. This is because the scales of the atmospheric motions resolved by the NWP model and the MPP may be significantly different if the spatial resolution of the MPP is several times finer than that of the NWP model. Despite the fact that current NWP models may have a fine spatial resolution (e.g., 2.5 km), medium or long range forecasts have a coarser resolution, while ADMs may be required to operate on grids of one or few hundred

metres. Hence, the small-scale movements that are present in the measurements and are treated as "noise" by the NWP model should be resolved by the MPP.

In this respect, Kovalets et al. (2005) demonstrated that, even if the NWP data are "analysis" data, i.e., if measurements in the area of interest have been assimilated in the NWP model run: (a) significant differences in local-scale dispersion modelling results can occur if only local meteorological measurements or only NWP data are used, (b) the meteorological fields calculated by the MPP through assimilation of measurements in NWP data are in better agreement with observations than the meteorological fields calculated by the MPP using only NWP data.

A typical timeline of events is depicted in Figure 2, where the time period covered by the NWP data starts at $t_{A,NWP}$ (analysis time) and ends at $t_{E,NWP}$. The time when the NWP model run is completed and the NWP data are available for use by the dispersion model is also indicated. The present time is denoted by t_{now}. Measured meteorological data that are obtained between $t_{A,NWP}$ and t_{now} can be exploited by the MPP code. If the dispersion model run starts at $t_{start,disp}$ and ends at $t_{end,disp}$, then the MPP processes both NWP and measured data for $t_{start,\ disp} < t < t_{now}$ and it processes only NWP data for $t_{now} < t < t_{end,\ disp}$.

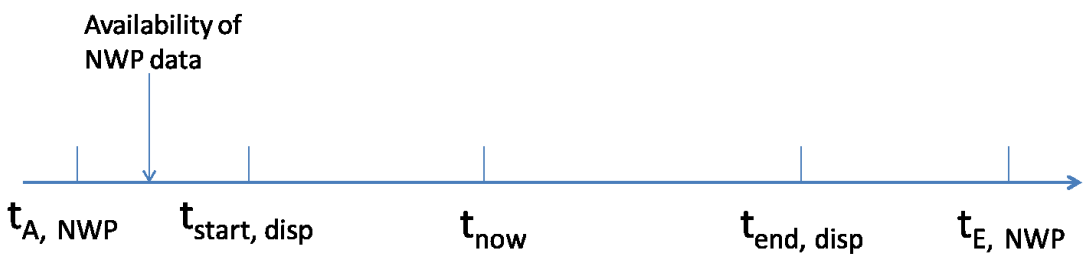


Figure 2 : NWP data cover the time period between tA,NWP (analysis time) and tE,NWP; dispersion modelling time period is between tstart,disp and tend,disp; the MPP processes both NWP and measured data for tstart, disp < t < tnow and it processes only NWP data for tnow < t < tend, disp.

A special case of meteorological measurement data are remote sensing products like radar or satellite products. Remote sensing products are usually available in near real-time and cover large areas. But these measurements do not measure directly the parameters required by the ADM. Usually reflectivity of radar or light is measured by remote-sensing products and these reflectivities need to be calibrated. These calibration effects can introduce additional uncertainties (Sørensen, 2017). The update frequency and resolution of remote sensing data is often in a few minutes and some hundred metres. If these are higher than required for ADM then averaging is needed.

Nowcasting products, i.e., extrapolations of radar results into the near future can close the gap between the measurements and the forecast. These products are usually available from the data-providers of the radar data, in the same format as the radar product and should be used in the same way as measurements. As can be seen in figure 3, nowcasting products give better results than NWP data during the first 1-2 hours.

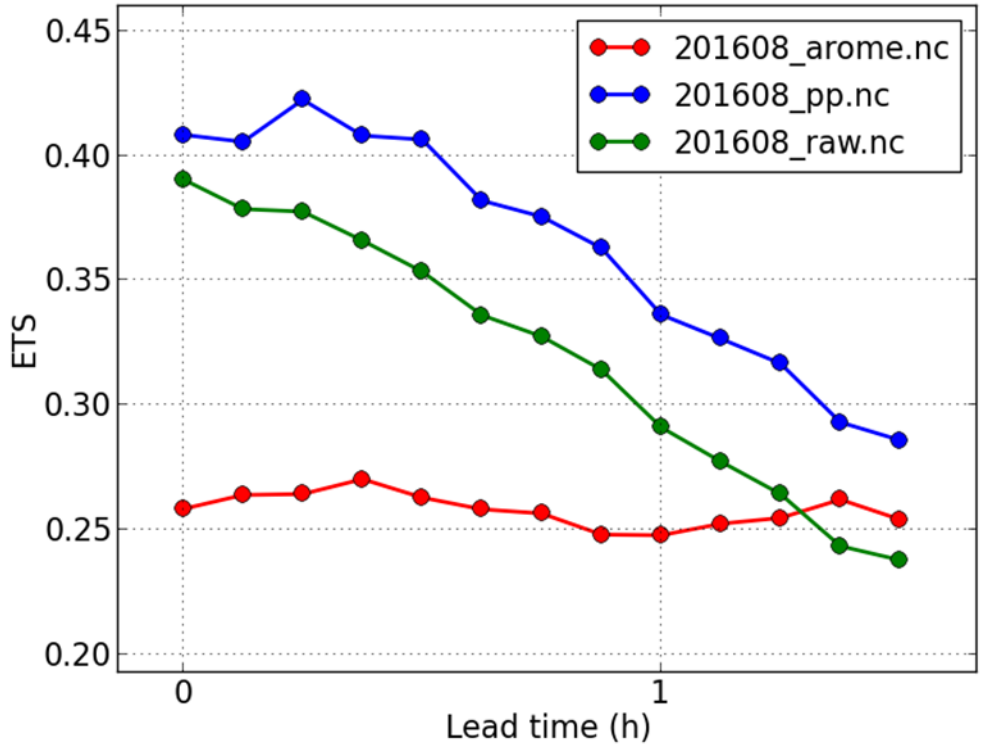


Figure 3 : Comparison of precipitation nowcasting products (blue and green) versus NWP data (red) for all Norwegian stations within 150km of a radar in August 2016. The equitable thread score is much higher and better within the first 1.5 hours for nowcasting than for NWP data.

Review of most relevant DA methodologies

According to what was mentioned in the Introduction, this report concerns the operation of ADMs on meteorological data pre-processed by a MPP code. As also mentioned, the combination of NWP data with observations in the frame of the MPP is a problem of 3-Dimensional Data Assimilation (3DDA). This section briefly reviews 3DDA methods that have been or are being used in MPP codes. For the sake of completeness, brief mention is made to the evolution of DA methods in NWP models too.

Statistical interpolation is a method that has been widely used for objective analysis of meteorological data (Daley, 1991). It was also referred to as “optimal interpolation” (OI). The method starts with an existing “background” field of the meteorological variable in question at the grid points of the MPP. The analysed field is calculated by adding “analysis increments” to the background field. The analysis increments are expressed as weighted averages of “observational increments” which are the differences between observations and background values at the locations of the observations. The weight coefficients are computed so as to minimize the analysis errors, from a system of equations that contain the background, the observations and the spatial interpolation errors, assuming that these are unbiased and uncorrelated with each other. Therefore, optimal interpolation accounts for observational and model errors. It uses information about statistics of meteorological fields and it interprets in a physical way observational data. So if points of observations are close to each other, meaning that these observations are correlated, then the optimal interpolation algorithm will assign them less weight. Statistical interpolation can be univariate or multivariate. The latter is applied to components of wind velocity for instance.

Another class of methods used for objective analysis of meteorological data are the methods of successive corrections. These methods start with a background or first-guess field (Daley, 1991). The analysed field is calculated iteratively, by adding at each iteration a weighted sum of observational increments (differences between observed value and analysis value of the previous iteration). The weights are defined a priori. In the method of iteration to the optimal solution (IOS) the background field and the observations are assumed to have constant root mean square errors (not equal to each other). If the error correlation functions are homogeneous and isotropic (e.g., they depend only on the distance between the observation and the grid point) then the iteration to optimal solution is equivalent to the optimal interpolation method. This kind of assumption is usually made for the scalar quantities, such as temperature and humidity.

Three-dimensional variational data assimilation (3D-Var) has progressively replaced OI in NWP models, as was done in the European Centre for Medium-range Weather Forecasts (ECMWF). Courtier et al (1998) describe this method and the improvements on the quality of NWP model forecasts for the global model of ECMWF. The 3D-Var method implemented in the UK Met Office weather forecast model has been described by Lorenc et al. (2000). 3D-Var is based on minimisation of a cost function that is the sum of a background term and an observation term (and possibly some constraints). The background term contains the differences between the analysed field and the background field. The observation term contains the differences between the observations and the model predictions at the observation locations. The two terms are weighted by the covariance matrices of the background and observation errors respectively. Additional terms or equations may be taken into account to impose conformity of the analysed fields with balance constraints. By setting equal to zero the gradient of the cost function, the analysis increments are calculated, which are then added to the background field to obtain the analysed field.

Four-dimensional data assimilation (FDDA) has allowed to take full advantage of satellite and other non-conventional observations, that represent different scales of motion. In FDDA observations over a period of time (am assimilation time window) are combined, instead of using observations at a single time instant. The observations can be inserted into the model as they become available. FDDA can be used either in an intermitted cycle of initializations and short-term forecasts or in a continuous way where forcing terms are added to the model equations to “nudge” the solution toward the observations. The development of the FDDA scheme in ECMWF model is described by Rabier et al. (2000), Mahlouf and Rabier (2000) and Kinker et al. (2000), while in the Met Office model is described by Rawlins et al. (2007).

3D-Var and FDDA methods have been implemented also in the Limited Area Models (LAMs) that are now operationally used in many European National Weather Services (e.g.,HIRLAM - http://hirlam.org/, ALLADIN - http://www.umr-cnrm.fr/aladin/, HARMONIE-AROME - http://hirlam.org/index.php/hirlam-programme-53/general-model-description/mesoscale-harmonie, COSMO - http://cosmo-model.cscs.ch/), or are freely available to download and install such as the WRF - Weather Research and Forecasting model - https://www.mmm.ucar.edu/weather-research-and-forecasting-model (Barker et al., 2004, Huang et al., 2009). The horizontal spatial resolution of LAMs can be in the order of 1 km, while their running time can be around 2 hours for a 2-day forecast with 1-hour temporal resolution (depending of course on the available hardware resources).

A remark that can be made reviewing the DA methods developed for NWP models is that they do not take into account specifically the processes in the atmospheric boundary layer (ABL). The latter would be more relevant to atmospheric dispersion modelling especially in local scale. For instance Barker et al. (2004) introduce in the 3D-Var method a mass balance equation that includes cyclostrophic and

geostrophic terms, while they use hydrostatic balance to calculate the temperature increments. Therefore it would be interesting to assess the combination of advanced parametrizations of ABL and simplified diagnostic equations of the ABL with variational DA methods in the framework of MPP codes.

An issue that is relevant to the use of DA methods in MPP codes is the delivery time of NWP data. Of course this depends on the extent of the geographical area that the forecast model covers and the time span of the forecast. Currently, at many European national weather services the delivery time for operational weather models is less than 2 hours after the synoptic hour at which the observations were made. The cycle time (how often the model is run) is mostly 3-hourly for short term weather forecasts. At a few institutes a rapid update cycle of 1 hour is employed or considered. Short delivery and cycle times increase even further the chance that relevant observations are assimilated in the NWP.

Considering these developments in NWP models, a re-assessment and evaluation of the procedures used in MPPs and their effects on results of ADMs is necessary.

Examples of 3DDA procedures applied in MPP codes

The CALMET MPP

Description and applications

A meteorological data objective analysis scheme is used in the MPP CALMET of CALPUFF system (Scire et al., 2000). The method assumes that observations have been assimilated in the NWP model computations. Wind velocity observational and NWP data are separately interpolated (through $1/r^2$ interpolation) to the grid points of the MPP. The assimilated wind field is a weighted average of the interpolated observational and NWP data. A 3-D divergence-minimising procedure is applied then (Goodin et al., 1980), to ensure mass consistency of the final wind field. The weight coefficient for the aforementioned interpolation depends on height above ground (giving more emphasis to NWP data at higher levels, on the assumption that observations are more representative of the local flow features, while NWP data represent better the large-scale flow features) and on the scales of motion that are to be resolved by the MPP close to the ground, in relation to the scales of motion resolved by the NWP model. The criterion used for the latter relies on the differences between the description of topography by the NWP grid and the MPP grid. If these differences are small, then the motions that are to be resolved by the MPP have the same scales as those resolved by the NWP, so no additional data assimilation (DA) to that already performed by the NWP model is needed. If the topography differences are large, then a local subgrid (to NWP) terrain could be important and local observations or diagnostic wind estimates near the surface should be emphasized.

A drawback of this methodology is that the overall weight coefficient does not depend on the distance of the closest observation station to the MPP grid point. The methodology is also very restrictive in its assumption that the observations have already been assimilated in the NWP model results.

Chandrasekar et al. (2003) present an evaluation of the CALMET diagnostic meteorological model. They “ingested” NWP from the prognostic meteorological model MM5 into CALMET to produce the background fields and then used the objective analysis feature of CALMET to assimilate meteorological observations. The latter consisted of upper air rawinsonde data (available every 12 h) from seven stations and hourly surface data from thirty surface stations and one overwater station. The CALMET results were validated through comparisons with data from a wind profiler located in the

computational domain, which of course was not taken into account in the objective analysis procedure. The comparisons were very satisfactory and so the authors concluded that this method of combining prognostic meteorological data and observations was an attractive option for generating accurate meteorological inputs for air quality modelling studies.

An application of CALMET and assessment of the effects of an assimilation of meteorological observations with NWP data through CALMET on the results of a photochemical dispersion model has been presented by Jackson et al. (2006). They produced two sets of meteorological data for the dates of a specific air pollution episode. One set was produced only from the NWP data calculated by the prognostic meteorological model MM5. The second set was calculated by CALMET, using as a first-guess or background field the MM5 data and assimilating wind observation data from 88 surface stations. Each meteorological data set was validated through comparison with observations and then they were used to drive the computations of a photochemical air quality model in simulating the particular air pollution episode. The authors concluded that using objective analysis improved the agreement of the calculated wind velocity fields with the observations. Also when the data assimilated meteorological fields were used to drive the photochemical dispersion model, they improved the agreement of calculated ozone concentrations with those observed during the air pollution episode.

The JRODOS MPP

Description

3DDA procedures have been developed initially for a stand-alone MPP by Kovalets et al. (2004) and later have been integrated in the MPP of the JRODOS (Java-based Real-time On-line DecisiOn Support) system (Kovalets et al., 2014, Andronopoulos et al., 2016). The function of the JRODOS MPP is to prepare a consistent set of meteorological data for use by the ADMs of the system (ATSTEP, RIMPUFF, DIPCOT, LASAT). In particular the JRODOS MPP delivers a fixed set of 3D variables (wind velocity, temperature, pressure and effective diffusivity coefficients) and 2D variables (such as precipitation, cloud cover, net radiation, sensible heat flux, stability category, friction velocity, Monin-Obukhov length, convective velocity and mixing layer height). The variables that exist in the input data of the JRODOS system are interpolated to the output grid of the MPP, while the variables that do not exist in the input data of JRODOS are calculated by empirical relationships on the output grid of the MPP. The JRODOS MPP uses user input, NWP data and measurement data. Measurement data from a large number of stations in the entire computational domain can be input to the system, in a specific file format developed for JRODOS ("real-time target format" - rttf). Measurement errors cannot be directly input; instead one error is implicitly assumed for all stations, which is taken into account through the ratio of the background to observation errors, as explained below and shown in Table 1.

If both NWP and measured meteorological data are available, the user can select to combine them through DA. If this selection is made, the system performs DA at the time-steps for which both NWP data and meteorological measurements exist in its database. In this case, the calculation of the aforementioned meteorological 3D and 2D variables is performed through the following steps:

1) Calculation of the first guess fields: wind velocity, temperature and other meteorological variables that eventually are contained in the NWP data set are interpolated on the horizontal computational grid of the MPP by $1/r^2$ interpolation on the height levels of the

NWP model. After that, linear, power-law or other types of interpolation (depending on the variable) are used in the vertical direction to pass from the NWP levels to the MPP levels[1].

2) Assimilation of the scalar variable measurements (such as surface temperature, cloud cover, net radiation, precipitation)
3) Assimilation of the wind velocity measurements
4) Correction of the resulting wind field with divergence minimizing procedure
5) Final calculation of all remaining meteorological fields, such as stability category, Monin-Obukhov length, friction velocity etc., based on established semi-empirical relationships

From the above it is concluded that 3DDA is performed only for the wind velocity, and 2DDA is performed for all the other variables.

Assimilation of the scalar fields' measurements (surface temperature, cloud cover, net radiation and precipitation) is performed using the previously mentioned objective analysis procedure "iterations to optimal solution" (IOS). In the specific formulation of the IOS method, two parameters need to be specified: the measurements radius of influence R_0 and the ratio of background to observation variances E_B^2/E_O^2. The observations' radius of influence is a length scale that enters in the calculation of the weight factor of observations as function of distance (exponential decay is assumed). The values that are adopted in this procedure are shown in Table 1.

Variable	**R_0 (km)**	**E_B^2/E_O^2**
Surface temperature	150	9
Cloud cover	150	9
Net radiation	150	6
Precipitation	50	9

Table 1 : Radius of influence (R0) and relative error (EB: background error, EO: observation error) used in the IOS procedure for different meteorological elements.

The values given in Table 1 were estimated by Gandin (1968) for 6-hour average measurements and for a relatively smooth topography. For smaller averaging times and / or for complex topographies the relative error is expected to increase and the radius of influence should be smaller. For example, quoting from WMO (2012) "synoptic observations should typically be representative of an area up to 100 km around the station, but for small-scale or local applications the considered area may have dimensions of 10 km or less". No systematic study for the assessment of R_0 or E_B^2/E_O^2 has been performed yet.

For the assimilation of the wind velocity measurements, extrapolation or interpolation of the measured wind velocities from the observational levels to the vertical levels of the MPP is carried out first. Then assimilation of the extrapolated or interpolated wind velocity values is performed on each of the vertical levels of the MPP. There are 2 available options for the assimilation of the measured wind velocity values: 1) the IOS method and 2) the multivariate optimal interpolation (OI) method. The 2nd option (multivariate OI) has been implemented since the assumptions behind the IOS method do not always hold for the wind velocity components (such as isotropy of correlation functions of u and v components).

[1] To achieve independence of the JRODOS ADMs from the NWP models and their output meshes, a meteorological input grid that is Cartesian in horizontal directions and terrain-following in the vertical has been defined for the ADMs. The JRODOS MPP delivers all its output variables on this grid.

In the case of IOS method, the relative error E_B^2/E_O^2 is calculated through a relationship that connects it to the weighting coefficient used in the CALMET methodology described in the previous section. The radius of influence R_0 depends on the root mean square (RMS) deviation of the terrain height above the sea level from the "mean" terrain height above the sea level (the height, averaged through all grid points). This dependence is given in Table 2 and it shows a decreasing radius of influence with increasing RMS, which is obvious from a physical point of view. The value R_0 = 150km (for the relatively smooth terrain) is taken from Gandin (1968).

Terrain elevation RMS deviation (m)	R_0 (km)
0 < RMS < 100 (plane)	150
100 < RMS < 200 (hilly)	100
200 < RMS < 300 (small mountains)	70
300 < RMS (mountains)	50

Table 2 : Dependence of the radius of influence R0 upon the RMS deviation of the terrain elevation

In the case of the OI method, exponential correlation functions of the *u* and *v* velocity components are assumed, according to Daley (1991). The equations to calculate the analysed velocity components contain the background values and weighted averages of observational increments (i.e., differences of observations and background values) at the points of observation. The weightings are calculated from a system of equations that are derived to minimize the analysis errors. The latter equations contain the correlation functions mentioned above and the relative errors of the values of the background field and observations. The relative errors are defined as in the case of the IOS method.

Finally, it is noted that the variables subject to DA procedures are wind velocity, temperature, cloud cover, net radiation and precipitation. This is because routine meteorological measurements exist more often for these variables. Variables such as mixing layer height, sensible heat flux, stability category, friction velocity and Monin-Obukhov length, for which routine measurements are not usually available, are affected by the DA procedures indirectly, through their dependence on the wind velocity and net radiation.

Evaluation

The DA methodology that is implemented in the JRODOS MPP has been evaluated by comparing calculated meteorological fields with measurements performed during the two European Tracer Experiment (ETEX) campaigns (Straume and Nodop, 1997). The ETEX database contains meteorological ground and upper air measurements starting at the dates of the 2 tracer gas releases (23 October and 14 November 1995) and extending for 3 days. NWP data from ECMWF are made also available for these periods. These data where given on a grid of 0.5 degrees horizontal spatial resolution, at the surface and 4 pressure levels (1000, 850, 700, 500 hPa). The ECMWF NWP data used by Kovalets et al. (2004) were purely prognostic data. The extent of the MPP computational domain was 400 × 400 km^2. Computations with the MPP were carried out in two modes: (a) using only the NWP data, (b) using both NWP data and measurements. The measurement data that were assimilated in the 2nd case originated from 8 ground-based synoptic weather stations located in the computational domain. Data from the remaining 71 observation stations located in the domain were only used for the comparisons of the measured wind fields with those calculated by the MPP in each of the above modes. Table 3 reports statistical indices (root mean square deviations – RMS – and systematic deviations or bias – BIAS) quantifying the level of agreement between MPP results and observations of wind speed (U) and direction (D) (from Kovalets et al., 2004). No dispersion computations were done in that work and the evaluation concerned only meteorological data.

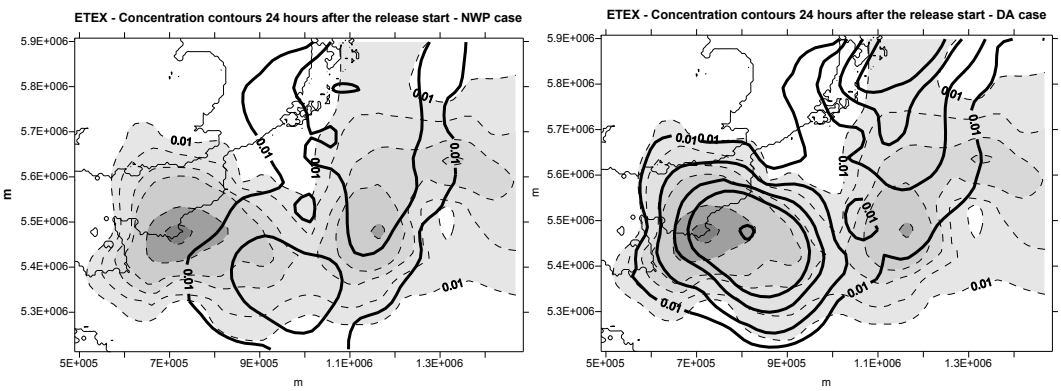
It appeared that the bias always improved when DA was used (either with optimal interpolation – OI – or with iterations to optimal solution – IOS – method) in comparison to results obtained with only the NWP data ("background"). The OI performed better, as expected, since it takes into account the information on the correlations of the wind fields to a greater extent than IOS. However the OI method appeared to be at that time and on a single-processor machine computationally 5-10 times more expensive than the IOS method. For ETEX1 the RMS was not affected by the DA procedures, while for ETEX2 the RMS was improved when using DA. Kovalets et al. (2004) attributed this to the weather conditions, which for ETEX1 were apparently better represented in the parameterizations of the NWP model than for ETEX2.

Variable	Background ETEX1	OI ETEX1	IOS ETEX1	Background ETEX2	OI ETEX2	IOS ETEX2
RMS_U (m/s)	2.57	2.44	2.51	2.21	1.94	2.0
$BIAS_U$ (m/s)	0.67	-0.08	-0.39	0.5	-0.18	-0.37
RMS_D (dec. deg.)	33	33	33	56	48	42
$BIAS_D$ (dec. deg.)	10.3	5.5	7.23	18.7	5.9	-1.3

Table 3 : Statistical indices for the level of agreement between calculated and observed wind fields; "Background" – only NWP data used; "OI" – NWP and observations through DA with OI method; "IOS" – NWP and observations through DA with IOS method.

Another evaluation of the DA methods that are implemented in JRODOS MPP was carried out by Davakis et al. (2007), who investigated their effects on the performance of atmospheric dispersion models that are driven by the MPP output. The ETEX1 was used as the case study. Two sets of meteorological fields were produced by the MPP: one set using only the ECMWF NWP data (prognostic data with 0.5 degrees horizontal spatial resolution, at the surface and 5 pressure levels) and one set using the ECMWF NWP for the background field and assimilating meteorological measurements. The meteorological measurements that were assimilated in the 2nd case were: near-ground wind velocity, near-ground temperature and cloud cover from 113 stations and vertical profiles of wind velocity from 7 sodar stations. The two sets of meteorological data were then used to drive atmospheric dispersion calculations in a Lagrangian puff model (DIPCOT). The calculated and measured concentrations were compared through statistical indices, time-histories of concentration at the sensors locations and contour plots of concentrations near ground surface.

By overlaying the contour plots of calculated and measured near-ground concentrations (Figure 4) it was concluded that the activation of DA procedures in the MPP resulted in better overlapping of the two plumes and a better agreement in the location and magnitude of maximum concentrations.



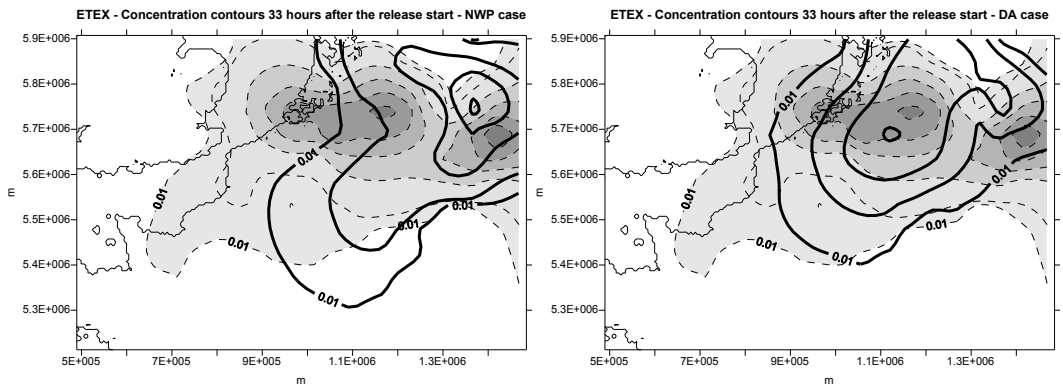


Figure 4 : Contour plots of experimental (dashed line) and calculated (solid line) concentrations, 24 h (upper) and 33h (lower) after release start, using only prognostic NWP data (left) and prognostic NWP data with assimilated meteorological measurements in the MPP (right), for ETEX 1 case.

The statistical indices (factor-of-2, 5 and 10, fractional bias - FB, normalized mean square error - NMSE, geometric mean bias – GM- and geometric mean variance - VG) that were calculated for comparing calculated and measured concentrations at the locations of sensors, were improved when DA was used in the MPP: the factors of 2, 5 and 10 increased, the FB was very close to zero and the NMSE was reduced. The GM and VG were not drastically affected. The latter shows that the DA procedures have a more pronounced effect on the larger concentration values that are predicted by the ADM. From the concentration vs. time plots at the sensor locations it is concluded that discrepancies between ADM results and measurements are reduced near the plume centreline when DA is used in the MPP. In conclusion, the comparison of observed concentrations with those that were calculated using the different sets of meteorological data showed that the usage of DA in the MPP code improved the performance of dispersion calculations.

Kovalets et al. (2014) report on a more recent operational test of the DA procedures in the JRODOS MPP. That test concerned a hypothetical release of radionuclides from a Nuclear Power Plant (NPP) in Ukraine and dispersion computations conducted through JRODOS. NWP data were calculated with WRF using global NWP data from the Global Forecasting System (GFS) operated by the US National Centers for Environmental Prediction (NCEP). The WRF horizontal spatial resolution was 5 km. The available measurements included data from an automated surface meteorological station which supplied each 10-minutes averaged values of 10 m wind speed and direction, 2 m temperature and humidity, net radiation, precipitation and pressure. In addition SODAR data were available from the NPP site, measuring wind speed, direction and temperature at heights starting at the height of 100m and going up from 500m to 2000m. NWP data and measurements were imported in the JRODOS database. The MPP was run in two modes: either processing only the NWP data, or processing the NWP data and assimilating the available measurements. Dispersion computations were conducted by the model RIMPUFF on these two processed data sets and typical results are showing the differences are presented in Figure 5 (from Kovalets et al., 2014).

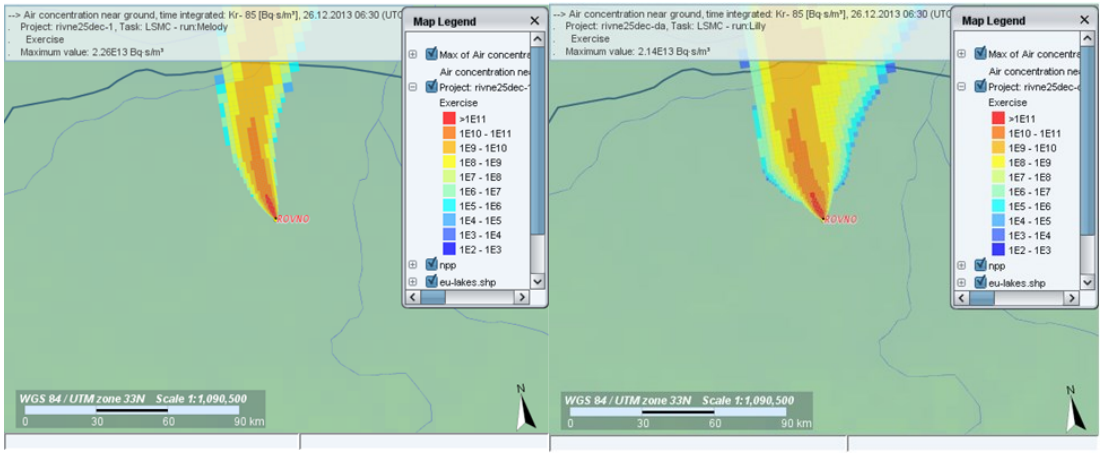


Figure 5 : Time integrated concentration distributions calculated by JRODOS RIMPUFF during 24 hours following a hypothetical stationary release of Kr-85 (1×1018 Bq/24 hours), without (left) and with data assimilation (right) in MPP (from Kovalets et al., 2014).

Conclusions

This report presented computational methodologies for optimally combining NWP data and meteorological observations to produce meteorological fields that can be used for atmospheric dispersion calculations. When meteorological data calculated through such 3DDA methods are applied in modelling real cases of dispersion or air pollution, it appears that they improve the agreement between calculated and observed concentrations of air pollutants.

Data-assimilation techniques used in NWP have advanced from OI to 3D-Var and 4D-Var resulting in the successful assimilation of non-conventional observations, such as satellite data. These improvements and the increase in temporal and spatial resolution of NWP, in combination with early delivery times, make it necessary to re-assess and evaluate the procedures used in MPPs and their effects on results of ADMs. In addition, since variational DA methods developed for NWP models do not specifically take into account small-scale processes in the ABL, it would be interesting to assess the combination of advanced parametrizations of ABL and simplified diagnostic equations of the ABL with variational DA methods in the framework of MPP codes.

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D 9.1.3 - Guidelines describing source term uncertainties

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Abstract

The main elements that emerged from the consultation of experts in charge of estimating the source term in case of a nuclear emergency are presented. Critical uncertain parameters related to the source that have a significant impact on the assessment of consequences have been identified. The main origins of the uncertainties and factors affecting the uncertainty level in a crisis situation are discussed. Those considerations provide hints to assess uncertainties related to the source in case of an emergency.

Source term parameters and related uncertainties proposed for CONFIDENCE case studies are to be propagated through the chain of atmospheric dispersion and radiological assessment models for both historical (for example the accident at the Fukushima Daiichi Nuclear Power Plant) and hypothetical scenarios, to better understand the effect on model outputs and thereby appraise the impact on decision making in the context of an emergency response.

<End of abstract>

Contents

Introduction

In the event of an accidental release of radionuclides into the atmosphere, dispersion calculations would be used to model the consequences and to assist in determining appropriate countermeasures. Environmental contamination depends on the characteristics of the releases, the trajectory of the radioactive plumes and the deposition episodes. The weather conditions (wind, atmospheric stability, etc.) determine the transport of the radioactive plume in the atmosphere, as well as its vertical and horizontal extension. The plumes are depleted during transport by dilution in the atmosphere and deposition processes. Dry deposition occurs in the absence of precipitation, whereas wet deposition is the dominant process during rainfall or snowfall episodes. The behaviour of the radionuclides in the atmosphere depends on whether they are in gaseous or particulate form, their size and their reactivity. These elements also influence their behaviour in relation to the deposition processes, as well as their absorption and their harmfulness to the human body. The composition of the releases and the characteristics of the radionuclides vary during the release phase according to the facility events that caused them.

Simulations are subject to significant uncertainties related to the source, to the meteorological conditions, those due to the atmospheric dispersion models and radiological assessment models. This chapter considers uncertainties relative to the source.

Scope of the review

This chapter considers uncertainties relative to the source. It does not consider uncertainties related to atmospheric dispersion model or meteorological origins. One of the main inputs of ADM is the characterization of releases. This includes the source term, that is, the temporal evolution of the release rate of each radionuclide released into the atmosphere at a release height; the thermodynamic characteristics of the emission such as their temperature and their ejection speed which influence the possible plume rise; the characteristics of radionuclides at the time they are released to the atmosphere, such as their physicochemical form, solubility and size if released as a particle.

Method of review and challenges

It is not in the scope of the CONFIDENCE project to conduct source term modelling. In particular, other European projects such as FASTNET (FASTNET, n.d.) are already dedicated to evaluate source terms and their associated uncertainties. The CONFIDENCE project is primarily oriented toward the use of meteorological ensembles. However, the Fukushima accident has highlighted that source term uncertainties can be very large, even years after the accident (Quérel et al., 2015; Mathieu et al., 2018; Nakajima et al., 2017); these uncertainties have a significant impact on the assessment of the environmental and health impact of accidents (Girard et al., 2016a; Périllat et al., 2016). Therefore, leaving out source term uncertainties in the simulations conducted by Work Package 1 (WP1) would lead to a significant underestimation of the output variability. To propagate uncertainties through atmospheric dispersion models, it is necessary to take into account all sources of uncertainties to the best of our knowledge. For that purpose, crisis management specialists and reactor physics experts outside of the CONFIDENCE project were consulted. Studies conducted in the framework of the FASTNET project were also used in order to provide a first evaluation of source term uncertainties. A summary of the elements collected are presented in this chapter.

Limitations

- The summary presented mainly relies on already existing studies. Some sources of uncertainties are not well known, underestimated, or cannot be quantified in the current state of knowledge. The aim of this report is to describe possible sources of uncertainties and to propose ways of taking into account a number of them, bearing in mind that some of them will be incorrectly modelled or left out.

- Most of the experts consulted belong to IRSN. The description of sources of uncertainty is therefore inevitably influenced by the method of expertise used in the context of crisis management in France and by the type of reactor.

- The considerations presented below mainly concern pressurized water reactors (PWR). For other types of reactors and nuclear facilities dedicated to the different phases of the fuel life cycle, as well as the production of isotopes for medical applications or military installations, conclusions may differ.

Nevertheless, some notions do not depend on the installation and the stakes remain the same. For example, the phase of the crisis, the method of expertise, access to information and human factors are concepts that significantly influence the uncertainties related to the release whatever the type of installation concerned.

Plan

This chapter begins with a brief description of uncertain source term parameters and their potential impact on atmospheric dispersion calculations. The rest of the document is devoted to the findings of the review. The possible causes of source term uncertainties are listed. The following part deals with factors influencing these uncertainties. Indeed, the level of uncertainty is highly dependent on the phase of the crisis (before, during or after releases), the methods and tools used for evaluation, and the type of accident.

Two examples of accidental situations are then given. The first illustrates uncertainties related to emergency thermohydraulics evaluations. The second uses the results of the European FASTNET project and provides an order of magnitude of the uncertainties due to the physical modelling of the reactors. Finally, the last part of the document is devoted to the source terms and their uncertainties for the case studies that will be dealt with the WP1.

Uncertain parameters of the source

This part lists the main uncertain parameters of the source term that can have a significant impact on the assessment of the consequences of an accident.

Timing and duration of major releases

There are two aspects to consider. The first is confidence that the release will be 2 hours in duration but uncertainty over what time the release will begin i.e. 5am to 7am or 6 am to 8am, for example – this is covered in “Timing of major releases”. The second aspect is confidence that the release will begin at a certain time, but uncertainty over the release duration i.e. 5 am to 7 am or 5am to 8am, for example.

It is crucial to correctly estimate the timing and the duration of major release event, whether it be the beginning of a release or a significant event leading to a major and brutal increase, such as the raft breakthrough or the activation of filtered containment venting system. The time available before the

start of a major release determines how long the authorities have to implement appropriate measures for the protection of the population and the environment. Moreover, knowing the timing of major releases is critical to align with the respective weather conditions that will drive the plume dispersion in the atmosphere, thus providing more accurate evaluations.

It is crucial to avoid a release occurring when the evacuation of the population is ongoing, which could happen if the time of the release or its duration was wrongly assessed. Another issue is to protect the most sensitive geographical area located downwind of the source at the time of a major release. In situations when the wind direction is not well established, uncertainties on the meteorological forecasts combine with those on the timing of the major releases to make the identification of potentially impacted zones tricky, if not impossible.

Released quantities

The quantity of each radionuclide released into the environment is one of the most important characteristics of a release, since it directly relates to the air and ground contamination. Upper bounds can be obtained when the core composition is known. In the case of an accident as complex as the one at Fukushima in 2011, the *a posteriori* estimated amount of radionuclides released varies by a factor of 1 to 4, depending on the radionuclides (NISA, 2011; NSC, 2011; SCJ, 2014; IAEA, 2015b).

Uncertainties about the temporal evolution of the release rates of each radionuclide can be even more important since they combine those on released quantities with the ones of the timing and the duration of releases. In the case of long releases, especially if the weather conditions are changing, uncertainties over the temporal evolution of the release rates can affect the estimation of the activity in the air and the deposits, in particular for the wet deposits resulting from the crossing between the plumes and precipitation in the right place and at the right time.

Isotopic composition

The composition of the releases and the characteristics of the radionuclides may vary during the release phase according to the facility events that caused them. The composition of the releases and the characteristics of the radionuclides depend, among others, on core age, on radioactive decay before the release time, on chemical reactions in the reactor and outside.

Hundreds of radionuclides can be released to the atmosphere during an accident, but only some of them have significant impacts in terms of activity in the environment and health impacts. For instance, for a nuclear power plant, iodine isotopes are responsible for thyroid cancers. Caesium isotopes are also of high interest, due to their significant contribution to gamma dose rates and their long lifetime in the environment. Other notable radionuclides families usually considered for nuclear power plant accident are tellurium and noble gases.

Physicochemical form, particle size

The behaviour of the radionuclides in the atmosphere depends on whether they are in gaseous or particulate form, their size and their reactivity. These elements influence their behaviour in relation to the deposition processes, as well as their absorption and their harmfulness to the human body, usually represented by dose coefficients.

Despite their importance, those parameters may be highly uncertain. The Fukushima accident has shown that uncertainties about isotopic composition, on the physical form and particle size may remain large even several years after intensive studies to better characterized the atmospheric releases (Mathieu et al., 2018).

Physicochemical form

Most radionuclides are emitted as particles, with the notable exception of noble gases (e.g. ^{133}Xe) and iodine isotopes. Noble gases do not undergo deposition or chemical processes, which reduces the sources of uncertainties related to them.

Iodine can be released in gaseous and particulate form. Two forms of gaseous iodine are usually considered, one highly reactive form corresponding to molecular iodine and a more volatile form corresponding to organic iodine which is also more persistent in the atmosphere. Iodine dose coefficients are different according to the chemical form. The gas-to-particles iodine ratio as well as the molecular-to-organic iodine ratio in release varies as a result of the chemical reactions and complex interactions in the containment. Some reactions are not well represented in models or understood. They are, therefore, causes of uncertainties.

Particle size distribution

The particle size distribution of the radionuclides released in the atmosphere will be different for a release due to building leaks, a stack release or an explosion. A stack release is usually filtered to retain most of the radionuclides. Only specific sizes of particles are not filtered. Releases due to building leaks are not filtered and their particle size distribution should be broader than the former. Releases consecutive to an explosion can enclose larger particles coming from the melting of the core (Abe et al., 2014). The size distribution of radionuclides released as particulate matter is not estimated by the release assessment tools used in crisis management. Even with tools able to simulate the whole phenomenology of the reactor accident, the complexity of processes at stake would lead to highly uncertain estimations.

In the atmosphere, large particles are quickly deposited; the small, very reactive ones fix themselves on atmospheric aerosols. Environmental measurements have shown that the aerosol size distribution observed at a distance from the release point corresponds to that of atmospheric aerosols (Dorrian, 1997; Kaneyasu et al., 2012; Masson et al., 2013). It is generally this hypothesis that is used for the modelling of the deposits and the calculation of the doses. At short distances, this hypothesis is probably not satisfactory. The lack of knowledge of the size distribution of the released particles can therefore induce uncertainties on the evaluation of the consequences in the near field.

Release height and plume rise

Release height and plume rise may have a direct impact on air activity concentrations at ground level. Global sensitivity analyses have shown that plume height uncertainties resulting from release height and plume rise have little impact on long-range consequences but can have a significant short-range impact (Girard et al., 2014; Périllat et al., 2015; Girard et al., 2016a). This concerns cases like the Fukushima accident for which the height of the plumes did not exceed a few hundred meters. For accidents such as Chernobyl, where the height of the plume resulting from the release height and plume rise was substantially above the boundary layer, uncertainties in the release height can have an impact at long distances (Brandt et al., 2002).

The physical release height is a function of the localization of the release source (stack, buildings leak). Ventilation systems favour a stack release. Building leaks may be dominant when ventilation systems are not operating. Even if the height of the chimneys or buildings can be known with precision, it is generally difficult to anticipate or even to identify *a posteriori* the release pathways. The physical release height can therefore be an uncertain parameter.

The plume rise is a function of the effluent temperature and the exit velocity as well as the thermodynamic characteristics of the atmosphere. Releases resulting from fires, explosions, or from a

steam generator tube rupture accident may be subject to significant plume rise. There are physical models used to estimate the plume rise but it is often not possible to initialize them with reliable input data. Indeed, the effluent temperature as well as the exit velocity may be monitored in case of a stack release but most of the time they are not known. Moreover, plume rise estimations also depend on atmospheric variables such as wind and stability, thus adding meteorological uncertainties to those depending on the source.

Physical release height and plume rise can be considered as a single parameter defined as the effective release height and used as input to atmospheric dispersion models. Uncertainties related to the effective release height are a result of cumulative uncertainties in the physical release height and plume rise.

Origin of source term uncertainties

Among the uncertain parameters, a distinction has to be made between those that exclusively depend on the type of accident, installation, and reactor state, and those which also depend on the meteorological situation and state of the atmosphere. This part is mostly devoted to the first kind of parameters. Thus, in the following, “source term” will refer to the time evolution and release rates of emitted radionuclides, unless stated otherwise.

Uncertainties about the source can have several origins. The lack of information, the risk of human error in a situation of great stress, the modelling errors and approximations of the tools used for the expertise are the main causes of the uncertainty.

Lack of information

In the first place, the management of an accident situation relies on access to information. Among the technical data needed to estimate potential or actual releases, it is crucial that the experts:

- have access to the measured values of key parameters (e.g. water level in the tank, containment pressure evolution) from the damaged nuclear power plant, in order to be able to work on assessing the situation and understanding what happened so far (diagnosis);
- know the age of the fuel, water inventory of the primary system in case of steam generator tube rupture;
- know the availability and integrity of critical safety functions;
- have frequent reports of what is implemented on-site to respond to the situation (accidental procedure that is currently applied; restauration works that are in progress; crucial actions that succeeded or failed), in order to have a clear view of the responding strategy and try to forecast the evolution of the situation (prognosis);
- have real-time access to measurements in the environment that can signal the occurrence of a release and provide information about its characteristics.

Expertise and estimation of the source term is possible if sufficient technical data is available. If there is a lack of information, experts have to make conservative assumptions, that lessen the expertise precision and increase related uncertainties. In an emergency situation, it is highly probable that at least some of the aforementioned features will be unknown or incorrectly assessed. The Fukushima accident showed that in case of an earthquake and tsunami followed by a station black-out, many

parameters that are normally available could not be used anymore. Communications were also difficult, leading to several misunderstandings between operators and off-site experts (IAEA, 2015b).

Human errors

Skilled and experienced emergency centres with assessment capabilities (accident phenomenology, plant operation, safety systems …) are required for emergency management. However, crisis management is reliant on individuals and the risk of human errors cannot be totally avoided. This risk is higher in an emergency situation where actions and decisions must be taken rapidly and consequences of a failure can be dramatic, thus putting a heavy burden on the shoulders of experts. This may contribute to the uncertainties related to the source in two ways. On the one hand, on-site operators may be mistaken in the choice of driving operations or in their implementation. On the other hand, whatever the training and the skill of the experts in charge of evaluating the source term, they can make errors in analysing the situation, leading to an erroneous estimate of the source term in terms of timing and/or quantities.

Modelling tools

Finally, the tools used to estimate releases are often based on modelling. The models are tainted with uncertainties due to approximations in the physical model parameterizations and processes not taken into account in the model. These uncertainties will be detailed below for PWR reactor modelling, with the use of FASTNET results.

Factors influencing uncertainties

The level of uncertainty on the source term depends on a certain number of factors such as the phase of the crisis, the accidental situation, the tools and the method of expertise used.

Phases of the accident

In the event of an accident occurring at a nuclear facility and leading to the release of radionuclides into the environment, the distinction is commonly made between (Steering Committee for the Management & of the Post-Accident Phase of a Nuclear Accident (CODIRPA), 2012):

a) the *emergency phase*, during which efforts focus on the accident and its immediate consequences (direct exposure to radioactive releases);
b) the *post-accidental phase*, during which efforts are aimed at managing the later consequences of the accident (population exposure due to radioactive deposition having contaminated the territories).

Emergency phase

The emergency phase is characterized by the need to take action very quickly in order to cope with the actual or potential release of radioactive substances into the environment likely to lead to significant population exposure. In this phase, uncertainties tend to be very large. In particular, important information may be missing due to lack of time; the risk of human errors is highest; few environmental measurements are available. During the emergency phase, it is useful to distinguish between the period of threat, where no releases have taken place and source terms are evaluated by anticipation, and the period during which environmental releases are ongoing.

Period of threat

During the period of threat resulting from facility failures, the operator implements actions designed to return it to an adequate level of safety and thereby prevent potential releases. The key issue is to

correctly anticipate the possible evolutions of the installation, including operators' actions and failure of safety devices. The source terms evaluated during the threat phase correspond to accidental scenarios defined on reasonably penalizing assumptions chosen to encompass the potential risks. The so-called *a priori* or "prognosis" source terms, combined with meteorological forecasts, are then used to plan counter-measures for the protection of populations.

The uncertainties related to the source are highest during the threat phase. At this stage of the crisis, uncertainty about the timing of the start of releases is the most critical, to determine the period when countermeasures can be implemented as well as the potentially impacted areas related to the meteorological conditions prevailing at the time of the release.

One of the aggravating factors is the impossibility of having an *a priori* knowledge on the real state of certain systems. Are the filters on the chimney totally intact? What leakage rate from the inner reactor building to the outside and to the auxiliary buildings must be considered to be representative of the actual state of the containment? Given these uncertainties, those relating to the physics modelled in the tools used to estimate the source term are secondary.

Period of release

Just after the start of the release, the main sources of uncertainties described above are removed. The timing of the beginning of the release, the integrity of the critical materials, the emission pathways are better identified. The estimated source terms are more reliable. Access to measurements in the environment also helps reduce these uncertainties.

At this stage of the crisis, the main source of uncertainties is related to the modelling tools used to estimate releases and to the knowledge of the physical phenomena prevailing in the facility.

Depending on the accident situations, the release phase can be divided into several periods. There can be several major releases, for instance if several reactors are involved as in the Fukushima case. For a PWR, in the case of a loss of coolant accident, the use of the exhaust ultimate filter constitutes a second major release event (see Accidental situation section). As for the threat phase, the projected time period before this second emission event is difficult to estimate, due to strong uncertainties. Soon after, the main sources of uncertainty fall and those of modelling tools are again dominant.

Post-accidental phase

The post-accidental phase takes place when releases are over and the facility is back to a safe state. It is composed of (Steering Committee for the Management & of the Post-Accident Phase of a Nuclear Accident (CODIRPA), 2012):

a) a transition period, during which understanding of the actual state of contamination of the various components of the environment is still imprecise and the risks of chronic exposure in individuals can still be high;

b) a long-term period characterized as the lasting contamination of the territories impacted and lower risk of chronic exposure in individuals.

The need to estimate releases is less important when the measurements allow for exhaustive characterization the state of contamination of the environment. Nevertheless, societal issues require that the exposure due to the plume be reassessed a posteriori. The issues are to evaluate the risk induced by exposure to short-lived radionuclides (e.g. ^{131}I), and to analyse and reconstruct the accident. The realistic estimation of the source term remains one of the key concerns of the post-accidental phase.

The multitude of measurements in the environment and a better understanding of the installation events, obtained thanks to the access and the analysis of more numerous and more reliable installation parameters, make it possible to considerably reduce the uncertainties on the source term.

However, the Fukushima accident showed that even several years after an accident, the evaluation of the source term is tainted with uncertainties (Mathieu et al., 2018). There are many sources of uncertainty. For example, short-lived radionuclides cannot be measured after the release phase; some episodes of release may have been poorly observed in the environment due to the lack of measurements in some locations, sensor malfunctions, and because much of the plume was advected over the sea. In addition, there are modelling errors and the problem of representativeness of the measurement compared to what the models can simulate which persist regardless of the phase of the accident.

Accidental situation

Every nuclear emergency situation has its own specific characteristics. As highlighted in the IAEA report (IAEA, 2015a), the simultaneous occurrence of a natural disaster caused by an earthquake followed by a tsunami and a nuclear emergency affecting several reactors is seen as one of the specific characteristics of the Fukushima accident. Until Fukushima, a similar conjunction of events had not been considered in safety studies. In such a context, in the early phase of the accident, uncertainties about the source term can only be considerable. For accidents where power and communications are still active, the access to installation parameters helps to limit uncertainties.

Accidental scenarios for a PWR reactor

The two main families of accidents that can lead to significant releases to the environment to be considered for a PWR design are the loss of coolant accident (LOCA) and the steam generator tube rupture (SGTR). A short reminder of the basic principles of PWR systems is given in Appendix 1.

LOCA accidents

In case of a LOCA, the steam released from the break at the primary circuit leads to temperature and pressure increase inside the containment. To avoid the core overheating, safety injection (SI) system can be used. If it does not start, is unavailable or in case of large break, the liquid water level inside the reactor vessel falls leading to core temperature increase. At the temperature of 700°C, the fuel clad bursts. It means at least two of the three containment barriers are degraded (the fuel assemblies and the primary circuit envelope). Fission products can be released to the containment and then to the environment. If the containment spray system is not available, the pressure of the containment building may increase and the natural leak flow rate through the concrete walls as well.

The expertise of such a situation consists in identifying the existence of a primary break, assessing its location and size, and estimating the projected time period before the core dewatering. If there is a risk of dewatering, the source term, i.e. the releases to the environment must be estimated.

The break size and location are key parameters for the source term estimation. The break size can be seen as a mathematical object: calculation methods can be applied for its estimation, independently from the break location. However, the break location can be really hard to assess: some physical “signatures” of the transient can be clues to make a more or less reasonable assumption. It means the break location assessment relies only on an expert judgement.

Many LOCA transients have a slow kinetic, i.e. the initiator appears at least six hours before the start of releases. The period of threat can be long enough to gather information and make a *prognosis*

estimate of the possible source term(s). A slow evolution of the accident may allow using uncertainty modelling techniques that require moderate computational time, in order to assist in decision making.

Steam generator tube rupture

In the case of a SGTR, a liquid leakage between the primary circuit and the secondary circuit appears, leading to the loss of the second containment barrier. For whatever reason, if a secondary valve (located on the steam line exiting the steam generator) is open, there is a risk of steam release into the environment. If a steam generator overflows, long-term liquid releases are to be feared. The expertise of this type of accident consists in estimating the number of broken tubes (the break size), the release type (steam and/or liquid) and the associated masses. Finally, if a release occurs or is probable in the future, the source term has to be estimated.

For this kind of accident, the key issue is to evaluate the released mass (nature and quantity) out of the steam generator.

SGTR accidents are typical of fast kinetic accidents, which means that the releases take place very quickly after the initiator. In this case, emergency organizations cannot be triggered before the release and the population's protection is organized according to a pre-established plan. The source term is then evaluated *a posteriori*, possibly with the help of environmental measurements.

Tools dedicated to the source term assessment

The uncertainties are highly dependent on the tools used for the source term evaluation. Two main approaches can be used, not exclusive from one another: the modelling of reactor physics, and the use of dispersion modelling and environmental measurements.

Modelling of reactor physics

The first approach is based on reactor physics and knowledge of the initial state of the facility. It consists of modelling the evolution of the state of the power plant and the events that may lead to a radioactive release. Integral severe accident reference codes offer the opportunity to study in detail severe accident scenarios, including the evaluation of source terms. The computer time needed to evaluate the outcome of a given scenario makes the use of these codes impossible in the context of emergency situation. Therefore, for crises management, two simplified approaches have been derived from integral severe accident reference codes.

The first approach consists of typical releases estimated on the basis of pre-computed scenarios. If the accident is similar to one of the standard scenarios, countermeasures can quickly be proposed and implemented. The scenarios are chosen to encompass all possible risks. Most countries have a library of pre-calculated source terms.

The Fukushima catastrophe highlighted that an accident can have specific characteristics that are not covered by scenarios computed beforehand. More generally, accidents are probably more likely to occur for scenarios not previously contemplated, because by the very nature of not contemplating such scenarios to occur, implies that suitable preventative measures have also not been contemplated and implemented. In this case, the only way to analyse the situation, anticipate the risks, identify the actions to be taken to prevent or limit those risks, and where appropriate assess releases into the environment, is to model the state of the facility. Some countries, such as France or the United States, have numerical models that make it possible to adapt the expertise to the current situation and to estimate a source term. They are based on simplified modelling of reactor physics, like the IRSN SESAME platform for example.

Coupling atmospheric dispersion modelling and measurements in the environment

The second family of methods for estimating releases is built from the coupling of the environmental measurements with atmospheric dispersion simulations to infer release rates. Inevitably, the quality of the source term correlates to the accuracy of the meteorological fields used as input for the atmospheric transport models and to the relevance of the measurements. There are methods called "simplified" (Chino et al., 2011) and "inverse" methods (Gudiksen et al., 1989; Davoine & Bocquet, 2007; Stohl et al., 2012b; Winiarek et al., 2012; Saunier et al., 2013) that can be used once the releases have started, i.e. from the release phase to the post-accidental phase.

Simplified methods are manual or semi-automatic and are based on a limited set of measurements. The inverse modelling techniques are more operational automatic methods based on mathematically rigorous approaches. They are in most cases variational methods.

Uncertainties related to the choice of evaluation tools

An expertise solely based on a library of pre-calculated source terms can be heavily faulted when the accident situation encountered does not correspond to the pre-defined scenarios. The more the situation moves away from the pre-defined scenarios, the more uncertain the source terms used. This was the case during the Fukushima accident. Simplified reactor physics modelling tools were able to adapt the response to the situation and thus reduce uncertainties.

Source term estimation tools based on inverse modelling techniques are only useful once releases have begun, when significant environmental measurements are available. The estimated source terms are reliable if the measurements are numerous and well distributed so as to sufficiently constrain the problem. Uncertainties over the estimated source term inherit uncertainties of weather conditions; those of atmospheric dispersion modelling and deposition; those on the measurements and representativeness error of the measurement with respect to the spatial and temporal scale of the model.

Method used for source term evaluation

Finally, the uncertainties are very sensitive to the evaluation method followed by the experts. The method followed in France in an emergency situation is called 3D/3P (cf. Appendix 1).

Uncertainties are taken into account by using penalizing assumptions. These are chosen in such a way as to minimize the delay before the beginning of the discharges. Other methods could lead to maximizing the quantities released. As a result, the quantification of uncertainties and the identification of uncertain parameters depend on the method of expertise.

Illustration of source term uncertainties for LOCA accidents

In the rest of this chapter, the focus will be made on a PWR accident type described above and relating to the loss of primary cooling accident (LOCA). Only one reactor is considered. This scenario was retained because it is a well-studied type of accident, with slow kinetics and therefore several phases with different kinds of uncertainties.

Uncertainties about the location of the break and its size

Emergency thermohydraulics evaluations are uncertain, because of the impossibility to know exactly the characteristics of the damaged power plant. This section illustrates the uncertainties in emergency thermohydraulics evaluations. Changing the location and size of the break can have a huge impact on

the dewatering time period in the case of LOCA transients. The resulting uncertainties are illustrated below.

The ability to diagnose the pair (location, size) of a primary break depends on its location. Table 1 schematizes the "comfort index" of the thermohydraulics expert to perform this diagnosis. This illustrates the influence of the accident scenario on the level of uncertainties. This example is valid within the French framework and tools if all the reactor data are available, for a given facility and accidental scenario. This table reflects the state of the art in the beginning of a French project aiming to investigate uncertainties in emergency thermohydraulics evaluations.

Location of the break	Comfort Index	
Top of the pressurizer		
Top of the reactor vessel		
Hot leg	With safety injection	Without safety injection
Pumps seals / primary motor pump		
Cold leg	With safety injection	Without safety injection

Table 1: An example of comfort index to diagnose the location of a 3" primary break. In green, available information should be sufficient to allow the diagnosis. Orange: some available pieces of information can constitute relevant clues - require additional assumptions. Red: too few pieces of information – diagnosis based on conservative assumptions.

From the expert's perspective:

- The primary break at the top of the pressurizer is the easiest to diagnose;
- Measured facility parameters can provide clues for locating a break at the top of the vessel or at the primary motor pump seal;
- In very precise situations, it appears that a break located on a primary loop of the reactor coolant system can be assessed on a hot leg or a cold leg, without being able to precise the cold/hot leg number. Generally and without enough information to conclude, the worst location in terms of time period before dewatering is assumed by the experts.
- Intermediate break size, between 1 and 4 inches, can lead to accidental transients that are particularly sensitive to scenario parameters such as effective break size and location, availability and activation of backup safety systems, and cooling.
- Size of the break can be estimated within +/- 1 inch for all considered locations.

Table 2 summarizes orders of magnitude for dewatering time periods estimated with an emergency calculation tool.

Considering a break located in the lower part of a cold leg, a 1-inch range in the break size evaluation can lead to a high variability in dewatering time periods. For a break size of 3 inches, an error in the location within the cold leg can lead to an error in the dewatering time period of 8 hours.

		2''	3''	4''
Top of the pressurizer		> 12 h	> 12 h	
Top of the fuel tank		> 24 h	> 14 h	
Hot leg	Upper part of the pipe		8 h	
	Lower part of the pipe	7 h	3 h	2 h
Cold leg	Upper part of the pipe		12 h	7
	Middle of the pipe		5 h	
	Lower part of the pipe	10 h	4 h	3 h

Table 2 : Dewatering time period estimated for several break locations and several break sizes for a 1300 MWe PWR, considered no safety injection means and a cooling operated by the steam generators.

The prognosis of the projected time period before dewatering is also dependent on the model used and the related assumptions. Sensitivity tests have been conducted at IRSN to estimate the projected time period before dewatering with three different calculation codes (one used for safety studies, the other two developed for emergency situations), considering a 3'' break located on the top of the vessel, with cooling operated thanks to the steam generators, accumulators that can inject water into the vessel, without safety injection. It was found that the dewatering time may vary between 14 and 28 h after the initiator.

Uncertainty due to physical modelling: Example of accidental LOCA scenarios

Description of FASTNET results used in the framework of the CONFIDENCE project

Integral severe accident reference codes offer the opportunity to study in detail severe accident scenarios, including the evaluation of source terms. The computer time needed to evaluate the outcome of a given scenario makes the use of these codes impossible in the context of emergency situation. In order to benefit from the knowledge of Integral severe accident reference codes, one can however rely on pre-calculated scenarios. The key issue is then the optimal use of the calculation database. If informative enough, this database can even be used for the building of an expert system and perform inference. In the framework of the FASTNET project (FASTNET, n.d.), the use of Bayesian Networks, in addition of other tools, is being investigated.

In particular, one of the sub-work packages of work package WP2 (Task 2.3 – ASTEC inversion) is dedicated to the building of a Bayesian network, using machine learning techniques on a set of pre-calculated scenarios by the ASTEC (Chatelard et al., 2014) severe accident code.

The general idea of this calculation data base is that it must

- represent a sufficiently large set of situations,
- be according to the whole accidental phenomenology,
- take into account some phenomenological uncertainties as well as some scenario related uncertainty.

The severe accident phenomenology taken into account goes from the initiating event to the establishment of molten corium-concrete interaction: for this version of the calculation database, the initiating event is the opening of a break on the primary circuit. Injection is supposed to be unavailable at the beginning of the accident and unrecoverable during the whole scenario.

The general progress pattern of the accident is as shown in Table 3.

Break
Loss of high pressure injection pumps
Loss of low pressure injection pumps
Loss of injection to primary pumps seals
Chemical and Volumetric Control System letdown line unavailable
Chemical and Volumetric Control System charging line unavailable
Reactor trip actuation on low pressurizer pressure
Closing normal pressurizer spray on low pressurizer pressure
Turbine isolation
Reactor scram
Pressurizer heaters unavailable (low pressurizer level)
Primary pump stop on high containment pressure and low primary pressure
Start of accumulator discharge
Steam generator level regulation at 33%
Isolation of accumulators
First fuel cladding creep rupture
Start of fission products release from fuel pellets
First slump of corium to lower plenum
Lower head vessel failure
Corium flows out of the lower head
Onset of molten corium-concrete interaction

Table 3: General progress pattern of the accident.

Table 3 is indicative, as the order of events may vary from one situation to another. The calculation stops conventionally after 72 hours.

The phenomenology simulated involves:

- thermohydraulics in the primary circuit and containment,
- core degradation related phenomena : fuel rod heat-up, ballooning and burst, exothermic clad oxidation, control rods behavior, fuel rod embrittlement or melting, molten mixture candling and relocation, corium accumulation within the core channels and formation of blockages, corium slump into the lower head and corium behavior in the lower head until eventual vessel failure,
- fission product release mechanisms from fuel rods or molten corium,
- fission transport in the primary circuit and in containment,
- fission products speciation and aerosols related phenomena ; a specific model has been developed for iodine behavior in liquid and gas phases ;
- Molten-core–concrete-interaction (MCCI) related phenomena: concrete ablation, corium oxidation and release of non-condensable gases (H2, CO, CO2) into the containment.
- Radioactive decay and associated residual power generation and dose rates.

Systems are also modelled: filtration and ventilation systems, etc.

The input deck models a French PWR 900 MW, with a quite simple modelling of the core (only one zone); this choice was made for the sake of computation speed. The modelling of the containment is

quite complete though, as the reactor building and the release routes through auxiliary buildings are taken into account.

For this version of the calculation data base, releases to the environment are related to the natural leakage of the containment and to the use of the exhaust ultimate filter. For some scenarios, the calculation stops too early to allow the activation of the use of the exhaust ultimate filter, since corium hasn't yet made its way through the total basemat height.

In the framework of the CONFIDENCE project, four kinds of initiating events have been extracted:

a) break of 3 inches occurring on hot leg;
b) break of 3 inches occurring on cold leg;
c) break of eleven inches occurring on hot leg;
d) break of eleven inches occurring on cold leg.

A variability of plus or minus one inch is assumed for the size of the break. Some variability is also considered when dealing with the containment leakage rate and distribution:

- The global release rate of the containment ranges by [1; 10] times the best-estimate amount (defined according to operator data).
- The best-estimate distribution of the leak rate to the various containment buildings is also supposed to have some variability in the range [1; 2] times the best-estimate value.
- And finally, should a vessel rupture occur, the mass of corium slump in the cavity is also understood to be uncertain: it may range from half the amount of corium left in the lower head at vessel rupture to the totality of it.

Epistemic uncertainties are mostly related to the fission products behavior: they come from literature, expert judgements, or IRSN's own experimental feedback (Cantrel et al., 2014; Chevalier-Jabet et al., 2014):

- Iodine behaviour : kinetics of some reactions in gaseous and liquid phase,
- Fission products released, for intact rod (not melted) geometry or for fuel magma configuration (very uncertain, not much data for this kind of configuration),
- Silver-Indium-Cadmium released from control rods: very imprecise modelling, research and development still ongoing on this subject.

Finally, fixed uncertainties related to MCCI have been taken into account [~10%]:

- Distribution of power in the various layers of corium,
- Ablation temperatures and enthalpies,
- Heat exchange coefficient of the corium with the concrete, properties of the corium (porosities, permeability…).

Analysis of FASTNET ensembles

Given these hypotheses, around 150 to 200 source terms have been calculated for the different sequences. On the four accidental scenarios, the behaviour of the source term ensembles is different from each other (Figure 1). For all of them, there are two major release events. The first release corresponds to the beginning of the core degradation, and is due to containment leakage. The second release is due to the use of the exhaust ultimate filter.

Releases do not end at the end of the 72 h simulation. The quantity emitted at the end of the 72 h simulation may therefore differ from the total quantity that would have been emitted at the end of release. For example, the value obtained for a release of ^{133}Xe at the end of the 3 inches break simulation in the cold leg location is not complete mainly because the second release occurs after 3 days of the simulation for most of the source terms (Figure 1).

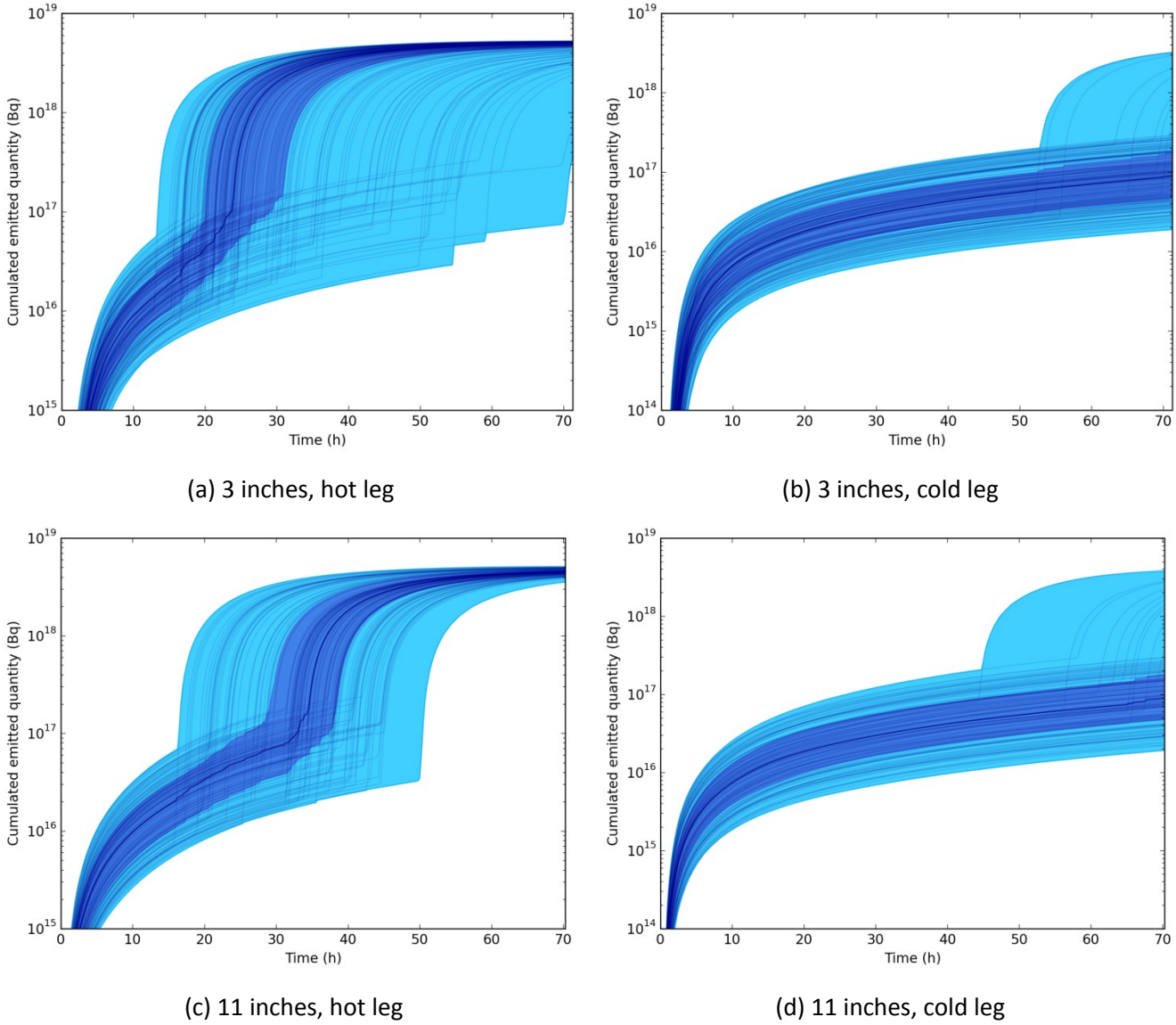
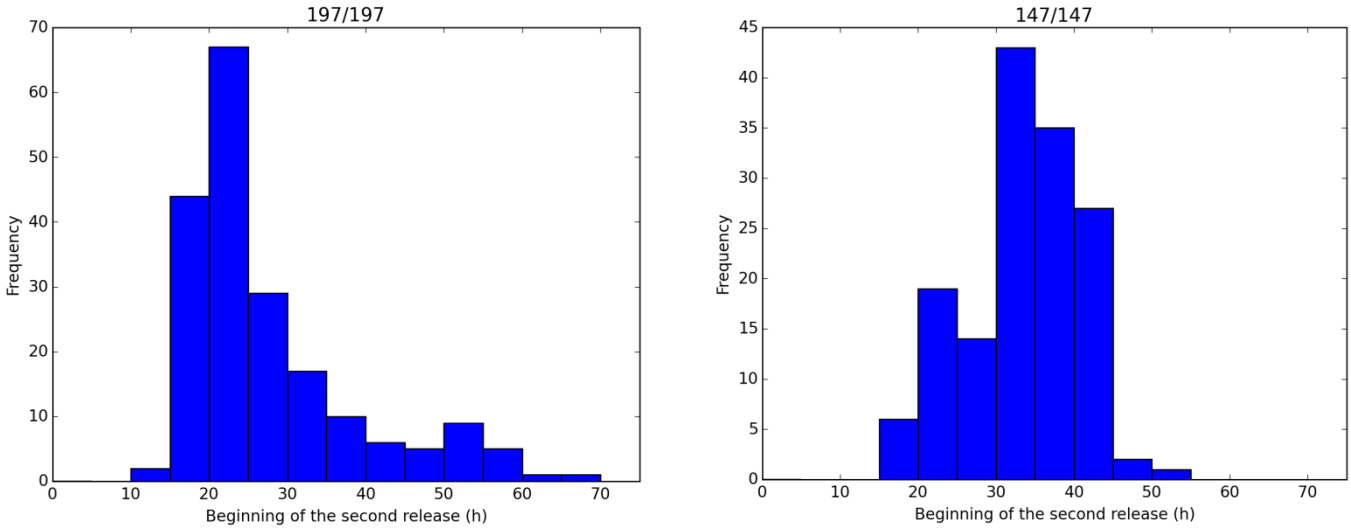


Figure 1: Evolution of the total emitted quantity of ^{133}Xe to the atmosphere for the four scenarios. The time scale gives the number of hours following the break occurrence. Each line corresponds to a member of the ensemble. The cyan corresponds to the envelop of the ensemble, while the deep blue corresponds to the fill between the 25th and 75th percentile. The dark blue line corresponds to the 50th percentile.

Uncertainty on timing

In the scenario considered, there is no uncertainty on the timing of the first release event due to the fast core dewatering. The fast core dewatering occurring just after the occurrence of the break is due to the relatively large size of the breaks and the unavailability of safety injections. The timing of the second release event is more uncertain. For the cold leg scenarios the filtered containment venting system is not activated within the first 72h except for about ten simulations.

For the hot leg scenario, all the source terms show a second release event (use of the exhaust ultimate filter). The second release event starts between the 13th and 70th hour after the break occurrence for the 3 inches ensemble of source term, with a mean of 27.6 hours and a standard deviation of 11.4 hours (see Figure 2(a)). For scenarios with a break of 11 inches, the second release event starts between the 16th and 50th hour with a mean of 33.5 hours and a standard deviation of 7.3 hours (Figure 2 (b)).



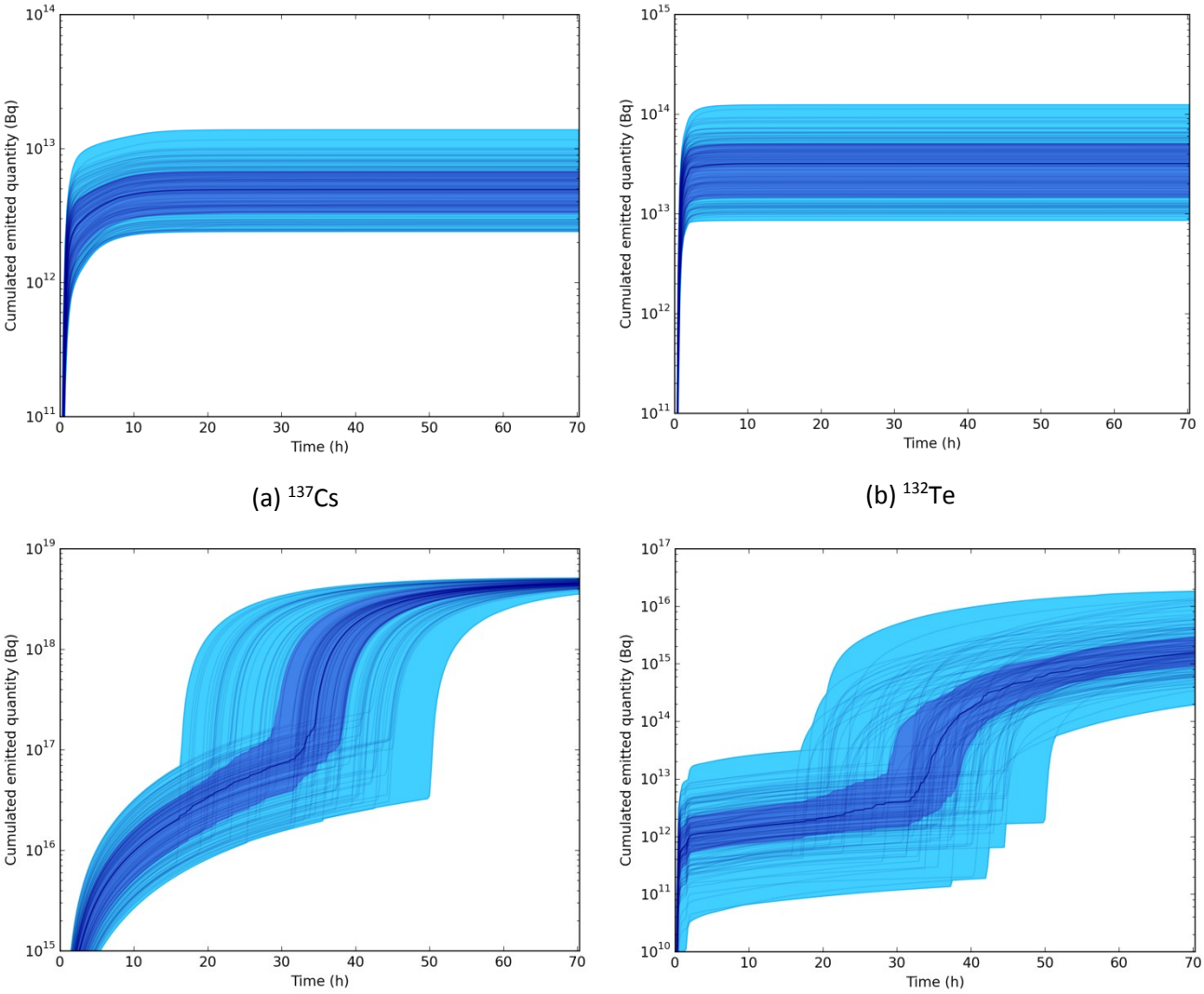
(a) 3 inches, hot leg

(b) 11 inches, hot leg

Figure 2: Histogram of the timing for the activation containment venting system on all the source terms of the ensemble for the ^{133}Xe time series of the hot leg scenarios. There is more uncertainty on the second release start with the smaller break.

Emitted amount of radionuclides

Examples of the temporal evolution of the released quantities are given in Figure 3 for the scenario corresponding to a break of eleven inches occurring on the hot leg location. Radionuclides behave differently depending on whether they are in particulate or gaseous form. The second release event is significant only for gases including noble gases. The majority of particles are supposed deposit in the confinement building before the use of the exhaust ultimate filter. They mainly remain trapped inside the building thanks to the filter efficiency. For instance, for most of the source terms, the second ^{137}Cs release is very low in magnitude. Only one released of Tellurium was modelled. Iodine releases have a temporal evolution slightly different to other radionuclides due to the specificity of iodine behaviour and chemical reactions that are modelled. The temporal evolution of a release of Methyl iodide (CH_3I) exhibits most of the temporal variability of Iodine releases.



(a) ^{137}Cs

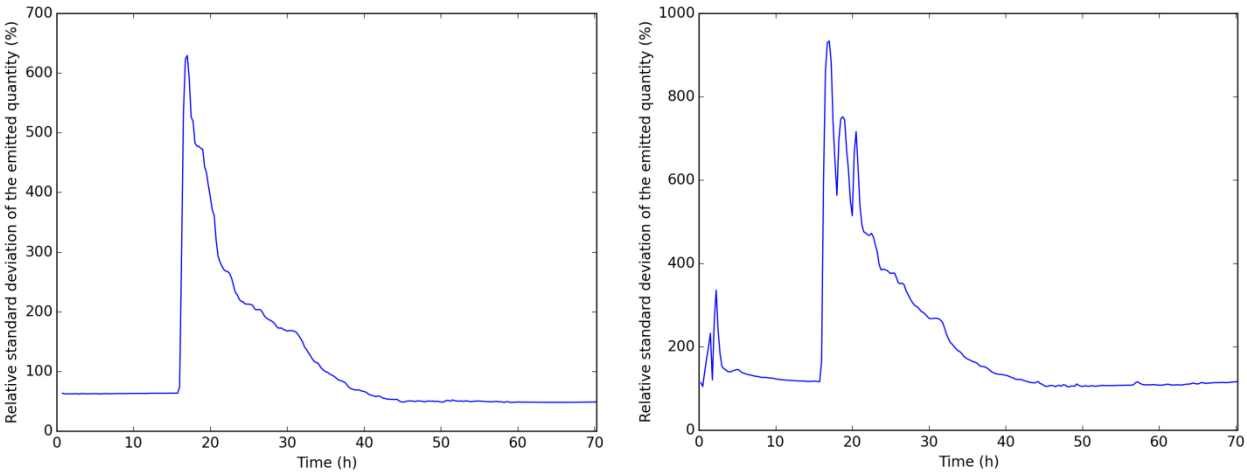
(b) ^{132}Te

(c) ^{133}Xe

(d) ^{131}I (sum of all forms)

Figure 3: Evolution of the emitted quantity of different radionuclides for the scenario corresponding to a break of 11 inches occurring on the hot leg location. The time scale gives the number of hours following the break occurrence. Each line corresponds to a member of the ensemble. The cyan corresponds to the envelop of the ensemble, while the deep blue corresponds to the fill between the 25th and 75th percentile. The dark blue line corresponds to the 50th percentile.

The ensemble spread for ^{137}Cs and ^{132}Te converges rapidly since they are not significantly impacted by the second release (Figure 3). Therefore, uncertainties after 24 hours may be considered representative of the overall uncertainties for these isotopes. For ^{133}Xe and ^{131}I, the second release is one or two orders of magnitude higher than the first release. This leads to a very large ensemble spread during the phase where the filtered containment venting system is opened (Figure 4). For ^{133}Xe, uncertainties should converge toward zero if simulations were carried out until the end of release, since all the matter within the reactor will be released (no deposition or chemical process). For ^{131}I, the complexity is higher due to chemical interactions and loss processes. Therefore, the uncertainty also varies in time.



(a) ^{133}Xe (b) ^{131}I

Figure 4: Evolution of the relative standard deviation of the instantaneous release of ^{133}Xe and ^{131}I in the scenario corresponding to a break of 11 inches occurring on the hot leg location. The time scale gives the number of hours following the break occurrence.

Table 4 details a summary of the uncertainties, represented by the standard deviation normalized by the mean of the ensemble, for several radionuclides at given times after the beginning of a release.

	^{132}Te	^{137}Cs	^{133}Xe	^{131}I
Maximum	74%	68%	257%	425%
24h	64%	42%	214%	410%
48h	64%	42%	31%	144%
72h	64%	42%	7%	112%

Table 4: Relative standard deviation of the total emitted quantity of different isotope for several instants following the break occurrence and for the maximum of the considered period.

Recommendations

This section presents the source parameters and related uncertainties which will be propagated through the chain of atmospheric dispersion and radiological assessment models for WP1 case studies. Two case studies will be used to better understand the effect on model outputs and thereby appraise the impact on decision making in the context of an emergency response.

- The Fukushima accident provides a case for *a posteriori* uncertainties, during the post-accidental phase. The source terms are provided by a bibliographical review.
- Hypothetical accident scenarios in Europe will also be tested, representative of *a priori* uncertainties, that is, from the emergency to the transitional phase. The FASTNET set of source terms described in this report will serve as a basis for this scenario.

Fukushima case study

Release height

All modelling projects simulate the consequences of the accident outside the Fukushima-Daiichi power plant site by considering a single release location. It is generally accepted that the release heights do not exceed 200 m. Different heights are estimated according to the release periods (Terada et al., 2012; Korsakissok et al., 2013; Morino et al., 2013; Draxler et al., 2015).

Source term

All the source terms published result from methods coupling the environmental measurements and the ADMs. Mathieu et al. (2018) present a review of the published source terms. Figure 5 shows the total quantities emitted during the course of the main episodes from the view point of the Japan territory contamination. The evaluated releases may vary significantly from one reference to another. Each source term has its own specific limitations. They reflect those of the meteorological data and those of the measurements most widely used to estimate releases. No consensus has therefore yet emerged that enables one source term to be identified as being more realistic than the others (Marzo, 2014; Hirose, 2016; Inomata et al., 2016; Saunier et al., 2016).

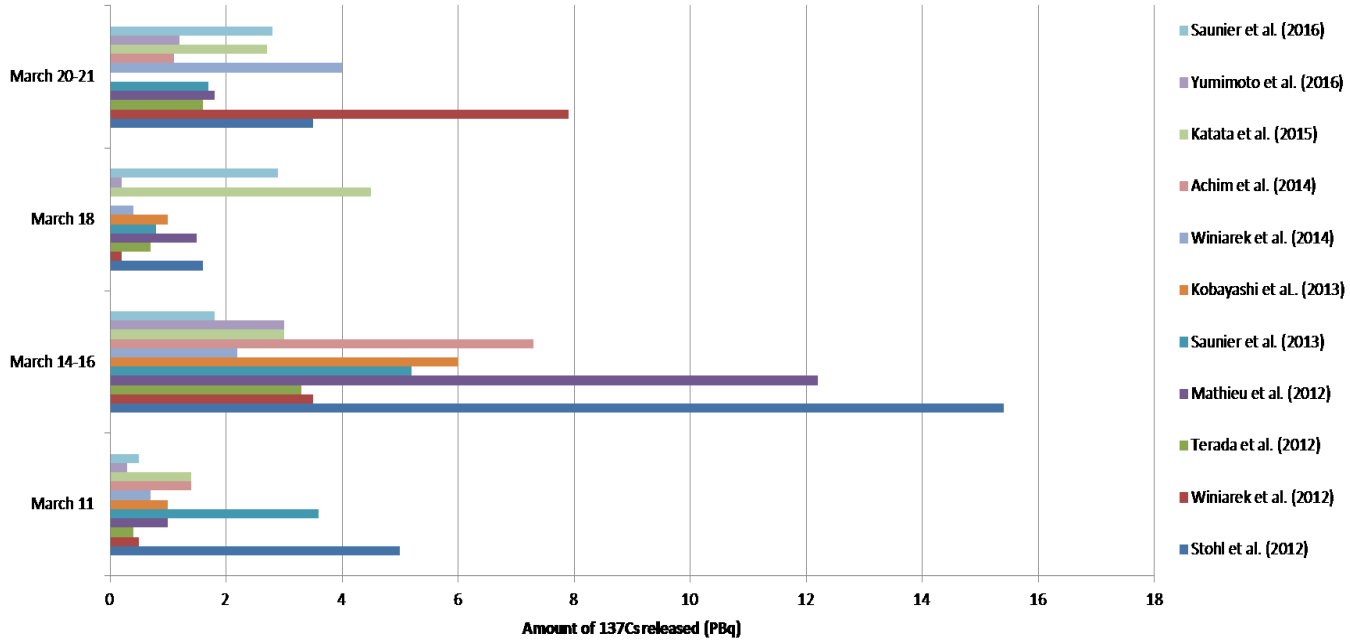


Figure 5: Quantities of ^{137}Cs emitted during the episodes of 11 March, 14-16 March, 18 March and 20-21 March. Each colour represents a different source term (from Mathieu et al., 2018).

Isotopic composition

The radioactive releases comprised of mainly volatile fission products, in gaseous or particle form. The dominant radionuclides in terms of activity and human impact, all gamma-emitters, being the noble gas ^{133}Xe, iodine in gaseous and particle form (^{131}I and ^{132}I), caesium (^{134}Cs, ^{137}Cs and ^{136}Cs), tellurium (^{132}Te). Other short-lived gamma emitters (^{129m}Te(^{129}Te), ^{99}Mo(^{99m}Tc), ^{140}Ba(^{140}La), ^{95}Nb and ^{110m}Ag) have been observed. Due to their high volatility, it is highly likely that the entire noble gas core inventories, from Units 1-3, were emitted into the atmosphere, mainly at the beginning of the release of each unit. Traces of plutonium, uranium and strontium isotopes were measured in the soil (Zheng et al., 2012; Yamamoto et al., 2014; Schneider et al., 2017) (Sakaguchi et al., 2014; Rosenberg et al., 2017). Overall, measurements of non-volatile radionuclides indicate that most of them probably remained trapped inside the reactors. Measurements indicate that most of the dose rate signal is due to ^{134}Cs, ^{137}Cs, ^{136}Cs, ^{137m}Ba, ^{131}I, ^{132}I, ^{132}Te, and ^{133}Xe.

The isotopic composition of plumes changes significantly, over time and according to the release events (Furuta et al., 2011; Hohara et al., 2011; Katata et al., 2012; Saunier et al., 2013; Igarashi et al., 2015; Katata et al., 2015) except for some radionuclides, which behave similarly. For instance, the ratio of ^{134}Cs to ^{137}Cs varies little, between 0.9 and 1.1 (Amano et al., 2012; Furuta et al., 2011; Haba et al., 2012; Hirose, 2012; Doi et al., 2013). However, the release composition is still relatively uncertain. The currently adopted consensus is to use the isotopic ratios estimated by the Japanese Atomic Energy

Agency, JAEA (Katata et al., 2012, 2015) from the analysis of environmental measurements and the core inventory of the plant. It recommends ratios of $^{137}Cs/^{131}I$ between 0.01 and 0.970 and ratios of $(^{132}I+^{132}Te)/^{131}I$ between 2 and 1. These values are used by most of the modelling studies and health impact evaluations (Mathieu et al., 2018). Few other studies estimated slightly different isotopic ratios. For instance, Saunier et al. (2013) estimated by inverse modelling approach the release rate of ^{134}Cs, ^{137}Cs, ^{136}Cs, ^{137m}Ba, ^{131}I, ^{132}I, ^{132}Te, and ^{133}Xe.

Physical form

Apart from the noble gases and the iodine, most of the radionuclides were transported in the atmosphere, in particle form. The gas-to-particulate iodine ratio varies significantly over time (IAEA, 2015c). On average, a little more than half the iodine was released in gaseous form (Lebel et al., 2016). During plume transport, the iodine remains predominantly in gaseous form even if the ratios vary. Two forms of gaseous iodine may have been emitted: a highly reactive form corresponding to molecular iodine and a more volatile form which is also more persistent in the atmosphere and behaves like organic iodine (Momoshima et al., 2012; Katata et al., 2015; Lebel et al., 2016).

Particle size

The size of the emitted aerosols is not known. With the exception of the iodine isotopes, the size distribution of the aerosols at about one hundred kilometres from the power plant was bimodal. The first Activity Median Aerodynamic Diameter (AMAD) maxima was around 1.5-1.6 µm (Doi et al., 2013; Miyamoto et al., 2014). The released radioactivity could be transported by atmospheric particles such as non-marine sulphates (Kaneyasu et al., 2012; Miyamoto et al., 2014).The secondary spike at around 6 µm is thought to stem from the re-suspension of deposited radioactivity and/or sea salt.

The particulate iodine would preferentially have been emitted in the form of highly reactive fine particles of the order of 0.1 µm, interacting quickly with the atmospheric aerosols to form the largest particles (Lebel et al., 2016). At about 100 km from the plant, the iodine was carried by a majority of particles of around 0.5 µm and secondarily by larger aerosols with the same size distribution (1.5-1.6 µm) as that of the other radionuclides.

Another particularity is the existence of 2 to 2.6 µm spherical hydrophobic particles with a high ^{137}Cs concentration at the beginning of the event of 14-16 March which contrasts with the observations of 20-21 March (Adachi et al., 2013). The Cs-bearing silicate glass microparticles remain too few in number to significantly influence the health impact.

The assessment of the health impacts of the accident and the modelling studies generally assume the size distribution measured by Kaneyasu et al. (2012). The caesium balls observed by Adachi et al. (2013) constitute the extreme values sometimes considered.

Recommendations for the Fukushima case

In order to be representative of the source term uncertainties that remain, WP1 participants will use several source terms as input of the atmospheric dispersion models. For instance, the following source terms could be used : Stohl et al., 2012; Terada et al., 2012; Saunier et al., 2013; Katata et al., 2015; Saunier et al., 2016; Yumimoto et al., 2016.

Atmospheric dispersion and deposition of ^{134}Cs, ^{137}Cs, ^{136}Cs, ^{137m}Ba, ^{131}I, ^{132}I, ^{132}Te, and ^{133}Xe will be simulated to allow ambient dose rate assessment. These eight species can be grouped into three families to which will be added the species in secular equilibrium:

- the caesium family including caesium and barium,
- the iodine family including iodine and tellurium,
- the noble gas family restricted to xenon.

Some source terms do not include release rate for the three families. In that case, isotopic composition proposed by JAEA (Katata et al., 2012, 2015) will be used to complete the source terms.

Additional perturbation may be added following the approach developed by Girard et al. (2016b). Perturbation can be applied to each family independently from one another

- Emission factors can be perturbed by a multiplicative factor inside [0.333 ; 3] bounds.
- Emission delay can be perturbed by an additive increment between [-6 h ; 6h].

The release height may be chosen between the ground level and 400 m (Girard et al., 2016b) to encompass all the uncertainties or between the ground level and 200 m to be more realistic (Terada et al., 2012; Morino et al., 2013; Korsakissok et al., 2013).

Uncertainties on the size distribution of radionuclides have an influence on the deposition processes. Therefore, they will be included in uncertainties related to the deposition modelling, by using suitable ranges of variations for deposition velocities and scavenging coefficients.

European case studies

The accidental scenario retained is a LOCA on a PWR. The timeline of the accident has been described in Table 3. The chosen break size is 11 inches. The variability of uncertain parameters was detailed in the above section describing the Uncertain parameters of the source, leading to a set of 147 source terms during 72 hours. This ensemble of source terms is representative of model uncertainties only.

There is a possibility to consider an additional scenario in the future, to take into account the lack of information concerning the availability of some safety devices (e.g. safety injection system). This would add some variability to the ensemble of source terms in the scenario corresponding to a break of 3 inches, especially on the timing of the start of the release which is currently the same for all ensemble members. As stated earlier in this report, uncertainties relating to the modelling of reactor (physics) usually dominate once the start of major release is established.

As it is, the ensemble spread is already large enough and shows important variability for two key parameters:

- The timing of the second release, corresponding to the use of the exhaust ultimate filter is around the 33.5 hours after the beginning of the release, with a standard deviation of 7.3 hours.

- The emitted quantities of radionuclides as a function of time. The uncertainty varies in time. Cumulated values are listed in the Table 5.

	^{132}Te	^{137}Cs	^{133}Xe	^{131}I
Maximum	1.24×10^{14}	1.38×10^{13}	5.10×10^{18}	1.82×10^{16}
75th percentile	9.47×10^{12}	2.42×10^{12}	3.84×10^{18}	3.48×10^{14}
50th percentile	9.16×10^{12}	2.41×10^{12}	3.75×10^{18}	3.03×10^{14}
25th percentile	8.88×10^{12}	2.40×10^{12}	3.66×10^{18}	2.49×10^{14}
Minimum	8.57×10^{12}	2.40×10^{12}	3.54×10^{18}	1.94×10^{14}

Table 5: Emitted quantities of different isotopes (in Bq) 72 hours after the initiator in the scenario corresponding to a break of 11 inches occurring on the hot leg location.

To propagate these uncertainties, several options can be chosen, depending on the computation burden and the feasibility:

- Using all 147 members of the ensemble;

- Using a well-chosen subset of source terms, representative of the overall uncertainty. 0th, 5th, 50th, 95th and 100th percentile ensembles could be considered ;

- Using the mean of the ensemble with crude perturbations on the timing and quantities inferred from the present study. The drawback of this approach is that it does not account for the complexity of different kinetics that appear in the ensemble of source terms, especially for iodine;

- Using the PCA described in Appendix 2; simulations would be conducted with the mean of the ensemble to which 1 or 2 components, multiplied by a factor, would be added. The emission of each isotope is then characterized by only 3 parameters:
  - The first score of the first PCA
  - The first score of the second PCA
  - The time shift of the second release

This method would better represent the variability in kinetics, as far as the second major release is concerned. However, it still has limitations for the representation of iodine behaviour.

Uncertainties on the size distribution of radionuclides have an influence on the deposition processes. Therefore, they will be included in uncertainties related to the deposition modelling, by using large ranges of variations for deposition velocities and scavenging coefficients.

As for the Fukushima case, the release height may be chosen between the ground level and 400 m.

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Appendix 1

Example of a PWR type reactor

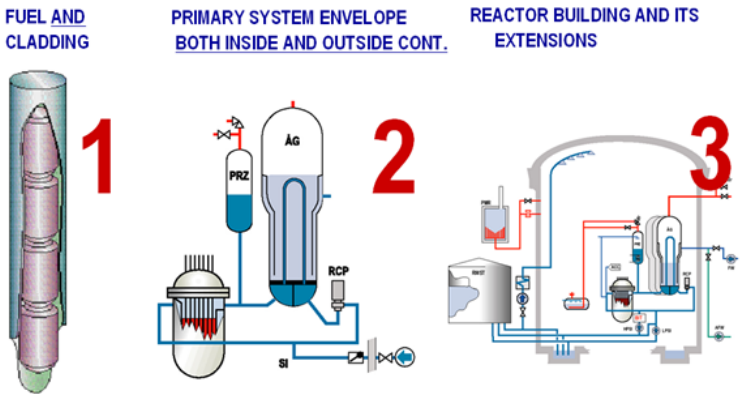
A barrier is a physical separation between radionuclides from the core and the environment.

Three barriers related to critical functions have been identified for a PWR (Figure 6):

1- Fuel and cladding ;
2- Primary system envelope, both inside and outside containment;
3- Reactor building and its extension

3 Safety Barriers

- Status of each barrier gives information on the occurrence of a release into the environment



- **Significant release into the environment if two barriers at least are degraded**

Safety functions ensuring integrity to the barriers

3 barriers	#1 Fuel and cladding	#2 Primary system envelope	#3 Reactor building and its extensions
Associated safety functions	• Subcriticality • Primary liquid inventory	• Removing heat from the primary system • Removing heat from primary pump seals	• Containment • Removing heat from the reactor building

Important:
These "safety functions" are not those from Final Safety Report

Figure 6 : Barriers and Critical safety functions for a PWR from F. Stephanie's presentation during the Technical Meeting to review the IAEA's Assessment and Prognosis procedures for Nuclear and Radiological Emergencies, 01/12/2016, Vienna.

Example of an expertise method for estimating the source: the French approach for PWR

During an emergency, experts follow pre-defined evaluation approaches

- to establish a consistent diagnosis of the on-going situation and its possible developments;
- to anticipate the likelihood of the occurrence of future releases into the environment, estimate the associated source term and projected time periods before release as well as the potential off-site consequences.

For instance the French approach developed by EDF and IRSN is a diagnosis-prognosis approach based on the study of the states of the three containment barriers: it is called the 3D/3P method (Figure 7). The 3D/3P approach aims to diagnose the on-going plant status, to prognose the expected evolution as well as the evolution in the event of an additional and major failure.

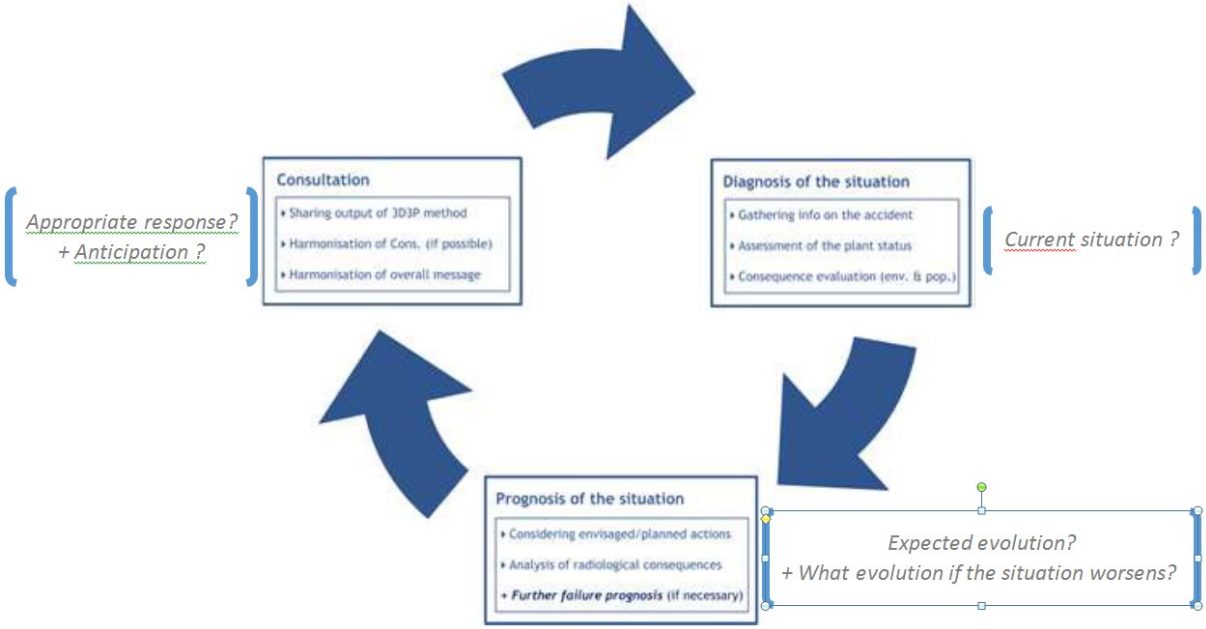


Figure 7 : Description of the 3D3P approach from S Fougerolle's presentation entitled "Source term calculation with 3D/3P methodology and PERSAN" during the FASTNET workshop - 7-8 nov 2016 in Bologna.

Appendix 2

Principal component analysis

In order to study the source term ensembles and to highlight which parameters characterized the uncertainties, a Principal Component Analysis (PCA) is setting up.

For the telluric time series, there is only one release in the atmosphere and the time series of all the members are similar to one another. In this case, a PCA is really easy to do and only few components can be considered to keep the consistency of the ensemble.

However, for the isotopes that have more than one release, the time shift of the second emission creates a complexity which is not well reconstructed when only considering few components of the PCA with 3 components. Considering the simple behaviour of the ensemble, a simple parametrization would benefit to the understanding of the source terms uncertainties.

To allow the PCA to be simplified, the idea is to implement two PCA: one for section before the second release, and one for section after the second release where the beginning of the second release is synchronized for each time series.

The first step is to detect the instants t_2 of the second release with a pic detection algorithm on its first derivative. Once these instants are detected, the time series are cut in t_2 to create two sets of time series. An example is shown Figure 8.

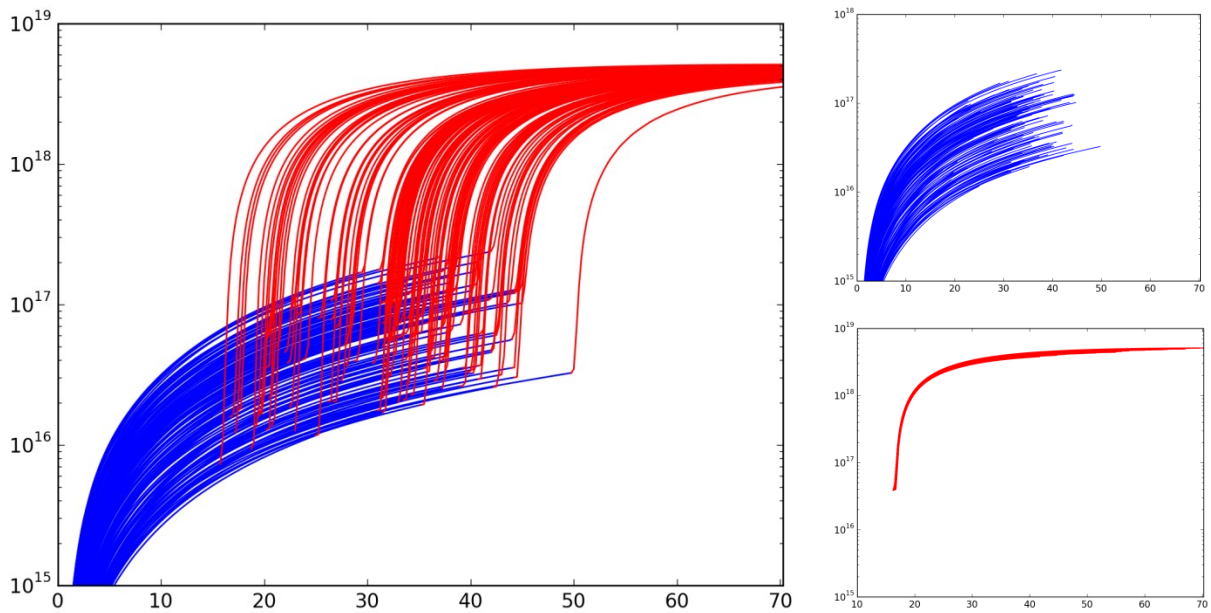


Figure 8: Cut of the Xe133 time series for the 11 inches source terms in hot leg. The first part (in blue) is defined as the time period between the beginning of the first release ($t = t_1 = 0$) and the beginning of the second release (t_2). The second part (in red) is defined as the time period between the beginning of the second release (t_2) and the end of the time series ($t = 72\mathrm{h}$). For the ACP, all the time series of the second part are synchronize at the first instant of the second release.

The second step is to extend the different time series of the ensemble to be able to run a PCA, because, since the cut, they do not have the same length anymore. It can be done by several methods. The way it has been done here is by using the Taylor formula as the last time step of each time series (Figure 9).

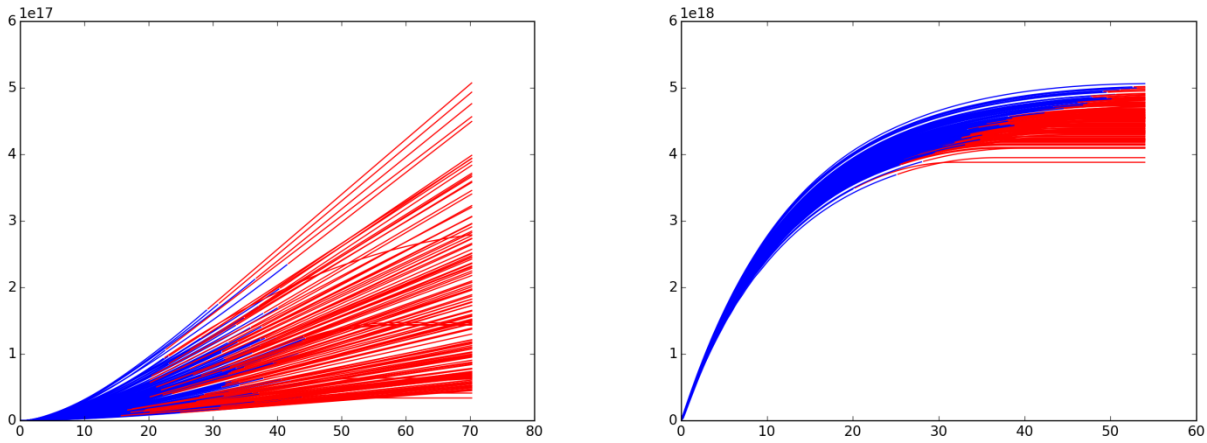
The third step is to run a PCA on the two parts of the time series. By doing so, we obtain information about the uncertainties on each time period of the release and because on each part, the evolution of

the time series is quite simple, only one component allows to properly characterize the evolution and the uncertainties of the ensemble (see Figure 10-11). This method works fine for the ^{133}Xe and for the caesium where the time evolutions are quite simple, while it is difficult to properly extend and to analyses the iodine time series because of their chaotic evolutions.

The emission of each isotope is then characterized by only 3 parameters:

- The first score of the first PCA
- The first score of the second PCA
- The time shift of the second release

Furthermore, for some of the isotope like the ^{133}Xe and the Caesium, there is a correlation between the coefficient of the first score of the second PCA and the time shift of the second release.



(a) First part (b) Second part

Figure 9: Cut of the ^{133}Xe time series for the 11 inches source terms in hot leg and prolongation of each part by the Taylor formula. In blue, the original part of the time series. In red, the extended part of the reconstructed time series.

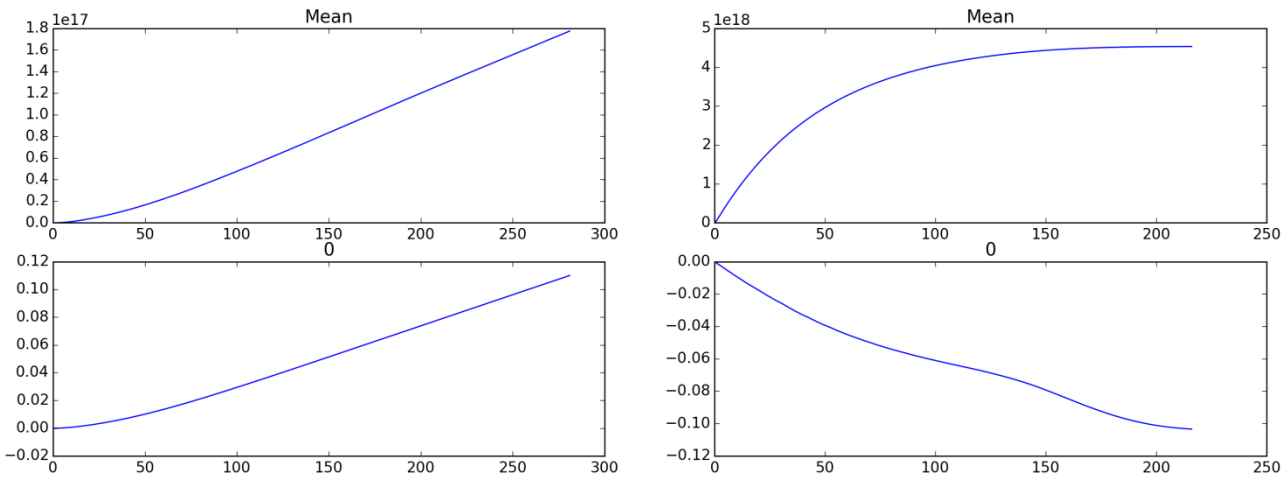
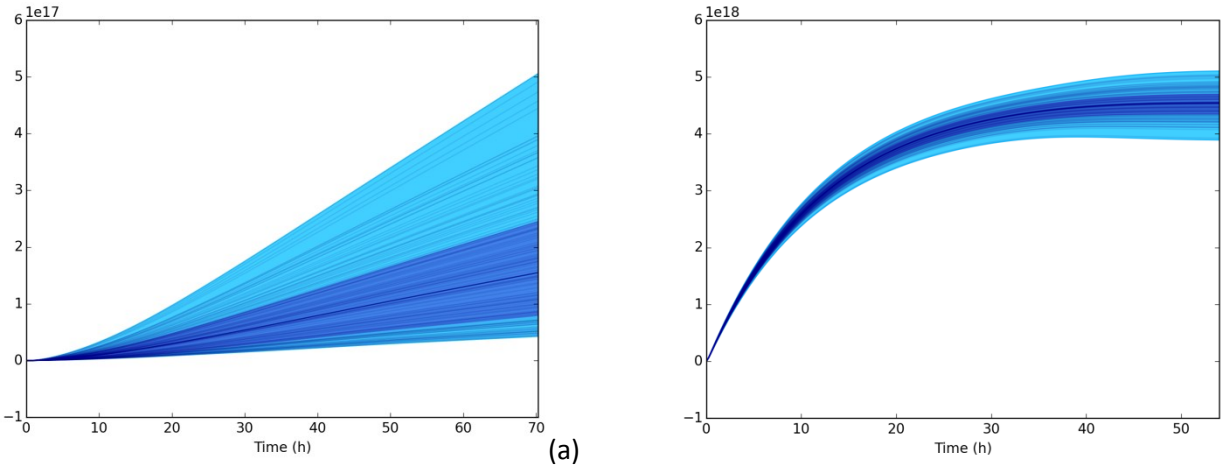


Figure 10: Plot of the mean and the first component for each part of the ^{133}Xe time series for 11 inches in hot leg.



(a)

First part

(b) Second part

Figure 11: Plot of the two parts of the ^{133}Xe time series projected on the first component of the Principal component analysis.

D 9.1.4 - Guidelines detailing the range and distribution of atmospheric dispersion model input parameter uncertainties

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Reviewer(s): WP1 members

Abstract

A literature review has been conducted to evaluate the range and distribution of atmospheric dispersion model-specific input parameter uncertainties. This review does not consider uncertainties associated with source term and meteorological inputs to an atmospheric dispersion model. Uncertainty ranges relating to the standard deviation of the cross wind (σ_y) and vertical (σ_z) Gaussian plume profile, the horizontal diffusivity term, K_u, the vertical diffusivity term, K_w, dry deposition velocity, surface resistance approach to dry deposition modelling, wet deposition scavenging coefficient parameter, *a*, wet deposition scavenging exponent parameter, *b*, and roughness length have all been recommended. Where possible accompanying probability distributions were also recommended. Where no alternative recommended approach can be implemented when describing the uncertainty range on the turbulent diffusion scheme for a Gaussian plume model, an alternate "second-choice" stability category, determined by expert judgement, is recommended. And it was identified that there is value in the application of model ensemble approaches for describing the uncertainty associated with the standard deviation of the cross wind and vertical Gaussian plume profile, and the below-cloud and in-cloud scavenging coefficient schemes.

These recommendations aim to facilitate the propagation of uncertainties through the chain of atmospheric dispersion and radiological assessment models both for historical scenarios (such as the accident at the Fukushima Daiichi Nuclear Power Plant) and for hypothetical scenarios. This will help improve understanding of the effect of input uncertainties on model output, and thereby appraise the impact on decision making in the context of an emergency response.

<End of abstract>

Contents

Introduction

Aims of the review

In the event of an accidental release of radionuclides into the atmosphere, dispersion calculations would be used in the early phase of the accident to model the consequences and to assist in determining appropriate countermeasures. The calculations would be subject to significant uncertainties. These would arise both from the model itself and from inputs such as the source term, meteorological data and model-specific input parameters.

In order to evaluate the range and distribution of these uncertainties, a literature review has been carried out. More specifically, the objective of the review was to propose a list of uncertain atmospheric dispersion model-specific input variables (not including source term related and meteorological input variables) that should be taken into account (when modelling an accidental release of radionuclides into the atmosphere), and recommend the respective uncertainty ranges and distributions inferred from the literature review.

In conjunction with the identification and description of source term and meteorological uncertainties associated with accidental radiological scenarios, the atmospheric dispersion model-specific uncertainties described here will enable a comprehensive assessment of the nature and impact of the atmospheric dispersion model (ADM) output uncertainties.

It is intended that such uncertainty ranges and distributions will be used in the propagation of uncertainties through the chain of atmospheric dispersion and radiological assessment models both

for historical scenarios (such as the accident at the Fukushima Daiichi Nuclear Power Plant) and for hypothetical scenarios. This will help improve understanding of the effect of input uncertainties on model output, and thereby appraise the impact on decision making in the context of an emergency response.

Scope of the review

The primary atmospheric dispersion model-specific uncertainties considered are turbulent diffusion (notably the standard deviation of the cross wind and vertical Gaussian plume profile and the diffusivity parameterization), dry deposition (notably dry deposition velocity) and wet deposition (notably wet scavenging coefficients). Note that Gaussian puff models were identified in a limited sense in the literature review and therefore such models and associated dispersion coefficients have been considered only briefly in this report. Other aspects of atmospheric dispersion model-specific uncertainty, such as surface roughness, are touched upon.

This report does not consider uncertainties with source term or meteorological origins (which are reviewed in parallel reports). For example, the process of wet deposition is often described by scavenging coefficients, dependent on both modelling parameterization (by way of scavenging parameters) and meteorological information (by way of precipitation rate). This report considers the former but not the latter. A further example, plume rise, is deemed to be a source term and not a model-specific process for the purposes of this study.

A requirement of some modelling approaches is that certain meteorological variables are determined indirectly from the Numerical Weather Prediction (NWP) data, in a pre-processing step. This step may be performed within the confines of the ADM. However this report only considers uncertainties in model-specific input and does not consider uncertainties in NWP meteorological data (which could be considered by way of a meteorological ensemble) or pre-processed meteorological data (which could be considered by way of sensitivity analysis techniques). This is demonstrated by the case of “boundary layer depth”. This is a necessary input parameter for some ADMs. It is deemed here to be a meteorological input parameter. It can be determined to differing degrees by some combination of model-specific (for example roughness length) and meteorological (for example surface sensible heat flux) input parameters. In this instance, only the uncertainty on the roughness length is considered in this report.

The literature review focused on studies centred on releases of radioactivity and subsequent atmospheric dispersion modelling; however, where appropriate, studies centred on atmospheric dispersion modelling of volcanic ash and air quality were considered if the findings of such studies were deemed to be transferable to radiological releases.

This report only considers atmospheric dispersion model-specific input parameter uncertainties and does not consider radiological assessment model-specific input parameter uncertainties.

The idea of unknown unknowns was developed by two American psychologists, Joseph Luft and Harrington Ingham. Unknown unknowns are risks, or in this case uncertainties, that come from situations that are so exceptional that they are inconceivable. This study will not account for potential unknown uncertainties.

Review terminology

The terms “range” and “distribution” are used throughout this report. The range describes the numerical upper and lower bounds on a particular scale, which could be the full range from the minimum to maximum value or could be a truncated range accounting for a percentile of the possible

values. The distribution is a mathematical function and graphical description of the probability of occurrence, typically of the form: uniform, triangular, normal, lognormal, etc.

Method of review and challenges

Approximately one hundred documents were considered in the first iteration of the review, of which approximately thirty were considered of sufficient relevance to be considered further in relation to the review of uncertain atmospheric dispersion model-specific input parameters.

Those thirty or so documents were shared among Work Package One (WP1) participants, who entered relevant information into review templates. Those templates have been used as the basis of the present report.

The derivation of the ranges and distributions of the atmospheric dispersion model-specific input parameter uncertainties undertaken here was on the basis of human inference of the literature unearthed, weighting the evaluation on the basis of the evidence presented in a subjective way. The ranges and distributions were not derived using any formal published methods or techniques.

Of the literature reviewed, the means for determining the specified ranges included: further literature reviews (Haywood, 2008) and expert elicitation (Harper et al, 1995b). However the proposed ranges tend to originate from studies comparing model and measured endpoints alongside a degree of expert elicitation. A fundamental ground-rule adopted by Harper et al (1995b) was that distributions would be elicited from experts only on parameters that are directly measureable in the environment. The literature reviews undertaken by the authors of the papers cited throughout this report (and in fact the literature review undertaken here also) add notable value by way of a cumulative weight of evidence. However there is also the risk of misinterpretation of ranges, how they were developed and their intended application. This misinterpretation may escalate through multiple applications of the same review findings.

The type of uncertainty being accounted for varies from one reference to another. For example Freeman et al (1986) consider only measurement uncertainty, Haywood (2008) consider only knowledge uncertainty (i.e. the imprecision resulting from a lack of knowledge of the nature of the release and state of weather etc.) and Quérel et al (2015) consider only model uncertainty. It was not evident from the literature reviewed that any studies develop ranges on the basis of a combination of all three forms of uncertainty.

In a number of publications identified, the full range of values a parameter may take in any accident are considered. For example, Velenyák (2016) perform a sensitivity analysis, propagating model input uncertainties through the Gaussian puff model integrated in the SINAC decision support software developed at the Hungarian Academy of Sciences – Centre for Energy Research, but scoping the full range of possible variability. Thus, for the stability category input parameter, the “full” range of categories from A to F (mindful that some methods categorise stability from A to G) were varied (for a baseline stability category D). Such variability is not representative of the degree of uncertainty that may arise for any one specific scenario and therefore is of limited value here. A further example is the joint US Nuclear Regulatory Commission (US NRC) and Commission of European Communities (CEC) study, titled, “Probabilistic Accident Consequence Uncertainty Analysis” (Harper et al, 1995; described in more detail in the section titled, “Gaussian plume modelling approach”). That study was not constrained by any scenario-specific conditions and was therefore very much open to interpretation. The uncertainty ranges elicited by each panel expert are likely to be inconsistent in terms of their derivation and therefore their applicability. In contrast to Velenyák (2016) and Harper et al (1995b),

Eleveld et al (2007) was very scenario specific in its consideration of uncertainty. Eleveld et al (2007) focus solely on four model scenarios: a dry and a wet (2 mm h^{-1}) scenario in combination with a low (10-20 m) and a high (200-600 m) effective release height. Therefore Eleveld et al (2007), which consider a small number of scenarios encompassing a narrow range of possible conditions, is also somewhat limited in terms of its value here. However, these two very different approaches, at the two extreme ends of the spectrum, are of value because they act to bound the problem.

As mentioned previously, it is intended that such uncertainty ranges and distributions will be used subsequently in the propagation of uncertainties through the chain of atmospheric dispersion and radiological assessment models both for historical scenarios (such as the accident at the Fukushima Daiichi Nuclear Power Plant) and for hypothetical scenarios. It is recognised that not all participants in WP1 will have the means and/or the desire to account for all uncertainties across all considered scenarios. Therefore, for the purposes of consistency (where necessary and possible), a single (default) value should also be determined. To assist in the derivation, mean, median and default values have been included in this report, but it is beyond the remit of this study to recommend single "universal" input parameters (or sets of input parameters).

Findings of the review

Turbulent Diffusion Scheme

A number of studies have been identified which evaluate the uncertainty on the ADM input parameters used to describe the turbulent diffusion. More often than not the authors of the respective reports or papers considered different models, applying different turbulent diffusion schemes, and expressing the range of uncertainty in a different manner. However, there was a tendency for models detailed in the literature reviewed to be categorised as either Gaussian plume or non-Gaussian models (notably Eulerian and Lagrangian particle models), considering the standard deviation of the cross wind (σ_y) and vertical (σ_z) Gaussian plume profile and the diffusivity parameterization, K, respectively. Therefore, the range of uncertainty on the turbulent diffusion scheme has been considered separately for these two types of models.

Multiple methods for describing the horizontal and vertical Gaussian distribution

The standard deviation of the cross wind (σ_y) and vertical (σ_z) Gaussian (puff and plume) profile are an inherent feature of the Gaussian (puff and plume) approach, however there are numerous forms of the description of the horizontal and vertical Gaussian distribution, for example Doury (1981) and Pasquill (1961) based on semi-empirical relations derived from experiments or Draxler (1976), mathematical treatment based on similarity theory, which incorporates turbulence intensity measurements linked to wind component fluctuations along the horizontal and vertical directions (Rabl et al, 2014). With so many methods of describing the horizontal and vertical Gaussian distribution, determining a single description of the uncertainty is more complex.

However, Périllat et al (2017) use the array of methods as an advantage, by considering all three aforementioned methods in an approach akin to a model ensemble. Périllat et al (2017) sought to propagate numerous input uncertainties through the Institut de radioprotection et de sûreté nucléaire's (IRSN's) Gaussian puff model, pX, for the Fukushima Daiichi Nuclear Power Plant accident scenario. There is scope to extend Périllat et al (2017) model ensemble further by including additional derivations of the standard deviation of the cross wind and vertical Gaussian plume profile. Examples include similarity theory based approaches derived by Hanna et al (1977) and Irwin (1979), and semi-empirical relations derived from experiments by Gifford (1961), Smith (1968), McElroy and Pooler

(1968), McElroy (1969), Briggs (1973), Gifford (1976), McMullen (1975), Vogt (1977) and Green et al (1980) (mindful that there exist a number of revisions and reformulations by the same and subsequent authors). Caveats include potential pre-processing to determine all required meteorological input parameters and the significant effort necessary to implement such approaches within the ADM.

Gaussian plume modelling approach

Uncertainty range on the standard deviation of the cross wind (σ_y) and vertical (σ_z) Gaussian plume profiles

A number of papers and reports assessed the uncertainty on the turbulent diffusion scheme by way of assessing the uncertainty on σ_y and σ_z, notably Harper et al (1995b), Jones et al (2000), Hanna et al (2007) and Irwin and Hanna (2005). As mentioned previously, determining a single description of the uncertainty is complex. This is in part due to the many methods of describing the horizontal and vertical Gaussian distribution, but is also due to σ_y and σ_z being representative and parameterisations rather than physical quantities which can be directly measured. Furthermore, the parameterisations are (typically) based on coefficients and distance (downwind) from the release (equation 1), where the latter is spatially dependent and the former are scenario dependent (notably meteorologically, and therefore temporally, dependent).

$$\sigma_{y,z} = a_{y,z} \cdot x^{b_{y,z}} \qquad (1)$$

Harper et al (1995b) state that, "given a fixed model, unless the code input parameters happen to be physical quantities that can be elicited directly (such as in the dry deposition case) an approach such as that adopted in this exercise may result in complicated mathematical treatments to generate code input variable distributions. If a case structure is designed to be independent of any particular analytical model, data may be elicited which are incompatible with the fixed models in the consequence codes. It is not apparent how to rationalize the distributions generated for the model parameters by using only information that is compatible to the fixed model".

Harper et al (1995b) provide a relatively comprehensive consideration of the numerical uncertainty on σ_y and σ_z. Formal techniques for expert judgement elicitation were used to develop uncertainty distributions of the standard deviation of cross-wind plume profiles (as well as plume centre-line concentration relative to source strength and off-centreline plume concentration relative to centreline concentration). This was done for a range of downwind distances (primarily 0.5, 1, 3, 10 and 30 km), and for a range of lapse rates (representing a range of non-neutral atmospheric stability conditions). Consideration of standard deviation of the vertical plume profiles was more limited (60 m and 600 m downwind and stable conditions only).

In the UK, neutral stability conditions are observed at least 50% of the time (Clarke, 1979), however Harper et al (1995b) only derive estimates of the probability distribution of the standard deviation of the Gaussian plume profiles in stable and unstable conditions. This is because Harper et al (1995) were not only interested in the uncertainty on model-specific input parameters but were also interested in the impact of such uncertainties on the radiological consequence assessment. Stable meteorological conditions were considered because of the recognised greater contribution to high values of early fatalities (in the event of very large postulated nuclear power plant accidents) in such weather conditions (when the standard deviation of the plume is small). And unstable meteorological conditions were considered because of the recognised greater contribution to high values of chronic cancers in such weather conditions (more dilution, less interdiction, wider spread and thus, more cancers).

A fundamental ground-rule adopted by Harper et al (1995b) was that distributions would be elicited from experts only on parameters that are directly measureable in the environment. However the primary input parameters (i.e. coefficients *a* and *b* in equation 1) are not directly measureable in the environment, and the elicitation parameters (σ_y and σ_z) for these phenomena were therefore not the input parameters. The elicitation parameters for dispersion were variables from which values for the input parameters could be derived. Mathematical processing techniques were therefore developed for this study, which enabled the development of distributions over input parameters from aggregated elicited distributions.

Harper et al (1995b) collate, from each (of eight) expert(s), the 0th, 5th, 50th, 95th and 100th percentile values from the cumulative distribution of σ_y and σ_z for each scenario. The individual expert distributions were then aggregated into a single cumulative distribution of σ_y and σ_z for each scenario assuming equal weighting (noting that two other weighting schemes were considered). PARFUM is a software package that was used to combine the experts' assessments. The study considered other software packages for combining the experts' assessments, but recommended the PARFUM software (which implemented the Sigma processing methodology (Cooke et al, 1994)).

For a limited number of scenarios and a limited number of receptors considered by Harper et al (1995b) the percentile values from the cumulative distribution of σ_y and σ_z have been summarised in Tables 1-5 (derived from Harper et al (1995a)). Note that the "minimum" and "maximum" tabulated columns are the minimum and maximum elicited values across the eight experts, respectively. The "mean" tabulated column is the mean of the eight elicited values (from each of the eight experts). The "aggregated" tabulated column is the aggregated value combining the eight elicited values (applying the Sigma processing methodology). There are no aggregated values in Table 5 because such values were not explicitly detailed in Harper et al (1995a).

It is evident that, for the values considered in Tables 1-5, the 100th percentile values from the cumulative distribution of the standard deviation of the cross wind and vertical Gaussian plume profiles were greater than the respective 0th percentile values across a range of factors from 6 to 19, with a mean of the range of factors of 12. A factor of 10 is deemed to be a representative value.

It is evident that, for the values considered in Tables 1-5 (barring the aggregated values), the 95th percentile value from the cumulative distribution of the standard deviation of the cross wind and vertical Gaussian plume profiles were greater than the respective 5th percentile value across a range of factors from 3 to 8, with a mean of the range of factors of 4. A factor of 4 is deemed to be a representative value.

It is notable that the aggregation of the distributions spans much of the range of the minimum (of the eight experts') 5th percentile value and maximum (of the eight experts') 95th percentile value and therefore there is a tendency for the aggregation of the distributions to be associated with a wider uncertainty band than any of the individual elicited distributions.

Quantile	Minimum	Mean	Aggregated	Maximum
0 %	35	90		140
5 %	76	188	92	277
50 %	153	346		550
95 %	270	660	1370	1780
100 %	667	1309		2400

Table 1: Percentile values from the cumulative distribution of the standard deviation of the cross wind Gaussian plume profile (m) in unstable conditions and 1 km downwind (Harper et al, 1995a)

Quantile	Minimum	Mean	Aggregated	Maximum
0 %	400	1580		3300
5 %	1580	3199	1880	6000
50 %	2700	6468		11500
95 %	4200	15373	33300	48000
100 %	7300	21333		40000

Table 2: Percentile values from the cumulative distribution of the standard deviation of the cross wind Gaussian plume profile (m) in unstable conditions and 30 km downwind (Harper et al, 1995a)

Quantile	Minimum	Mean	Aggregated	Maximum
0 %	10	21		35
5 %	21	44	23	88
50 %	41	91		163
95 %	61	175	270	285
100 %	72	222		315

Table 3 Percentile values from the cumulative distribution of the standard deviation of the cross wind Gaussian plume profile (m) in stable conditions and 1 km downwind (Harper et al, 1995a)

Quantile	Minimum	Mean	Aggregated	Maximum
0 %	122	334		700
5 %	248	917	366	1860
50 %	487	1937		3480
95 %	726	4136	5920	7600
100 %	852	5417		8600

Table 4: Percentile values from the cumulative distribution of the standard deviation of the cross wind Gaussian plume profile (m) in stable conditions and 30 km downwind (Harper et al, 1995a)

Quantile	Minimum	Mean	Maximum
0 %	3	4	6
5 %	3	6	11
50 %	7	13	18
95 %	15	22	34
100 %	18	40	70

Table 5: Percentile values from the cumulative distribution of the standard deviation of the vertical Gaussian plume profile (m) in stable conditions and 600 m downwind (Harper et al, 1995a)

Harper et al (1995b) consider atmospheric dispersion of radionuclides, in contrast to Hanna et al (2007) and Irwin and Hanna (2005), who consider the atmospheric dispersion of toxic chemicals. However, for the purposes of understanding turbulent diffusion scheme uncertainty, all three approaches are equally applicable.

Hanna et al (2007) consider annual average concentrations from routine emissions; in contrast Irwin and Hanna (2005) consider observed concentrations averaged over 10 minute periods. However, in both studies the spatial domain was relatively small (i.e. a few tens of kilometres or less).

Both Hanna et al (2007) and Irwin and Hanna (2005) recurrently cite the work of Hanna (2002) and Draxler (1984) in their descriptions of turbulent diffusion scheme uncertainty. Hanna (2002) led an informal expert elicitation concerning uncertainties in σ_y and σ_z, whereby six developers of widely used Gaussian dispersion models were asked to estimate the uncertainties. Draxler (1984) report data from field experiments involving the dispersion of tracers, which could subsequently be used to estimate uncertainties in Gaussian plume model variables, such as the lateral and vertical dispersion coefficients, σ_y and σ_z.

Hanna (2002) perform a reanalysis of the observations of σ_y and σ_z from many field experiments (detailed in Draxler (1984)) to determine the range of the scatter of the points in the σ_y and σ_z plots, and revealed a consistent factor of (approximately) ten range of variation in the plotted points. That is, for a given median σ_y and σ_z estimate (as from a best-fit line) at a given downwind distance or travel time and for a given stability, the observed σ_y and σ_z values covered an order of magnitude range.

Hanna (2002) also advocate that the 90% uncertainty range in σ_y and σ_z (i.e. from 5th to 95th percentiles) was approximately a factor of two to three (for hourly averaged observations).

Jones et al (2000) expand upon the study by Harper et al (1995b), by applying σ_y and σ_z uncertainties ascertained in the latter study, to estimate the respective uncertainties on the coefficients $a_{y,z}$ and $b_{y,z}$ (for the atmospheric dispersion modelling approach implemented in COSYMA). Jones et al (2000) estimate a and b for a range of atmospheric stability conditions (including neutral conditions, as well as unstable and stable conditions) and percentiles of the distribution (including 20, 35, 65 and 80, as well as 0, 5, 50, 95 and 100). The parameters a_y, b_y, x (the distance downwind from the release location to the receptor location) and σ_y are related as described in equation 1. Thus, the 100% uncertainty range on σ_y (Harper et al, 1995a) approximately equates to the application of the 20th to 80th percentiles on both a_y and b_y (Jones et al, 2000) and the 90% uncertainty range on σ_y approximately equates to the application of the 35th to 65th percentiles on both a_y and b_y. For the 100% uncertainty range in σ_z, application of the 30th to 70th percentiles or 35th to 65th percentiles on both a_y and b_y are more likely to be appropriate and for the 90% uncertainty range in σ_z, application of the 40th to 60th percentiles on both a_y and b_y are more likely to be appropriate.

Uncertainty range on the turbulent diffusion scheme by way of varying the stability category

Velenyák (2016), Dabberdt and Miller (2000), Pandya et al (2013), Haywood (2008), Chutia et al (2013) and Dhyani and Sharma (2017) all account for turbulent diffusion scheme uncertainty by considering alternative stability categories (to a greater or lesser degree). Dabberdt and Miller (2000) model H_2SO_4 concentrations by way of a non-steady-state puff-type dispersion model, TRIAD, and account for uncertainty by way of an alternate "second-choice" stability category determined by expert judgement. Pandya et al (2013) model two flammable and two toxic material releases using the Phast model and assuming neutral and stable stability (stability category D and F), and thereafter accounting for uncertainty by considering that for 20 % of the time the stability category may vary up and down in equal proportions i.e. 10 % C, 80 % D, 10 % E and 10 % E, 80 % F, 10 % G, respectively. Haywood (2008) apply stability category D by default and then performed a sensitivity analysis, varying input parameters in turn to a plausible minimum and maximum (applicable to a specific emergency situation), assuming stability category C and E conditions sufficiently scoped the potential uncertainty. Chutia et al (2013) apply a Gaussian puff model in the modelling of ammonia and accounted for uncertainty by way of a broad range of Pasquill stability categories (B, D, E and F). Dhyani and Sharma

(2017) use the CALINE4 air pollution model to describe the dispersion of carbon monoxide and accounted for uncertainty by altering the stability categories from A to D and from D to F (and the range of categories in between) and also varied the mixing height from 25 m to 2500 m (and a range of values in between).

Gaussian puff modelling approach

Uncertainty range on the standard deviation of the downwind (σ_x), cross wind (σ_y) and vertical (σ_z) Gaussian plume profiles

Hanna et al (1982) discuss different methods for determining the dispersion coefficients for application in Gaussian puff models. Zannetti (1990) note that if Gaussian puff models are used to simulate the dispersion from instantaneous or semi-instantaneous sources (whereby the release duration is short compared to the travel time) the dispersion coefficients derived for application in Gaussian plume models should not be (but often are) applied. This would be appropriate only when simulating average characteristics, eg one hour average concentrations, of a continuously emitted plume.

Only a single study considering the uncertainty on dispersion coefficients in respect of a Gaussian puff model was identified. Eleveld et al (2007) consider an "initial" size of the horizontal dispersion coefficient (σ_y) ranging from 10 to 250 m, however the associated atmospheric condition(s) and the distance between the release and the receptor location, representative of "initial", are unclear (though a distance of approximately 100 m can be inferred by way of Jones et al (2000)). Thus, the full range in σ_y observed here was a factor of 25. Eleveld et al (2007) also consider the vertical dispersion coefficient (σ_z) to vary by a factor of two (larger and smaller) i.e. a factor of 4 across the full range. Note that Eleveld et al (2007) sought to determine activity concentrations assuming relatively small averaging timesteps and a relatively small spatial domain (of the order of a few tens of kilometres).

Eulerian and Lagrangian Modelling approaches

A number of Eulerian and Lagrangian particle model studies have been identified which evaluate the uncertainty on ADM input parameters used to describe turbulent diffusion. In all of the studies bar one, the uncertainty on the diffusivity parameterisation, K, is considered. Two studies looked at radiological dispersion, both using Polair3D. The remaining studies applied NAME and focussed on non-radiological scenarios (mostly volcanic ash dispersion). For the purposes of understanding turbulent diffusion scheme uncertainty, non-radiological contaminants are generally deemed to be suitably applicable.

Horizontal diffusivity, K_u

Girard et al (2014) and Girard et al (2016) apply an Eulerian transport model, Polair3D, in two sensitivity analysis studies applying two distinct methods. The release resulting from the Fukushima Daiichi Nuclear Power Plant accident was modelled over the whole of Japan. The turbulent diffusion scheme was described by constant and homogeneous diffusion coefficients in the horizontal plane, ranging from 0 to 1.5 x 10^4 m^2 s^{-1}, and derived on the basis of a literature review. It is recognised that the input uncertainties were broadly applicable but that future work should consider their refinement.

Harvey et al (2018), Webster et al (2015), Devenish et al (2012b) and Devenish et al (2012a) all use the UK Met Office's NAME (Numerical Atmospheric-dispersion Modelling Environment) model to describe the atmospheric dispersion of volcanic ash following the eruption of Eyjafjallajökull in 2010 (over relatively large spatial domains, i.e. distances of hundreds to thousands of kilometres).

Harvey et al (2018) consider the standard deviations of the horizontal velocity fluctuation, σ_u, and the corresponding horizontal Lagrangian timescale, τ_u, to determine the diffusion due to free tropospheric

turbulence (which is specified by a diffusivity, K_u). Harvey et al (2018) assume σ_u ranged from 0.0025 to 2.5 m s^{-1} (with a default value of 0.25 m s^{-1}) and assume τ_u ranged from 100 to 900 s (with a default value of 300 s). Thus, a K_u range of approximately 0 to 5.6 x 10^3 m^2 s^{-1} was inferred.

Webster et al (2015) consider and tabulate velocity fluctuations and timescales, and the corresponding diffusivity, K. Webster et al (2015) consider a range of diffusivities varying, in part, according to the Numerical Weather Prediction (NWP) model considered (and thus varying according to the spatial and temporal resolution of the respective NWP model). The diffusivities were determined from velocity variances and Lagrangian timescales for hourly observations over a number of locations and different years' worth of data. Across the entire dataset a horizontal diffusivity range of 3.1 x 10^2 to 1.7 x 10^4 m^2 s^{-1} was detailed, however narrower ranges applied to specific NWP models. For example, for the UK Met Office's UKV (1.5 km spatial and 1 hour temporal resolution) the diffusivity was observed to vary between 3.1 x 10^2 and 3.9 x 10^3 m^2 s^{-1}, corresponding to the largest range in K and the finest (combined) resolution of any of the Met Office's NWP models; for more coarsely resolved models the range in the observed values of K were reduced. Furthermore, there existed smaller diffusivities which were not observed and hence in terms of uncertainty, akin to Harvey et al (2018), Girard et al (2014) and Girard et al (2016), a lower bound of 0 m^2 s^{-1} seems sensible.

Devenish et al (2012b) scope the sensitivity of the horizontal meander in a much more simplistic manner by "switching it off". In a similar vein Devenish et al (2012a) also switches off the horizontal meander, but in addition, increases it by an order of magnitude.

Harvey et al (2018) and Webster et al (2015) also both consider the unresolved mesoscale velocity, σ_m, and associated timescale, τ_m, describing the low frequency horizontal eddies with scales that lie between the resolved motions of the input meteorological data and the small three-dimensional turbulent motions represented in the turbulence parameterisation scheme. Harvey et al (2018) assume σ_m ranged from 0.27 to 1.74 m s^{-1} (with a default value of 0.8 m s^{-1}) and assume τ_m was fixed at 6120 s. Thus, a K_m range of approximately 450 to 19000 m^2 s^{-1} was inferred. Webster et al (2015) recommend K_m parameter values of 2000 m^2 s^{-1} to 9000 m^2 s^{-1} across the range of UK Met Office's NWP models, from UKV (1.5 km spatial and 1 hour temporal resolution) to Global (60 km spatial and 3 hour temporal resolution), respectively. This assumes that σ_m ranges from 0.55 to 0.95 m s^{-1} and τ_m ranges from 6500 to 10000 s, mindful that these are a range of recommended values and the intention is not to scope the expected range of uncertainty.

Vertical diffusivity, K_w

The majority of the literature detailing horizontal diffusivity uncertainty considerations, also detail vertical diffusivity uncertainties.

In the vertical plane Girard et al (2014) and Girard et al (2016) assume diffusion coefficients computed by Louis (1979) above the boundary layer and within the stable boundary layer, and assumed the method developed by Troen and Mahrt (1986) within the unstable boundary layer, applying an uncertainty factor of +/- 3, encompassing 95% of possible values (as recommended by Hanna et al (2001)).

Harvey et al (2018) consider the standard deviations of the vertical velocity fluctuation, σ_w, and the corresponding vertical Lagrangian timescale, τ_w, to determine the diffusion due to free tropospheric turbulence (which is specified by a diffusivity, K_w). Harvey et al (2018) assume σ_w ranged from 0.001 to 1 m s^{-1} (with a default value of 0.1 m s^{-1}) and assume τ_w ranged from 20 to 300 s (with a default value of 100 s). Thus, a K_w range of approximately 0 to 3.0 x 10^2 m^2 s^{-1} was inferred. Note that the range of

plausible values for each parameter (including K_w) was determined by Harvey et al (2018) from a small expert elicitation exercise combined with a literature review.

In the original scheme (i.e. the default scheme in NAME) considered by Dacre et al (2015) the vertical diffusivity did not vary in time or space above the boundary layer and was assumed to be constant (1 m^2 s^{-1}). However Dacre et al (2015) consider a new space-time varying vertical free-tropospheric diffusion scheme (based on a clear air turbulence index) and for this scheme adopted a vertical diffusivity ranging from (approaching) 0 to 9 m^2 s^{-1}, accounting for the associated uncertainty.

Again, Devenish et al (2012b) and Devenish et al (2012a) scope the sensitivity in a much more simplistic manner, whereby the related uncertainty was accounted for by switching off the vertical turbulence.

On the basis of the Eulerian (Polair 3D) and Lagrangian (DIPCOT, NAME and SNAP) models reviewed, it is apparent that all such models use a meteorological pre-processor to calculate the boundary layer diffusivity, K, from boundary layer parameters supplied by the NWP model. However, the level of difficulty in attributing an uncertainty range on the boundary layer diffusivity, K, varies depending on the model.

Prandtl number

Chettouh et al (2013) model the atmospheric dispersion of NO_2 emissions from a crude oil tank fire and considered the propagation of input parameter uncertainties through the model. Chettouh et al (2013) apply a diffusivity approach but in the form of the (turbulent) Prandtl number, representing the ratio of the momentum diffusivity to the thermal diffusivity. Chettouh et al (2013) assume a Prandtl number range of 0.7 – 1 suitably represented the associated uncertainty (where a Prandtl number of 0.7 implies that the thermal diffusivity > momentum diffusivity).

Chettouh et al (2013) detail formulae for the (turbulent) Prandtl number and the Schmidt number, based on a coefficient of thermal diffusion and a coefficient of mass diffusion, respectively (as the denominator), and the viscosity (as the numerator). It is thought that using these equations, knowledge of the respective coefficients, and the application of a single viscosity value, the thermal diffusivity and the corresponding mass diffusivity can be determined. These diffusivities were then applied in conservation of energy and conservation of mass equations, respectively. The focus of the study was dispersion over spatial scales of the order of one kilometre from the release. Therefore only relatively local diffusivity was considered. Chettouh et al (2013) assume a spatially constant viscosity and therefore a three dimensionally constant diffusivity (i.e. a single value describing diffusivity in the horizontal and vertical planes).

Probability Distribution

When perturbing the input parameter values to represent the respective uncertainties, and then propagating these uncertainties through an atmospheric dispersion model and the subsequent chain of radiological assessments, it is helpful to consider the distribution of the uncertainty as well as the range.

Hanna et al (2007) advise that for straight-line Gaussian plume dispersion models applying σ_y and σ_z the distribution of perturbation is lognormal. Irwin and Hanna (2005) consider random bias and error factors on σ_y and σ_z and they characterised the biases as a log-normal distribution. A log-normal distribution was seen to be a reasonable characterisation for all of the random error distributions (although a normal distribution was seen to be indicated at 10 of the 26 experiment sites). And although the distribution was not explicitly stated by Jones et al (2000), it is evident that the distributions of the coefficients a_y, b_y, a_z and b_z were non-uniform.

Eleveld et al (2007) assume (for a Gaussian puff model) that the initial horizontal dispersion coefficient (local to the release), σ_y, and the vertical dispersion coefficient fraction, Fraction σ_z (the increase in the standard deviation of each puff at each time step), were both uniformly distributed.

Girard et al (2014) and Girard et al (2016) assume that the horizontal diffusion was uniformly distributed between 0 and 1.5×10^4 m^2 s^{-1} and the vertical diffusion was log-normally distributed. When considering the propagation of input parameter uncertainties through an atmospheric dispersion model for a release of NO_2 following a crude oil tank fire, Chettouh et al (2013) assume a continuous uniform distribution.

For all Gaussian approaches considering uncertainty by way of varying the stability category, as considered by Dhyani and Sharma (2017) and Pandya et al (2013), the distribution of the perturbation was not specifically applicable, as discrete values (rather than a distribution) were considered.

Dry Deposition Scheme

Non-radiological studies tend to consider chemicals that have little radiological significance and that have unique dry-depositing properties. Consequently, the findings of such studies have limited applicability. Thus, only radiological studies are considered here.

When considering dry deposition modelling and related uncertainties, it is evident that the method of the dry deposition modelling approach is of more relevance than the type of atmospheric dispersion model. For example Korsakissok et al (2013) consider a Gaussian puff model (pX), Girard et al (2014) and Girard et al (2016) consider an Eulerian transport model (Polair3D) and Haywood et al (2010) consider a Lagrangian particle model (NAME), however all authors considered a dry deposition velocity modelling approach alongside the accompanying uncertainties. In contrast Haywood et al (2010), Saito et al (2015) and Harvey et al (2018) all apply the same type of model (Lagrangian particle model), however they all consider different dry deposition modelling approaches (dry deposition velocity, dry deposition scavenging coefficient and surface resistance approaches, respectively). Therefore the rest of this section is split in to sub-sections by differing dry deposition modelling approaches.

Significantly more sensitivity studies pertaining to dry deposition velocities were identified than studies describing deposition by way of a resistance analogy. This reflects what was unearthed via the literature review and does not necessarily reflect the standing of the approach and its representativeness of the deposition process.

Across all modelling approaches, but most notably for the dry deposition velocity approach, the modelling of particulates (or aerosols) and gaseous and vapour forms of iodine tends to be considered separately, and thus will be differentiated here.

Note that the studies identified in this review do not explicitly consider the dependency of dry deposition on particle size and the associated uncertainties unless otherwise stated (however it is recognised that particle size has a significant impact on dry deposition rate (Webster and Thomson, 2011)).

Dry deposition velocity

The uncertainty relating to the assumed particle size is considered in a parallel report and therefore is not considered explicitly in this report. However, the contribution from the particle size uncertainty should be implicit in the uncertainty attributed to the dry-deposition velocity (i.e. the model-specific term). None of the studies cited below acknowledge that the dry deposition velocity uncertainty ranges detailed include the uncertainty associated with the particle size (distribution), but this is assumed.

A number of studies considered here (Girard et al (2014), Girard et al (2016), Korsakissok et al (2013), Périllat et al (2017) and Saito et al (2015)) focus specifically on the accident at the Fukushima Daiichi Nuclear Power Plant. It is recognised that dry deposition processes can vary as a function of the different environments and surface properties. However it is not evident that the dry deposition modelling in these studies was modified in any way for the Fukushima scenario, and on reflection, it is likely that significant modifications (from the default modelling input parameters) were not necessary and that the associated uncertainties are likely to be similar in range and distribution to a comparable accident were it to occur in Europe.

Périllat et al (2017) consider dry deposition velocities of 2 x 10^{-3} m s^{-1} for particulates, perturbed by a multiplicative factor of 0.5 and 2 (reflecting the lower and upper bounds, respectively) and encompassing 95% of the possible values, i.e. 1 x 10^{-3} to 4 x 10^{-3} m s^{-1}. Périllat et al (2015) perform a sensitivity analysis using the Morris method and considered dry deposition velocities ranging from factors of 1/3 to 3 of the default value, specifically for isotopes of Caesium, but generalised here to apply to all particulates. Korsakissok et al (2013), Haywood (2008) and Haywood et al (2010) all perform relatively simple forms of sensitivity analysis whereby a baseline set of input parameters were developed and then for each parameter in turn its value was varied across a plausible range. Korsakissok et al (2013) consider dry deposition velocities for particulates ranging between 5 x 10^{-4} and 5 x 10^{-3} m s^{-1} (with a default value of 2 x 10^{-3} m s^{-1}). Haywood (2008) and Haywood et al (2010) assume a baseline dry deposition velocity for 1 µm particles of ^{137}Cs of 1 x 10^{-3} m s^{-1}, within a range of an order of magnitude either side (i.e. 1 x 10^{-2} m s^{-1} to 1 x 10^{-4} m s^{-1}), representative of the plausible minimum and maximum values within the context of a baseline accident, and again assumed here to generalise to all particulates. Note that Haywood (2008) and Haywood et al (2010) determine such an uncertainty range on the basis of a literature review and author experience.

Harper et al (1995b) estimate uncertainty ranges on dry deposition velocities using formal expert judgement elicitation techniques. The mean (and the minimum to maximum range in brackets) of the eight individual expert elicitations, as detailed in Harper et al (1995a), have been summarised in Table 6. Note that Harper et al (1995a) derive dry deposition velocities for a range of particle sizes (primarily 0.1, 0.3, 1, 3 and 10 µm), a range of environments and surfaces (primarily urban, meadow and forest) and two different wind speeds (2 and 5 m s^{-1}). The values in Table 6 apply to a 1 µm particle for a meadow environment and 5 m s^{-1} wind speed (noting that there was relatively little variability across the two different wind speeds). Note also that for methyl iodide tabulated results the 95th percentile value was greater than the respective 100th percentile value for the maximum of the experts elicitations; this was because three of the eight experts did not elicit 100th percentile values, and (at least) one of those three experts was relatively conservative in their estimated value for the 95th percentile.

The approach outlined by Harper et al (1995b) was subsequently implemented by Jones et al (2000) in the suite of models, COSYMA, as part of a study to analyse the uncertainty in the predictions of the consequences of accidental releases. The uncertainty ranges on the dry deposition velocities derived by Jones et al (2000) are detailed in Table 7.

	Minimum	5th percentile	50th percentile	95th percentile	Maximum
Particulates	5×10^{-5} (3×10^{-5} – 1×10^{-4})	1×10^{-4} (5×10^{-5} – 3×10^{-4})	2×10^{-3} (3×10^{-4} – 7×10^{-3})	2×10^{-2} (2×10^{-3} – 7×10^{-2})	3×10^{-2} (3×10^{-3} – 1×10^{-1})
Elemental iodine	6×10^{-3} (5×10^{-5} – 4×10^{-2})	6×10^{-3} (8×10^{-5} – 4×10^{-2})	3×10^{-2} (7×10^{-4} – 2×10^{-1})	8×10^{-2} (2×10^{-3} – 3×10^{-1})	1×10^{-1} (3×10^{-3} – 5×10^{-1})
Methyl iodide	8×10^{-5} (0×10^{0} – 3×10^{-4})	3×10^{-4} (5×10^{-7} – 2×10^{-3})	8×10^{-3} (8×10^{-6} – 5×10^{-2})	4×10^{-2} (2×10^{-5} – 3×10^{-1})	9×10^{-3} (3×10^{-5} – 3×10^{-2})

Table 6: The range of uncertainty considered for different percentiles of the dry deposition velocity (m s-1) input parameter (Harper et al, 1995a)

	Minimum	5th percentile	95th percentile	Maximum
Particulates	1×10^{-6}	2×10^{-5}	1×10^{-2}	3×10^{-2}
Elemental iodine	1×10^{-6}	6×10^{-5}	9×10^{-2}	2×10^{-1}
Methyl iodide	1×10^{-8}	6×10^{-7}	5×10^{-2}	2×10^{-1}

Table 7: The range of uncertainty considered for different percentiles of the dry deposition velocity (m s-1) input parameter (Jones et al, 2000)

Girard et al (2014) and Girard et al (2016) consider dry deposition velocities with a range 5×10^{-4} to 5×10^{-3} m s^{-1}, representative of 95% of all of the possible values across the full distribution, applicable to all considered species and all considered chemical and physical forms (i.e. both particulates and gaseous and vapour forms of iodine).

The Atmospheric Dispersion Modelling Liaison Committee (ADMLC) funded a review of deposition velocity (and washout coefficient) (ADMLC, 2001). The review concentrated on particles in the size range of a tenth to a few microns AMAD and iodine in elemental and organic forms. When quantifying dry deposition, two types of value were detailed, a "best judgement" value and a "conservative" value. The conservative value was assumed to approximate the 90th percentile of that distribution and was based purely on expert interpretation (no formal statistical analysis was carried out). Best judgement and conservative deposition velocity values of 6.61×10^{-4} and 3.35×10^{-3} m s^{-1}, respectively, were recommended for 1 µm particles depositing on meadow grass and low crops. For comparative purposes best judgement and conservative deposition velocity values of 2.42×10^{-3} and 8.95×10^{-3} m s^{-1}, respectively, were recommended for 2 µm particles depositing to the same surface types. A best judgement and conservative deposition velocity value of 6×10^{-4} and 3×10^{-3} m s^{-1}, respectively, were recommended for particles in the range 0.1 to 1.0 µm AMAD dry depositing on grass (lawns etc), roofs and paved areas. ADMLC (2001) also recommend a dry deposition velocity distribution to vertical building surfaces (such as walls, windows and roofs) but for reasons of brevity these values are not detailed here.

Périllat et al (2017) consider dry deposition velocities of 7×10^{-3} m s^{-1} for all gaseous or vapour forms of iodine, perturbed by a multiplicative factor of 0.5 and 2 (reflecting the lower and upper bounds, respectively) and encompassing 95% of the possible values, i.e. 3.5×10^{-3} to 1.4×10^{-2} m s^{-1}. Périllat et al (2015) consider dry deposition velocities ranging from factors of 1/4 to 4 of the default value for isotopes of iodine (however it is not clear if this applies to particulate, gaseous and/or vapour forms). Korsakissok et al (2013) consider dry deposition velocities for particulates ranging between 1×10^{-3} m s^{-1} to 2×10^{-2} m s^{-1} (with a default value of 7×10^{-3} m s^{-1}). Haywood (2008) and Haywood et al (2010) assume a baseline dry deposition velocity for ^{131}I (in elemental vapour form) of 1×10^{-2} m s^{-1}, within

the range 1 x 10^{-1} m s^{-1} to 1 x 10^{-3} m s^{-1}, again representative of the plausible minimum and maximum values within the context of a baseline accident. ADMLC (2001) recommend a best judgement and conservative deposition velocity value of 6.7 x 10^{-3} and 1.0 x 10^{-2} m s^{-1}, respectively, for elemental iodine vapour depositing on meadow grass and low crops. For methyl iodide depositing on to the same surface, a best judgement and conservative deposition velocity value of 1 x 10^{-5} and 1 x 10^{-4} m s^{-1}, respectively, was recommended. ADMLC (2001) advocate a best judgement and conservative dry deposition velocity value of 2.6 x 10^{-3} and 1.0 x 10^{-2} m s^{-1}, respectively, for elemental iodine vapour dry depositing on grass (lawns etc), and advocated further ranges for other urban surfaces (roofs, paved areas, walls, windows and doors; where the conservative value was set arbitrarily).

Dry deposition scavenging coefficient

Saito et al (2015) employ dry deposition scavenging coefficients; defined as the ratio of the dry deposition velocity (the numerator) and the depth of surface (depositing) layer (the denominator). Saito et al (2015) assume dry deposition scavenging coefficients as a function of particle size distribution (assumed to be log-normal with a mean diameter of 1 µm, a standard deviation of 1.0 and an upper bound of 20 µm). Saito et al (2015) compare modelled (from the JMA regional transport model) with observed deposition for the Fukushima Daiichi Nuclear Power Plant accident. The dry deposition velocity was set to 1 x 10^{-3} m s^{-1} for particulates and 1 x 10^{-2} m s^{-1} for depositing gas and the depth of the surface layer was set to 100 m for both tracer types. To scope the uncertainty the scheme was switched off and surface layer depths of <100 and <40 metres above ground level (magl) were considered.

Surface resistance

The dry deposition velocity (v_d) can be determined by the surface resistance analogy,

$$v_d = \frac{1}{R_a + R_b + R_c} \qquad (2)$$

where R_a is the aerodynamic resistance, R_b is the laminar sublayer resistance and R_c is the surface resistance.

Eleveld et al (2007) consider using a resistance analogy to describe the dry deposition of ^{131}I. Eleveld et al (2007) quote a surface resistance of 120 s m^{-1} with a perturbation of 60 – 200 s m^{-1}. Assuming that the surface resistance is much greater than the sum of the aerodynamic and laminar sub-layer resistance, then this equates to a dry deposition velocity of 8 x 10^{-3} m s^{-1} with a perturbation of 5 x 10^{-3} – 2 x 10^{-2} m s^{-1}.

ADMLC (2001) consider the uncertainty on the laminar sublayer resistance (R_b) for dry depositing particles and considered the uncertainty on the surface resistance (R_c) for different chemical forms of iodine dry depositing, across a range of surface types. In the vicinity of grass meadows, crops and forests, and in the particle size range 0.1 to 1.0 µm, ADMLC (2001) recommend a best estimate and conservative estimate of R_b of 300 and 50 s m^{-1}, respectively (assuming constant values for R_a, 10 s m^{-1}, and u*, 0.2 m s^{-1}). In an urban environment, considering 0.1 to 1.0 µm particles dry depositing on to grass (lawns etc), roofs and paved areas, a best estimate and conservative estimate of R_b equal to 1500 and 250 s m^{-1}, respectively, were recommended (where in both cases R_a = 100 s m^{-1}). Vertical building surfaces such as walls, windows and roofs were thought to be characterised by much lower deposition velocities for submicron particles; in this instance best and conservative estimates of 2 x 10^4 and 2 x 10^3 s m^{-1}, respectively, were recommended for R_b. For isotopes of iodine in elemental vapour form a best estimate of R_s = 50 s m^{-1} and conservative estimate of R_s = 0 s m^{-1} were recommended for dry

deposition on to meadow grass and crops (where R_a = 12 s m^{-1} and R_b = 8 s m^{-1}). A surface resistance range of 25 to 250 s m^{-1} was also quoted in ADMLC (2001); it is thought that this reflects the full range (from 0th to 100th percentile), but this is not clear. For grassed areas in an urban environment ADMLC (2001) deem that there is no strong reason for the surface resistance to differ from that for extended grass and crop canopies. Note that ADMLC (2001) consider that a "conservative" value approximates the 90th percentile of the distribution, however no formal statistical analysis was carried out to obtain the values quoted.

Probability Distribution

Girard et al (2014), Girard et al (2016) and Périllat et al (2017) all consider the distribution of the dry deposition to be log-normal. Korsakissok et al (2013) assume that the distribution of perturbation should conform to the Gaussian law (but it is unclear whether a normal or log-normal distribution was more appropriate here). Eleveld et al (2007) assume a triangular probability distribution. And Alcamo and Bartnicki (1987) consider four different distribution shapes in their assessment, including uniform, triangular, truncated normal and irregular.

Wet Deposition Scheme

The literature review revealed only one prevalent method for describing wet deposition, the scavenging coefficient approach. Irrespective of the model type considered, the scavenging coefficient approach was routinely applied. For example Périllat et al (2017) consider a Gaussian puff model (pX), Quérel et al (2015) consider an Eulerian transport model (ldX), and Leadbetter et al (2015) and Marzo (2014) both consider Lagrangian particle models (NAME and FLEXPART, respectively), however all authors applied a scavenging coefficient approach.

The parameterisation of the scavenging coefficient, Λ (in units s^{-1}), is typically of the form,

$$\Lambda = aI^b \qquad (3)$$

where *I* is the rain intensity in mm h^{-1}, *a* is the scavenging coefficient parameter in units of s^{-1} mm^{-1} h and *b* is the scavenging exponent parameter (unitless). It should be assumed that this approach was applied in the studies described unless otherwise stated.

All of the studies identified recognise both below-cloud and in-cloud scavenging coefficients and many of the studies identified consider different coefficients and different associated uncertainties for these two scavenging processes. The main body of this section of the report comprises of a thorough analysis of the ranges of uncertainty of below-cloud and in-cloud scavenging coefficients as detailed in the literature. However the uncertainty associated with the conditions that activate the application of the scavenging approach are also considered.

No sensitivity studies considering wet deposition as a function of particle size were identified (however it is recognised that particle size has a significant impact on wet deposition rate (Baklanov and Sørensen, 2001)). This reflects what was unearthed via the literature review and does not necessarily reflect the standing of the approach and its representativeness of the deposition process.

Haywood (2008) and Haywood et al (2010) do not consider a scavenging coefficient approach for modelling wet deposition, but instead consider that wet deposition is represented empirically as enhancement factors to dry deposition, representing light and heavy rainfall. More significantly, rather than focusing on the uncertainty in the modelling of wet deposition, Haywood (2008) and Haywood et al (2010) consider that there is uncertainty relating to whether it will rain, as well as the rainfall rate, and represents this uncertainty by way of three discrete deposition velocities. This relates to the

meteorological uncertainty and not the model-specific uncertainty and is therefore not considered further in this report.

Below-cloud and in-cloud scavenging coefficients

Girard et al (2014) and Girard et al (2016) assume that the uncertainty on the below-cloud and in-cloud scavenging coefficient parameter, *a*, ranged from 1 x 10^{-7} to 1 x 10^{-4} s^{-1} mm^{-1} h and the uncertainty on the below-cloud and in-cloud scavenging exponent parameter, *b*, ranged between 0.6 and 1.

Périllat et al (2017) and Korsakissok et al (2013) assume that *b* (the exponent) was constant (1) with no associated uncertainty range but the scavenging coefficient parameter, *a*, was uncertain and defined a range (about a default of 5×10^{-5} s^{-1} mm^{-1} h). Périllat et al (2017) assume that the scavenging coefficient parameter was perturbed between 1.7 x 10^{-5} and 1.5 x 10^{-4} s^{-1} mm^{-1} h (i.e. a factor of 3 increase and decrease with respect to the default value). This encompassed 95% of the possible values. Korsakissok et al (2013) assume that the scavenging coefficient parameter was perturbed between 1 x 10^{-5} and 1 x 10^{-4} s^{-1} mm^{-1} h.

Leadbetter et al (2015) qualitatively compare modelled and measured ^{137}Cs deposition concentrations following the Fukushima Daiichi Nuclear Power Plant accident, where model runs considered different wet scavenging parameters. The scheme in the NAME model recognises that wet deposition may vary for different types of precipitation (notably large-scale or dynamic and convective, and rain and snow), however no differentiation was made between large-scale and convective precipitation by Leadbetter et al (2015). Furthermore, the scheme recognises that wet deposition may vary for different types of wet deposition processes (notably rainout, washout and the seeder-feeder process). However, orographic rainfall was not considered by Leadbetter et al (2015). Leadbetter et al (2015) consider uncertainty ranges on scavenging coefficient and exponent parameters as detailed in Table 8. The in-cloud parameter values and allied uncertainties detailed in Table 8 apply to both snow and rain but below-cloud values and uncertainties only apply to rain. The ranges were derived from Sportisse (2007). Leadbetter et al (2015) conclude that deposition concentration predictions (using NAME) were slightly improved when the deposition due to in-cloud precipitation was increased. However, this could be principally due to uncertainty in the precipitation, or the scavenging coefficient parameter, *a*, or the scavenging exponent parameter, *b*, or some combination of the three.

		Minimum	Minimum	Default	Maximum
Scavenging coefficient parameter, *a*	In-cloud		3.36 x 10^{-3}	3.36 x 10^{-4}	3.36 x 10^{-5}
	Below- cloud		8.40 x 10^{-4}	8.40 x 10^{-5}	8.40 x 10^{-6}
Scavenging exponent parameter, *b*	In-cloud		0.59	0.79	0.99
	Below- cloud		0.59	0.79	0.99

Table 8: The full range of uncertainty considered for different scavenging coefficient (s-1 mm-1 h) and exponent parameters describing wet deposition (Leadbetter et al, 2015)

Marzo (2014) model the global transport of radionuclides emitted during the Fukushima Daiichi Nuclear Power Plant accident and performed a model versus measurement intercomparison, followed by a limited sensitivity study. Marzo (2014) assume a below-cloud scavenging coefficient parameter, *a*, of 1 x 10^{-4} s^{-1} mm^{-1} h and a below-cloud scavenging exponent parameter, *b*, of 0.8. The scavenging coefficient parameter, *a*, was decreased to 1 x 10^{-5} s^{-1} mm^{-1} h to scope uncertainty.

Saito et al (2015) assume a below-cloud scavenging coefficient parameter, *a*, of 2.98 x 10^{-5} s^{-1} mm^{-1} h and a below-cloud scavenging exponent parameter, *b*, of 0.75 but modified these values to 8.4 x 10^{-5} s^{-1} mm^{-1} h and 0.79, respectively, to account for uncertainty. A further model run was undertaken

setting the below-cloud scavenging coefficient and exponent parameters for snow to 2.98 x 10^{-5} s^{-1} mm^{-1} h and 0.3, respectively. In addition, one run was carried out with no below-cloud scavenging.

Both Marzo (2014) and Saito et al (2015) consider a distinct in-cloud scheme of to the typical form detailed in equation 3. However neither study postulated the associated uncertainties.

		Minimum	5th percentile	95th percentile	Maximum
Particulates	a	2.00 x 10^{-3}	5.10 x 10^{-3}	4.81 x 10^{0}	5.31 x 10^{0}
	b	1.94 x 10^{-2}	2.13 x 10^{-1}	2.20 x 10^{0}	2.89 x 10^{0}
Elemental iodine	a	2.33 x 10^{-4}	6.97 x 10^{-3}	2.13 x 10^{0}	2.42 x 10^{0}
	b	2.53 x 10^{-2}	2.27 x 10^{-1}	1.90 x 10^{0}	2.96 x 10^{0}
Methyl iodide	a	1.00 x 10^{-4}	5.00 x 10^{-4}	5.87 x 10^{-1}	6.72 x 10^{-1}
	b	2.63 x 10^{-2}	1.58 x 10^{-1}	2.35 x 10^{0}	3.27 x 10^{0}

Table 9: The range of uncertainty considered for different percentiles on the scavenging coefficient, a (s-1 mm-1 h), and scavenging exponent, b, input parameters (Jones et al, 2000)

Harper et al (1995a) consider the range of uncertainty on the fraction of the contaminant (elemental iodine, methyl iodide and particulates for a range of particle sizes) removed by rain (for a range of rainfall rates), by way of different percentiles (specifically 0, 5, 50, 95 and 100).

The approach outlined by Harper et al (1995b) (using formal expert judgement elicitation techniques) was subsequently implemented by Jones et al (2000) in the suite of models, COSYMA. The uncertainty ranges on the scavenging coefficient parameter values derived by Jones et al (2000) are detailed in Table 9.

Harvey et al (2018) consider default values and corresponding uncertainty ranges on the in-cloud and below-cloud scavenging coefficient parameter, a, and scavenging exponent parameter, b, for both rain and snow, as detailed in Table 10, noting that Harvey et al (2018) model a release of ash following a volcanic eruption, rather than a radiological release.

	Rain		Snow	
	a	b	a	b
In-cloud default	3.36 x 10^{-4}	0.79	5.2 x 10^{-5}	0.79
In-cloud range	1.0 x 10^{-6} to 1 x 10^{-2}	0.4 to 1.1	1.0 x 10^{-6} to 1 x 10^{-1}	0.2 to 1.2
Below-cloud	8.4 x 10^{-5}	0.79	8.0 x 10^{-5}	0.305
Below-cloud range	1.0 x 10^{-6} to 1 x 10^{-2}	0.4 to 1.1	1.0 x 10^{-6} to 1 x 10^{-1}	0.2 to 1.2

Table 10: The range of uncertainty considered on the scavenging coefficient parameter, a (s 1 mm 1 h), and scavenging exponent parameter, b, for both in-cloud and below-cloud modelling of rain and snow (Harvey et al, 2018)

Like Harper et al (1995b) and Harper et al (1995a), Eleveld et al (2007) account for uncertainty on the wet deposition modelling process by way of an uncertainty range on the scavenging coefficient, Λ, rather than the scavenging coefficient parameter, *a*, and scavenging exponent parameter, *b*. Eleveld et al (2007) assume a default scavenging coefficient, Λ, of 5.8 x 10^{-5} s^{-1} with an additional perturbation of 1 x 10^{-5} – 1 x 10^{-4} s^{-1} (for ^{131}I).

ADMLC (2001) recommend a best estimate and conservative estimate of the below-cloud scavenging coefficient of 4 x 10^{-5} and 4 x 10^{-4} s^{-1}, respectively, on the basis of a rainfall intensity of 1 mm h^{-1} and submicron particles (0.1 – 1.0 µm). A corresponding range for the in-cloud scavenging coefficient of 3 x 10^{-5} to 3 x 10^{-4} s^{-1} was recommended. For below-cloud wet deposition of elemental iodine vapour ADMLC (2001) advise on the application of a best estimate deposition velocity of 2.8 x 10^{-3} m s^{-1}, and a respective conservative value of 2.8 x 10^{-2} m s^{-1} (assuming a rainfall rate of 1 mm h^{-1}); such values can be converted to a scavenging coefficient by dividing by the height of the deposition layer of the

atmosphere (a depth of 100 m was recommended). Note that ADMLC (2001) consider that a "conservative" value approximates the 90th percentile of the distribution, however no formal statistical analysis was carried out to obtain the values quoted.

Webster and Thomson (2014) provide a technical description of the former and updated wet deposition schemes in NAME. In this update the below-cloud scavenging coefficient and exponent parameters remained the same, but the in-cloud scavenging coefficient parameter, *a*, was revised (by up to a factor of 6) for rain and snow and the in-cloud scavenging exponent parameter, *b*, was revised (by a factor of 2.6) for snow. This can be viewed as indicative of the order of magnitude of the uncertainties on such parameters.

Conditions on the application of the scavenging coefficient approach

The literature review revealed a number of conditions that trigger and constrain the implementation of the scavenging coefficient approach across a number of different models. These conditions include cloud (notably the presence of cloud and cloud height), precipitation (notably rate) and temperature diagnostics. These are all meteorological inputs to the model, however as well as the associated meteorological uncertainties there are also uncertainties in the model-specific assumptions made.

For example Girard et al (2014) and Girard et al (2016) apply the Eulerian transport model, Polair3D. Implicit in the model is the assumption that the in-cloud scavenging coefficient is applied from the lowest cloud base height within the cloud thickness and the below-cloud scavenging coefficient is applied from the ground to the lowest cloud base height.

Saito et al (2015) apply Japan Meteorological Agency's regional transport model, which, for the below-cloud scavenging scheme (for particulates only), assumes that the deposition rate only applies to particles below 3000 metres above sea level (masl), but Saito et al (2015) modify this value to 1500 masl to account for uncertainty.

Embedded within the UK Met Office's NAME model is the caveat that the wet deposition scheme is only used if the precipitation is greater than a threshold value. The default threshold value is 0.03 mm h^{-1}. However Harvey et al (2018) consider the precipitation threshold to vary from 0 to 0.1 mm h^{-1} in an effort to scope the uncertainty.

Furthermore, Webster and Thomson (2014) provide a technical description of the former and updated wet deposition schemes in NAME. A significant modification to the scheme was the introduction of a mixed temperature phase ($238.15 \leq T \leq 273.15$ K), where the scavenging coefficient parameter, *a*, and scavenging exponent parameter, *b*, were linearly interpolated between the rain and snow/ice values (in contrast to the former model which assumed a step change for a temperature of 270 Kelvin). There is clearly some uncertainty associated with this assumption also.

Multiple methods for describing wet deposition

Quérel et al (2015) assess the performance of a range of wet deposition schemes, by comparing modelled and measured ^{137}Cs deposition concentrations for the Fukushima Daiichi Nuclear Power Plant accident scenario. Quérel et al (2015) consider below-cloud and in-cloud scavenging schemes of varying complexity, some adhering to the characteristic form described by equation 3, others comprising of differing input parameters. Quérel et al (2015) consider below-cloud scavenging schemes proposed by Laakso et al (2003), Andronache (2004) and the current IRSN wet deposition scheme, all approaches which vary only with precipitation intensity. Quérel et al (2015) also consider below-cloud scavenging schemes proposed by Slinn (1977) and Quérel et al (2014) which determine the collection efficiency by way of taking into account particle and raindrop size distributions,

combined with (three) different representations of raindrop spectra. Quérel et al (2015) also applied a number of in-cloud scavenging schemes, some with sole dependence on precipitation intensity (Jylhä (1991), Scott (1982) and Ellenton et al (1985)), but also two schemes (Roselle and Binkowski (1999) and Pudykiewicz (1988)) with other physical parameter dependencies . The scheme proposed by Roselle and Binkowski (1999) was a function of cloud liquid water content and estimated cloud lifetime, as well as precipitation intensity. The scheme proposed by Pudykiewicz (1988) was entirely independent of precipitation and was a function of relative humidity instead. Null scavenging coefficients were also tested separately for both in-cloud and below-cloud scavenging schemes. Thus, Quérel et al (2015) did not consider the uncertainty within an individual scheme but identified a broad range of schemes for scoping model uncertainty akin to a model ensemble approach.

A model ensemble approach such as the one applied by Quérel et al (2015) could be extended to account for a broader range of characteristic scavenging coefficient schemes, for example those highlighted in the previous section and additional schemes such as the in-cloud schemes considered by Marzo (2014) and Saito et al (2015), and the scheme described by Baklanov and Sørensen (2001).

Probability Distribution

Périllat et al (2017) consider the distribution of the scavenging coefficient parameter, α, to be log-normal. Korsakissok et al (2013) assume that the distribution of the perturbation on the scavenging coefficient parameter, α, should conform to the Gaussian law (but it is unclear whether a normal or log-normal distribution is more appropriate here). Eleveld et al (2007) assume a triangular probability distribution on the scavenging coefficient, Λ. And Alcamo and Bartnicki (1987) consider four different distribution shapes in their assessment, including uniform, triangular, truncated normal and irregular.

Roughness length

Roughness length is equivalent to the height at which the wind speed theoretically becomes zero (in a log wind profile) and is a parameter often used in ADMs to determine horizontal (mean) wind speeds within the vertical wind profile.

A number of sensitivity analysis studies considered the uncertainty range of the roughness length, but often the range reflected the full range across all possible scenarios. For example Dhyani and Sharma (2017) perform a sensitivity analysis of the modelling of traffic pollutants in an urban environment by the CALINE4 model, varying the roughness length from 0.03 (representing open terrain) to 4 m (representing a central business district). Eleveld et al (2007) consider roughness lengths of 0.001 m (representing the sea) to 3 m (representing the centre of big city or high trees).

The uncertainty ranges of the roughness length documented by Hanna et al (2004), Twenhöfel et al (2007), Pagnon et al (2011) and Pandya et al (2013) appear to be more reflective of a range of surface types for a single scenario (and thus more appropriate for application in this study). Hanna et al (2004) derive uncertainty ranges on the basis of data analysis and expert elicitation approaches for a benzene and 1.3-butadiene modelling study around the Houston Ship Channel. AERMOD was one of two (Gaussian plume) models considered by Hanna et al (2004) and an uncertainty range of a factor of +/- 3 was applied. Twenhöfel et al (2007) investigate the uncertainty analysis in the early phase of nuclear emergency management, focusing on cases defined by the Kincaid dataset, notably the PWR5 accident scenario, which was used as the reference case. Based on this reference scenario, Twenhöfel et al (2007) consider a roughness length range of 0.03 – 0.3 m. Furthermore, Pagnon et al (2011), performing a sensitivity analysis of dispersion modelling of hazardous chemicals in an emergency situation, consider a roughness height range of 0.1 – 1.0 m. Pandya et al (2013) studied the uncertainty

analysis for releases of toxic and flammable materials from industrial sites (using the Phast ADM), and in contrast to other studies, consider a relatively short roughness length range of 0.5 – 1.5 m.

Pandya et al (2008), modelling the atmospheric dispersion of toxic gases, consider roughness lengths in the range 0.0001 to 3 m, however it appears that the study considered up to six "binned" roughness lengths, with uncertainty considered individually for each bin.

A range of distributions on the roughness length were considered across the different studies identified here. Hanna et al (2004) assume a log-normal distribution, Pandya et al (2013) and Eleveld et al (2007) assume a triangular distribution and Twenhöfel et al (2007) and Pandya et al (2008) assume uniform distributions.

Recommendations

Turbulent Diffusion Scheme

- **Consider the application of a model ensemble of approaches for describing the uncertainty associated with the standard deviation of the cross wind (σ_y) and vertical (σ_z) Gaussian (puff and plume) profile.** The application of a model ensemble considering an array of approaches for describing the standard deviation of the cross wind (σ_y) and vertical (σ_z) Gaussian profile has been demonstrated by Périllat et al (2017). Its success relies heavily on the sample size of the different approaches, which in turn can make this method of describing the uncertainty on the turbulent diffusion scheme relatively effort expensive, however it seems that there is value in trialling such an approach.
- **An uncertainty range of a factor of 10 and 3, applicable to the 0th to 100th percentile range and 5th to 95th percentile range, respectively, are recommended for the standard deviation of the cross wind (σ_y) and vertical (σ_z) Gaussian plume profiles.** The weight of evidence identified in the literature review supports the definition of uncertainty on σ_y and σ_z rather than on the coefficients *a* and *b* (typically used to determine σ_y and σ_z). In mind of the propagation of input parameter uncertainties through the atmospheric dispersion and radiological assessment chain of models for historical and hypothetical accident based scenarios, the most robust and applicable study findings, suitably constrained by scenario-specific conditions but not limited to a narrow range of scenarios, were those outlined by Hanna et al (2007) and Irwin and Hanna (2005). It was recognised that the expert elicitation considered by Harper et al (1995b) was not well steered, however for turbulent diffusion there exists good agreement between the uncertainty ranges derived by Hanna et al (2007), Irwin and Hanna (2005) and Harper et al (1995b). It is noteworthy that these studies specifically apply to relatively small spatial domains (i.e. of the order of a few tens of kilometres); it is not clear whether such recommended ranges are applicable to long range dispersion studies. Thus uncertainty ranges of a factor of 10 and 3, applicable to the 0th to 100th percentile range and 5th to 95th percentile range, respectively, are recommended for the standard deviation of the cross wind (σ_y) and vertical (σ_z) Gaussian plume profiles. However it is recognised that the ranges recommended here for the 0th to 100th percentile and 5th to 95th percentile may not fit "neatly" if both applied to the recommended probability distribution, and therefore one or the other should be universally applied by all participants contributing to a single study.
- **Where no alternative recommended approach can be implemented, describing the uncertainty range on the turbulent diffusion scheme by way of an alternate "second-choice" stability category, determined by expert judgement, is recommended (for Gaussian puff or**

plume modelling approaches). Consideration of the uncertainty range on the turbulent diffusion scheme by way of varying the stability category was observed in numerous studies, but no single approach was observed across multiple studies. The approach described by Dabberdt and Miller (2000), accounting for the uncertainty by way of an alternate "second-choice" stability category, determined by expert judgement, is deemed to be suitably representative and practical (in part due to its simplicity to implement).

- **An uncertainty range of 0 to 1 x 10^4 m^2 s^{-1}, applicable to the 0th to 100th percentile range, is recommended for the horizontal diffusivity term, K_u.** The weight of evidence identified in the literature err towards the definition of uncertainty on K_u rather than on the standard deviations of the horizontal velocity fluctuation, σ_u, and the corresponding horizontal Lagrangian timescale, τ_u, typically used to determine the diffusivity. However, the uncertainty associated with σ_u and τ_u could be determined on the basis of the studies cited in this report. There exists remarkably good agreement between Webster et al (2015), Harvey et al (2018), Girard et al (2014) and Girard et al (2016) in respect of the estimated range of uncertainty on the horizontal diffusivity term, K_u. It is noteworthy that these studies specifically consider relatively large spatial domains (i.e. of the order of hundreds or thousands of kilometres). A maximum uncertainty range of 0 to 1 x 10^4 m^2 s^{-1} is considered suitable. However Webster et al (2015) illustrate that this uncertainty range can be refined according to the Numerical Weather Prediction (NWP) model being considered.
- **An uncertainty range of a factor of 6, applicable to the 2.5^{th} to 97.5^{th} percentile range, is cautiously recommended for the boundary layer vertical diffusivity term, K_w.** Only Girard et al (2014) and Girard et al (2016) quote boundary layer uncertainties, as recommended by Hanna et al (2001). On this basis an uncertainty range of a factor of 6, applicable to the 2.5^{th} to 97.5^{th} percentile range, is cautiously recommended for the boundary layer vertical diffusivity term, K_w.
- **An uncertainty range of 0 to 3 x 10^2 m^2 s^{-1}, applicable to the 0th to 100th percentile range, is cautiously recommended for the free tropospheric vertical diffusivity term, K_w.** The vertical diffusion and associated uncertainty considered by Harvey et al (2018) was representative of that observed in the free troposphere, above the boundary layer. Harvey et al (2018) utilised a small expert elicitation exercise combined with a literature review in the derivation of an uncertainty range on K_w. This approach was deemed to be robust. Therefore, an uncertainty range of 0 to 3 x 10^2 m^2 s^{-1}, applicable to the 0th to 100th percentile range, is cautiously recommended for the free tropospheric vertical diffusivity term, K_w.
- Considering the weight of evidence and in accordance with the most robust and applicable studies reviewed, **it is recommended that the probability distribution attributed to the standard deviation of the cross wind (σ_y) and vertical (σ_z) Gaussian plume profile is log-normal, the probability distribution attributed to the horizontal diffusivity (K_u) is uniform and the probability distribution attributed to the vertical diffusivity (K_w) is log-normal.**

Dry Deposition Scheme

- **An uncertainty range of a factor of 100 and 10, applicable to the 0th to 100th percentile range and 2.5^{th} to 97.5^{th} percentile range, respectively, are recommended for the dry deposition velocity (for all radionuclides and chemical forms).** The uncertainty ranges derived by Jones et al (2000) have been disregarded, because it was recognised that the expert elicitation considered by Harper et al (1995b) was not well steered, and therefore very broad ranges were

derived (specifically in respect of the lower bound). In mind of the propagation of input parameter uncertainties through the atmospheric dispersion and radiological assessment chain of models for historical and hypothetical accident based scenarios, the most robust and applicable study findings, suitably constrained by scenario-specific conditions but not limited to a narrow range of scenarios, are those outlined by Girard et al (2014), Girard et al (2016), Korsakissok et al (2013), Haywood (2008) and Haywood et al (2010). ADMLC (2001) is supportive of these studies for iodine in gaseous or vapour forms but less so for particulates, where a tendency to consider a broad particle size range is likely to have led to relatively large estimates in the uncertainty range. Thus uncertainty ranges of a factor of 100 and 10, applicable to the 0th to 100th percentile range and 2.5^{th} to 97.5^{th} percentile range, respectively, are recommended for the dry deposition velocity (for all radionuclides and chemical forms). However it is recognised that the ranges recommended here for the 0th to 100th percentile and 2.5^{th} to 97.5^{th} percentile may not fit "neatly" if both applied to the recommended probability distribution, and therefore one or the other should be universally applied by all participants contributing to a single study.

- **Unless the conditions of the scenario suggest otherwise, an uncertainty range of 1×10^{-4} to 1×10^{-2} m s^{-1}, applicable to the 0th to 100th percentile range, and an uncertainty range of 5×10^{-4} to 5×10^{-3} m s^{-1}, applicable to the 2.5^{th} to 97.5^{th} percentile range are recommended for the dry deposition of particulates approximating 1 µm AMAD in size.**
- **Unless the conditions of the scenario suggest otherwise, an uncertainty range of 1×10^{-3} to 1×10^{-1} m s^{-1}, applicable to the 0th to 100th percentile range, and an uncertainty range of 2×10^{-3} to 2×10^{-2} m s^{-1}, applicable to the 2.5^{th} to 97.5^{th} percentile range are recommended for the dry deposition of elemental iodine vapour.**
- **An uncertainty range of 50 – 200 s m^{-1}, applicable to the 0th to 100th percentile range, is recommended for the surface resistance, R_c, for elemental iodine vapour.** There exists very good agreement between the proposed uncertainty ranges suggested by Eleveld et al (2007) and ADMLC (2001), hence an uncertainty range of 50 – 200 s m^{-1}, applicable to the 0th to 100th percentile range, is recommended for the surface resistance, R_c, for elemental iodine vapour. ADMLC (2001) also applied the surface resistance analogy to modelling dry deposition of particulates. ADMLC (2001) consider a broad particle size range, which is likely to have led to relatively large estimates in the uncertainty range of the laminar sub-layer resistance, R_b. There is exists doubt whether such uncertainty ranges of R_b are representative of individual scenarios and these ranges have not been substantiated by other literature. Therefore, an uncertainty range of R_b for particulates is not recommended here.
- Considering the weight of evidence and in accordance with the most robust and applicable studies reviewed, **it is recommended that the probability distribution attributed to the dry deposition velocity is log-normal.**

Wet Deposition Scheme

- **An uncertainty range of a factor of 10, applicable to the scavenging coefficient parameter, *a*, and an uncertainty range of 0.5, applicable to the scavenging exponent parameter, *b*, where both are applicable to the 2.5^{th} to 97.5^{th} percentile range, are recommended.** The weight of evidence identified in the literature review supports the definition of uncertainty on the scavenging coefficient parameter, *a*, and scavenging exponent parameter, *b*, rather than on the scavenging coefficient, Λ. The uncertainty ranges derived by Harper et al (1995b) and Jones

et al (2000) have been disregarded, because it was recognised that the expert elicitation considered by Harper et al (1995b) was not well steered, and therefore very broad ranges were derived (specifically in respect of the lower bound). It was not clear why the uncertainty ranges assumed by Harvey et al (2018) were relatively large, however this study focused on the modelling of ash, which is likely to be characterised by an extensive particle size distribution and therefore has the potential for a very broad range of scavenging coefficients. In respect of the uncertainty on the scavenging coefficient parameter, *a*, there existed reasonable agreement between Périllat et al (2017), Korsakissok et al (2013) and Saito et al (2015). In respect of the uncertainty on the scavenging exponent parameter, *b*, there existed reasonable conformity between Girard et al (2014), Girard et al (2016), Leadbetter et al (2015) and Saito et al (2015). It is not acceptable to simply consider the full uncertainty range on the scavenging coefficient parameter, *a*, and scavenging exponent parameter, *b*, identified across all studies. Nor is it acceptable to consider the uncertainty ranges on the scavenging coefficient parameter, *a*, and scavenging exponent parameter, *b*, where there exists the most agreement across all studies. This is because different studies may be weighting the uncertainty on the wet deposition scheme preferentially towards one parameter or the other. Therefore, there is a strong possibility of significantly over or under representing the overall degree of uncertainty on the wet deposition scheme. Attempts to address this issue have been subjective in manner. Thus an uncertainty range of a factor of 10, applicable to the scavenging coefficient parameter, *a*, and an uncertainty range of 0.5, applicable to the scavenging exponent parameter, *b*, where both are applicable to the 2.5th to 97.5th percentile range, are recommended. For a single accident scenario (such as Chernobyl or Fukushima) Baklanov and Sørensen (2001) indicate that the uncertainty ranges recommended here are not an underestimate. It is recognised that there exist uncertainties relating to the model-specific assumptions made in respect of the conditions on the application of the scavenging coefficient approach. However, the magnitude of such uncertainties is unclear, and it is likely that such uncertainties are not dominant relative to the magnitude of the uncertainties on the scavenging coefficient itself (emanating from the uncertainties on the scavenging coefficient parameter, scavenging exponent parameter and precipitation rate).

- Considering the weight of evidence and in accordance with the most robust and applicable studies reviewed, **it is recommended that the probability distribution attributed to the scavenging coefficient parameter, *a*, is log-normal.** No evidence has been identified upon which to base a recommendation for the probability distribution attributed to the scavenging exponent parameter, *b.*

- **Consider the application of a model ensemble of approaches for describing the uncertainty associated with the wet deposition scheme.** The application of a model ensemble considering an array of approaches for describing the below-cloud and in-cloud scavenging schemes has been demonstrated by Quérel et al (2015). Its success relies heavily on the sample size of the different approaches, which in turn can make this method of describing the uncertainty on the wet deposition scheme relatively effort expensive, however it seems that there is value in trialling such an approach.

Roughness length

- **Unless the conditions of the scenario suggest otherwise, an uncertainty range of a factor of 10, applicable to the 0th to 100th percentile range, is recommended for the roughness length.** The uncertainty ranges of the roughness length documented by Hanna et al (2004), Twenhöfel

et al (2007) and Pagnon et al (2011) consider a range of surface types reflecting a single scenario (and are therefore appropriate for application in this study). Furthermore, all documented uncertainty ranges demonstrate good agreement. Therefore, unless the conditions of the scenario suggest otherwise, an uncertainty range of a factor of 10, applicable to the 0th to 100th percentile range, is recommended for the roughness length.

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D 9.1.5 - Guidelines for ranking uncertainties in atmospheric dispersion

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Reviewer(s): WP1 members

Abstract

A literature review has been conducted to investigate the extent to which the uncertainty on atmospheric dispersion models' various input variables has an effect on the models' outputs, and in particular to determine which input variables are most influential in the sense of giving rise to the largest uncertainties on those outputs. The wide range of models, parameters and scenarios uncovered in the review meant that it was difficult to make a meaningful comparison among them; however, certain patterns were apparent. Consequently, rather than determining a quantitative ranking, parameters have been grouped into approximate categories according to the influence their uncertainties might have on modelling results.

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Contents

Introduction

In the event of an accidental release of radionuclides into the atmosphere, dispersion calculations would be used in the early phase of the accident to model the consequences and to assist in determining appropriate countermeasures. The calculations would be subject to significant uncertainties. These would arise both from the model itself and from inputs such as source term and meteorological data.

In order to investigate the potential importance of these uncertainties, a literature review has been carried out. More specifically, the objective of the review was to identify the extent to which the uncertainty on atmospheric dispersion models' various input variables has an effect on the models' outputs. In particular, an attempt has been made to determine which input variables are most influential in the sense of giving rise to the largest uncertainties on the model outputs. Ideally this would lead to a notional ranking of input variables in order of influence. The input variables considered included those related to source terms and meteorology as well as model-specific inputs.

The present review relates to accidental radiological releases. However, its scope has also included studies of routine releases and non-radiological releases where such studies provide relevant information.

Parameters that are unrelated to atmospheric dispersion are not covered by this review, even if they could be used in radiological assessments in some other way.

Relation to the rest of the CONFIDENCE project

An aim of the CONFIDENCE project is to understand, reduce and mitigate the uncertainty that exists in decision support systems. This includes the uncertainty associated with atmospheric dispersion models. Work Package 1 (WP1) concentrates on the modelling of such uncertainties during the emergency phase. The results of WP1 will be used in other work packages that will investigate and aim to improve decision making in the presence of uncertainty.

In practice, there may be many sources of uncertainty. Identifying those that are most significant should assist with focusing the subsequent work appropriately

Method of review

Around one hundred documents were considered in the first iteration of the review, of which approximately forty were considered of sufficient relevance to be considered further in relation to the *ranking of input parameters* subtask. Those forty or so documents were shared among participants, who entered relevant information into review templates. Those templates have been used as the basis of the present report.

The papers reviewed and used in the rankings below were:

Alameddine and El-Fadel (2005); Alcamo and Bartnicki (1987); Beyea and DeCicco (1992); Cheng and Sandu (2009b); Cheng and Sandu (2009a); Dacre et al (2015); Devenish et al (2012a); Devenish et al (2012b); Dhyani and Sharma (2017); Diez et al (2014); Eleveld et al (2007); Freeman et al (1986); García-Díaz and Gozalvez-Zafrilla (2010); Girard et al (2014); Girard et al (2016); Hanna (2007); Hanna et al (2007); Harper et al (1995); Harvey et al (2018); Haywood (2008); Haywood et al (2010); Horwedel et al (1992); Jones (1986); Jones et al (2000); Kolczynski et al (2009); Korsakissok et al (2013); Leadbetter et al (2015); Levy et al (2002); Marzo (2014); Mensink and Maes (1997); Paesler-Sauer and Jones (2000); Pagnon et al (2011); Pandya et al (2013); Pandya et al (2008); Périllat et al (2017); Pineda Rojas et al (2016); Quérel et al (2015); Saito et al (2015); Sriram et al (2006); Twenhöfel et al (2007); Velenyák (2016).

Preliminary comments on the findings of the review

First of all, it must be acknowledged that determining a meaningful ranking of parameters is difficult. Ideally, the literature search would have uncovered a range of studies that all considered the same parameters and compared them using the same measures. In practice, this is not what was found. Rather, the papers found in the literature search describe a wide range of studies in which many different types of comparisons were carried out. For example:

- The parameters considered in each study were different. Indeed, it is doubtful that any two studies compared exactly the same set of parameters.
- Most of the studies did not deal with radiological scenarios. This does not mean such studies are of no use, but it means that additional care must be taken when assessing their applicability to the present work, particularly in cases where some of the parameters are specific to chemical processes.
- A variety of different tools and methods were used, including Monte Carlo methods, ensembles, single parameter perturbations, expert elicitation.
- Different scenarios were considered.
- Different endpoints were considered. This is relevant not only to the physical quantity measured (such as ground concentration or dose), but also other factors such as the time period over which measurements were taken. Different input parameters might influence airborne concentrations one day after the start of a release, compared to airborne concentrations averaged over a whole year, for example.

- Different model types were considered. Gaussian models were the most common, but there were also several examples of Eulerian and Lagrangian models.
- Different types of releases were considered. These varied from short accidental releases to long-term routine releases and also included complicated historical releases such as occurred at Fukushima.
- Although around one hundred documents were considered in the first iteration of the review, the number of studies identified to be of relevance to CONFIDENCE was not that large. This has resulted in a relatively small sample size.

There are significant differences in the range of input parameters considered in the different studies. There is also a wide range of scenarios considered. Consequently, care should be taken not to draw overly broad conclusions. This point is emphasised in Jones (1986), which explains that the uncertainty in model predictions will depend on the specific situation, so that it can be misleading to make general statements about uncertainty in results arising from uncertainty in given parameters. Two examples are given. One is that airborne concentration at short distances from a tall stack is very sensitive to vertical dispersion parameters, but that in the case of a short stack it will be much less so. The other example given is the effect of variations in plume depletion parameters on airborne concentration calculations at small and large distances from a release.

Even for a given scenario, uncertainty can vary, for example with distance from the release. This is demonstrated in Sriram et al (2006). In that study, Gaussian Plume methods were used to model ground-level concentration of material released from a power station. Modelling error was attributed to uncertainty in the atmospheric stability, wind speed and wind direction. This was found to decrease with distance from the release along the plume centre line. The errors were expressed by finding the ratio of the results when the uncertainties mentioned above were and were not taken into account. At 1 km from the release, the ratios were found to be more than a factor of ten higher than at 2 km from the release. Ratios were calculated out to a distance of 10 km and appear to decrease approximately exponentially in the specific scenarios studied.

Finally, the validity of any individual study will partly depend upon the wisdom of the choice of parameters and parameter ranges used in that study. However, such considerations are beyond the scope of the present review.

Findings of the review

The difficulties of drawing general conclusions from a diverse range of studies is discussed above. Before addressing the details of individual studies, it may be of some use to consider what the rankings might be if they were determined in a simplistic way.

Rankings based on parameters most often found to be influential

One way of ranking the parameters would be to count the number of studies that conclude that each parameter is influential. This would be a very crude measure, because no parameter was assessed by every study and some parameters will have been considered in more studies than others. Some parameters are better understood or easier to vary than others and are consequently studied more often. For example, there are many more studies that vary wet scavenging coefficients than there are studies that consider the calculation of boundary layer depth and vary how it is defined. This is despite the fact that in models where the definition of diffusivity is different above and below the boundary

layer, the location of the boundary layer can have a significant impact on air concentration predictions at the surface.

A less crude measure might have been to normalise the values by dividing the number of studies in which a parameter was found to be influential by the number of studies in which that parameter was considered (whether or not it was found to be influential). Unfortunately, this was not feasible. This is because papers sometimes focused on the parameters that were found to be influential and gave insufficient detail of the other parameters considered. Also, some modellers may have deliberately selected parameters that were likely to be influential, whereas others may not have done this. In combination with the relatively small sample size, these factors meant that meaningful normalisation would not have been possible.

If the parameters were to be ranked in the simplistic un-normalised way described above, the rankings would be as below. The figures in brackets indicate the number of studies that found the associated parameter to be influential or very influential. In a few cases, parameters were awarded half a point because they were designated as moderately influential. A full list of the papers on which the statistics below are based can be found in the *Method of Review* section above. However, the number of *studies* represented by the figures below is less than the number of *papers*. This is because some studies have more than one paper associated with them, and some papers do not clearly identify any parameters as significant.

Source term (12)

Wind direction (10.5)

Wind speed (8.5)

Plume rise (6)

Precipitation (5)

Release height (5)

Dry deposition velocity (4)

Scavenging/washout parameters (4)

Vertical diffusion parameters (4)

Stability class (3.5)

Horizontal diffusion parameters (3)

Mixing height (3)

Release duration (2)

Release timing / time shift (2)

Surface resistance (2)

The parameter *traffic volume* is not considered to have any relevance to the present review and so has been excluded even though it scored two points. Those two points arose from studies in which a significant consideration was the effect that emissions from road traffic had on air quality.

All other parameters were identified as influential by fewer than two of the studies considered.

Source term has been interpreted broadly enough to include such phenomena as release rates and chemical emission variables. However, it does not include release height, release duration (*per se*) or particle size considerations, which were treated separately. *Plume rise* was interpreted to include phenomena such as exit temperature, flue gas temperature and exit velocity.

Precipitation can include rate or cumulative amount of precipitation, but does not include scavenging or washout parameters, which are considered separately.

If non-radiological studies were excluded, the rankings would be as below.

Wind direction (7)

Source term (5)

Scavenging/washout parameters (4)

Dry deposition velocity (3)

Plume rise (3)

Precipitation (3)

Mixing height (2)

Release duration (2)

Release timing / time shift (2)

Surface resistance (2)

Wind speed (2)

Release height (1.5)

Parameters scoring only 1 or 0 have been excluded.

Again, if this were used in isolation, it would be a very crude measure indeed. This is particularly so, as the non-radiological rankings are based on only about 15 studies, which is a very small sample size.

Despite the simplicity of the rankings above, there are certain notable features.

Source term scores highly. This is as might be expected, particularly as it has been interpreted in the above rankings as including amount and rate of material released. Where these were considered, they were always found to be significant. The main reason for *source term* not to have scored even more highly is that many studies did not include it in their analysis.

Wind direction also scored highly, particularly for the radiological studies. When wind direction is considered, it is usually found to be one of the most influential parameters. It is particularly critical in the case of Gaussian Plume modelling. It is sometimes omitted from analyses altogether because it can so radically affect the output. One non-Gaussian example of this is Eleveld et al (2007), which, despite being based on Lagrangian puff modelling, states that

> *For practical reasons the wind direction variation was left out from the uncertainty analysis as it can change the model output completely.*

There are exceptions to the general pattern of wind direction being important, but these relate to the nature of the studies themselves. For example, Hanna et al (2007) examines annually-averaged

concentrations from routine emissions and does not find wind direction to be a particularly influential parameter. However, the conclusions are not directly applicable to accidental emissions.

Wind speed ranked highly for non-radiological studies, but not for radiological. This could just be an anomaly caused by the small sample size, or it could be a result of the different endpoints that tend to be considered in radiological and non-radiological studies. Also, a higher proportion of non-radiological studies related to long-term averaged results.

Scavenging/washout parameters scored fairly highly for the radiological studies, but scored zero for the non-radiological studies. Deposition tends to be much more important for radiological studies than for chemical studies because of the exposure pathways related to radioactive material deposited on the ground, in particular external irradiation and ingestion of contaminated foodstuffs.

If only accidental, emergency and other short-term releases were considered, the rankings would be as below. Note that this category has been interpreted to include most non-routine releases, and so includes some that are not strictly "short term" (most notably, the Eyjafjallajökull eruption).

Source term (7)

Wind direction (7)

Plume rise (4)

Precipitation (4)

Scavenging/washout parameters (4)

Release height (3.5)

Wind speed (3.5)

Dry deposition velocity (3)

Vertical diffusion parameters (3)

Horizontal diffusion parameters (2)

Mixing height (2)

Release duration (2)

Release timing / time shift (2)

Surface resistance (2)

Parameters scoring only 1 or 0 have been excluded.

The above rankings are based on approximately sixteen studies. Excluding Eyjafjallajökull studies would not make much difference. The main change would be that vertical and horizontal diffusion parameters would drop out of the list.

It is worth noting that all of the radiological-based studies relate to short releases, so the "radiological" studies are a subset of the "short-term release" studies. Consequently, the rankings for "radiological" studies are fairly similar to the rankings for "short-term release" studies.

An additional way of carrying out a simplistic ranking is to first group the parameters according to the process they are associated with and then rank those processes. In some cases, subjective judgement

is required to allocate parameters to groups. If all studies (even non-emergency and non-radiological ones) were included, the ranking would be as below. Further explanation of which parameters have been allocated to which group is provided below the ranked list.

Source term (12)

Turbulent diffusion (10.5)

Wind direction (10.5)

Effective release height (10)

Wet deposition (9)

Wind speed (8.5)

Dry deposition (7)

Model-specific parameters (2)

Release duration (2)

Release timing / time shift (2)

The *turbulent diffusion* group includes stability class, mixing height, vertical diffusion parameters and horizontal diffusion parameters.

The *effective release height* group includes stack/source/release height, plume rise, exit temperature, venting temperature, flue gas temperature and vertical source profile.

The *wet deposition* group includes precipitation and scavenging/washout parameters.

The *dry deposition* group includes dry deposition velocity, surface resistance, particle size and particle size distribution.

The *model-specific parameters* group includes grid cell size, time step and boundary conditions.

The *source term, wind direction*, *wind speed*, *release duration*, *release timing / time shift* "groups" are unchanged from how they were defined in the previous rankings (i.e. have not been grouped with any other parameters).

Groups scoring fewer than two points were excluded from the list above.

If the non-radiological and non-emergency studies were excluded, the "process" ranking would be as below.

Wet deposition (7)

Wind direction (7)

Dry deposition (5)

Source term (5)

Effective release height (4.5)

Turbulent diffusion (4)

Release duration (2)

Release timing / time shift (2)

Wind speed (2)

Model-specific parameters (1)

Consideration of most relevant papers

Although the above simplistic rankings do reveal certain patterns, the small sample size means that they are of only limited value. In addition, they notionally assign the same importance to each of the studies considered. This could be misleading because some of the studies relate to scenarios that are very different from what CONFIDENCE WP1 is intended to address. Also, some studies are more comprehensive than others.

More focused attention is now given to those studies that consider scenarios analogous to the ones envisaged by CONFIDENCE WP1. The most relevant studies would appear to be those described in the papers: Eleveld et al (2007); Girard et al (2014); Girard et al (2016); Harper et al (1995); Haywood (2008); Haywood et al (2010); Jones et al (2000); Korsakissok et al (2013); Leadbetter et al (2015); Paesler-Sauer and Jones (2000); Twenhöfel et al (2007).

Twenhöfel et al (2007) includes an uncertainty analysis in early phase nuclear emergency management, and as such is highly relevant. The study was carried out by the Dutch National Institute for Public Health and the Environment (RIVM) and the uncertainty analysis was carried out in relation to the Dutch long-range Lagrangian puff model NPK-PUFF input parameters. RIVM's UNCSAM program was used to calculate the ranking of the input parameters with respect to their contribution in the overall uncertainty. The Partial Rank Correlation Coefficient (PRCC) was used as the uncertainty analysis indicator. Time-integrated air concentration (TIAC) and deposition were the two endpoints considered. The results for the two endpoints were not exactly the same, but generally speaking the analysis revealed that the most significant contributions to the uncertainty arose from the release rate, mixing height, wind speed, wind direction and precipitation rate.

Wind direction was found to have the highest values of PRCC. For TIAC the maximum PRCC was 0.98 and the minimum was -0.70. For deposition, the maximum PRCC was 0.94 and the minimum was -0.66. Values of magnitude greater than 0.5 were considered significant in the analysis. A PRCC value of 1 would imply a perfect positive correlation, whereas a value of -1 would imply a perfect negative correlation. A value of 0 would indicate that there is no correlation.

The analogous values for wind speed were -0.93, -0.63, -0.84 and -0.49.

The values for release rate varied depending upon which radionuclide was considered, but the largest analogous values were 0.80, 0.86, 0.76 and 0.82.

When there was rainfall, the PRCC values for precipitation were -0.72 and 0.86 for TIAC and deposition respectively.

Eleveld et al (2007) covers similar subject matter to *Twenhöfel et al (2007)* and also has a stated objective of identifying the most important dispersion model input parameters. The study again used NPK-PUFF. A short-range version of NPK-PUFF was developed and validated and was applied in the study. A sensitivity analysis was carried out. As above, the computer program UNCSAM was used and the Partial Rank Correlation Coefficient (PRCC) was used as the uncertainty analysis measure. A wider range of scenarios was considered than was the case for Twenhöfel et al (2007), so it is more difficult to draw general conclusions. Also, the paper states that:

> *important contributors to the model uncertainty, the horizontal dispersion process and the variability of the wind field data, are not fully considered in the analysis so far.*

The sensitivity analysis concludes by saying:

> *In addition to the mixing height and wind direction deviation, other parameters were subjected to the sensitivity analysis. Parameters with large responses with respect to the ranking results further include the effective emission height, the time step (Eleveld, 2002) and the cell size of the equidistant grid. Less sensitive parameters are the initial horizontal dispersion coefficient σ_y, vertical dispersion coefficient σ_z, surface resistance r_c, roughness length z_0, and the Lagrangian time scale t_{Lh}.*

The subsequent uncertainty analysis does not include all of the most significant parameters and gives more mixed results, but shows that "it is clear that the outcome of the ranking of parameters is very scenario specific".

Korsakissok et al (2013) is a local-scale simulation and sensitivity study that focuses on atmospheric dispersion and ground deposition from the Fukushima Nuclear Power Plant accident. The study was carried out by IRSN (Institut de Radioprotection et de Sûreté Nucléaire, France). The model used is pX, which is IRSN's Gaussian puff model and which is part of the operational platform C3X, used by IRSN's Emergency Response Centre in the event of an accidental radioactive release.

The results were found to be most sensitive to source term, and also sensitive to wind direction and dispersion parameters. The narrow plume that was being modelled is likely to have contributed to the significance of uncertainty in wind direction.

Girard et al (2014) and *Girard et al (2016)* are two more studies that apply dispersion modelling to the Fukushima accident. The model used is the Eulerian transport model Polair3D (Mallet et al, 2007). The output variables considered were the gamma dose rate time series at stations over Japan and ^{137}Cs deposition maps at the end of the event. Girard et al (2014) used the method of Morris to carry out a sensitivity analysis, whereas Girard et al (2016) carried out a variance-based sensitivity analysis using the method of Sobol'. In each case, the objective was to rank the inputs according to their influence on the outputs of the model and to study their interactions.

The most influential inputs were found to be the winds, the emission amplitude for the caesium and iodine families, the time shift and, to a lesser extent, the source altitude. The cloud thickness and emission factors for other species were found to have only a weak influence.

However, the study's more detailed analysis revealed a more complicated picture. Although it was generally possible to identify a small number of influential inputs, different inputs were influential for different outputs. Aggregated scalar outputs (for example mean deposition on the entire domain) were found to be mainly driven by perturbations on emitted quantities, whereas local scalar outputs (for example maximum value of the ambient gamma dose rate for a certain station) were found to be most sensitive to wind perturbations. In addition, local outputs were found to interact significantly, whereas global outputs were found to be mostly driven by first-order effects. Strictly speaking, this means that none of the inputs should be considered negligible as a source of uncertainty.

Leadbetter et al (2015) also focuses on the Fukushima accident. Among its objectives was to determine whether the model is more sensitive to the forcing meteorology or the wet scavenging coefficient when considering predictions of ^{137}Cs deposits. The UK Met Office's NAME model (Jones et al, 2007)

was used. Specifically, an examination was conducted of the sensitivity of NAME predictions of total deposits from Fukushima to the forcing meteorology and the wet scavenging parameterisation. Results were compared to measured deposits from soil and airborne observations using a number of statistical measures.

As a result of the study, it was discovered that if the range of scavenging coefficients was equivalent to the range of meteorological inputs then for the case considered in the study, NAME's sensitivity to the scavenging coefficients was equal to its sensitivity to the meteorological inputs.

An additional finding was that the pattern of deposits was modelled more accurately by higher resolution models. However, the use of radar rainfall did not increase the accuracy of the model predictions. Also, slightly better deposits were predicted by the model when the deposition originating from in-cloud precipitation was increased.

Haywood (2008) describes a study to identify the key sources of imprecision in assessments carried out in the early phase of a response to a radiological emergency, when few off-site measurements have been obtained. A straight line Gaussian plume model was used, as described in NRPB-R91 (Clarke, 1979). A simple sensitivity analysis was carried out in which a baseline set of input parameters was developed and then each parameter was varied in turn and the effect on the predicted extent of countermeasures was calculated. In a few instances a combination of input parameters were varied in a single model run. In particular, the study sought to determine whether the key influences are parameters relating to the accident itself (some of which may only become known a while after the release has started) or parameters affecting the dispersion (for which data may be more readily available).

The study expressed the need for urgent countermeasures in terms of the distance on the plume centre line out to which the appropriate Emergency Reference Level (NRPB, 1990; NRPB, 1997) was exceeded, (assuming a 10 year old child). The countermeasure extents were based on the addition of the total effective inhalation dose from the cloud and the effective external dose from deposited activity to 2 days, compared against the criteria of the lower ERLs for sheltering and evacuation.

The parameters that were found to separately have the most influence on the predicted downwind extent of countermeasures were:

- the duration of the release,
- the extent of plume rise,
- an inaccurate wind direction (including changes with height),
- a high deposition velocity (possibly as a result of large particle sizes),
- the effect of heavy rain (though this was more influential for ^{137}Cs than for ^{131}I).

The results obtained by considering several factors in combination showed that combined effects did not significantly alter the results (in comparison to the effects considered singly), and they tended to be dominated by a single factor.

Haywood et al (2010) used the UK Met Office's NAME model (Jones et al, 2007) to carry out a study that was otherwise analogous to Haywood (2008). NAME was used in its Lagrangian particle mode.

The key parameters were found to be:

- release duration
- wind direction

- enhanced deposition velocity and rainfall (for those radionuclides for which deposition contributes significantly to dose)
- an elevated release height such as might arise if there were substantial energy associated with the release (the significance of this depends on the distance from the release point).

Large particle size was also found to be significant in certain circumstances. “Large” in this context means of the order of 10 µm AMAD, rather than the study’s default of 1 µm AMAD (Haywood, 2018). However, as the increased particle size was actually modelled by using an enhanced dry deposition velocity, it is actually the dry deposition velocity parameter that is most directly relevant. Presence and degree of rainfall were also found to be significant in certain circumstances. However, release height, Pasquill meteorological stability category and wind speed were not found to be significant in relation to the endpoints considered.

Paesler-Sauer and Jones (2000), *Jones et al (2000)* and *Harper et al (1995)* are linked and all relate to the same overall study. Although Harper et al (1995) is more general than the other two papers and does not limit its conclusions to a single model, Paesler-Sauer and Jones (2000) and Jones et al (2000) specifically consider the atmospheric dispersion and deposition module of COSYMA (KfK and NRPB, 1991). The module models atmospheric dispersion using a modified version of the Gaussian plume dispersion model that allows for hourly changes in atmospheric conditions. An objective of the study was to identify those parameters whose uncertainty makes major contributions to the overall uncertainty, and which should be included in subsequent analysis of the COSYMA system as a whole. The study evaluated the uncertainty on air and ground concentration, individual doses and risks, the extent of countermeasures and the numbers of health effects in the population.

The study found that the relevance or otherwise of input parameters depended on the endpoints considered. Specific examples were as follows.

The parameters whose uncertainty (primarily expressed as the ratio of the 95th to the 5th percentile of the probability distribution on the expectation value of the consequence) made a major contribution to the overall uncertainty for the “extent of early countermeasures” endpoints were the deposition velocity of elemental iodine and some of the parameters describing atmospheric dispersion, particularly in Pasquill stability category E/F conditions.

The parameters whose uncertainty made a major contribution to the overall uncertainty for the “early fatalities” endpoints were similar to those for countermeasures.

For “areas relocated or affected by milk bans”, the most important parameter uncertainties were the deposition velocities of elemental iodine and aerosols and some of the dispersion parameters.

For fatal cancers, the parameters whose uncertainty made major contributions to the overall uncertainty were the deposition velocity and washout coefficient of aerosols, and some of the dispersion parameters.

Overall, the parameters that were considered significant enough to be included in the subsequent analysis of the COSYMA system were identified as the deposition parameters for aerosols and elemental iodine together with the dispersion parameters.

It should be noted, however, that some parameters that have been found to be most influential in other studies were not considered at all in this study; in particular, source term and wind direction

Ranking and categorisation of parameters

The relatively small number and varying scope of the studies considered means that it is not possible to determine a rigorous quantitative ranking of parameters that would apply in all circumstances relevant to CONFIDENCE WP1. However, certain patterns are apparent that enable suggestion of an approximate qualitative ranking.

Since a rigorous quantitative ranking would not be meaningful, and may even be misleading, a slightly different approach has been adopted. This can be termed a "categorisation" of parameters. Specifically, a series of categories of influence have been defined and parameters have been assigned to the most appropriate category rather than being given a strict ranking. The categories are themselves approximately ranked according to how influential the parameters in them are (i.e. Category 1 is a higher "rank" than Category 2); however, as discussed below, any form of ranking will depend on the scenario being considered and should never be treated as absolute.

In the case of more complex models, the categorisations below may become less applicable. This is dealt with in more detail in the following section.

Category 1: The two most influential parameters are source term and wind direction.

Source term, in the narrow sense of amount or rate of material released, will always be significant. The uncertainty on the source term will often be directly proportional to the uncertainty on the endpoints of the modelling.

Wind direction will be significant in nearly every emergency scenario. A small uncertainty in wind direction can lead to a large uncertainty in some endpoints. This tends to be particularly significant in models that assume a simplistic Gaussian plume. It should also be borne in mind that wind direction may change with height. This can increase the significance of uncertainties in other parameters. For example, if wind direction changes significantly with height, uncertainty in effective source height can lead to a large deviation of the location of a modelled plume from the location of the corresponding observed plume.

Category 2: The second category includes parameters that will often (but not always) be influential and that are capable of having a large influence in some circumstances. This includes plume rise, release height, wind speed, release timing (or time shift).

Some models may not actually distinguish between *plume rise* and *release height*. If the simplistic rankings above had treated these as a single parameter, it would have ranked near the top of the list. However, the influence of these parameters will be strongly dependent upon the distance from the release. One example is that uncertainty in release height alone could mean inhalation dose at a point near to a release is modelled as being anywhere between a very high value and zero. By contrast, at a distance far from a release, where the plume is well mixed, the influence of release height and plume rise may be minimal.

The influence of *wind speed* will be very dependent on the scenario, and particularly endpoints, considered. It may have a significant effect on decisions related to arrival time of a plume (such as a decision whether to evacuate), but may have little effect on endpoints related to values calculated by integrating over a time period including the passage of the whole plume (such as time integrated airborne concentrations or deposition).

The influence of the *release timing* parameter will have some similar considerations to those of the wind speed parameter (discussed above).

Category 3: The next category is parameters that are sometimes not relevant at all, but that can be very influential in some circumstances. This category includes parameters related to phenomena that may or may not occur, such as rainfall. The parameters in this category are precipitation, scavenging coefficients, dry deposition velocity, surface resistance, particle size distribution.

Precipitation and *scavenging parameters* (or *washout parameters*) are very influential for certain endpoints in certain weather conditions, most obviously for deposition endpoints in scenarios where rainfall occurs. In scenarios where no rainfall occurs, uncertainty on these parameters is irrelevant. Another way of stating this would be to say that scenarios in which rainfall is not considered have an implicit assumption that the uncertainty on the precipitation parameter is zero (and that its value is known to be zero), whereas the uncertainty on the scavenging/washout parameters would in that case be irrelevant. In addition, there are different types of uncertainty associated with precipitation: there is uncertainty over whether rainfall will occur, uncertainty as to how much will fall and uncertainty as to where it will fall. Showery weather can mean high uncertainty at a given location, as rain may not fall at all, but if rain does fall it may well be heavy.

The maximum influence of *dry deposition velocity* will be less than for wet deposition, but will apply whether or not there is any precipitation.

Surface resistance tends to relate only to dry deposition.

Particle size distribution can have a significant effect on deposition. In fact, it did not score very highly in the simplistic rankings above, but this is most likely a consequence of the high number of Gaussian Plume models covered in the review (which are unlikely to include a parameter to represent particle size distribution), along with the fact that some of the studies dealt with non-particulate species. In practice, the influence of particle size will be highly dependent on the scenario, in particular on the nature of the release (not least, whether an explosion occurred). The relationship between dry deposition and particle size is highlighted by Figure 6 of Thatcher et al (2002). Although that paper concerns deposition indoors, and so in that sense is not relevant to the present review, it gives an indication of the uncertainties associated with the particle size and deposition relationship. The relationship between wet deposition and particle size is highlighted in Feng (2007). Moreover, Mala et al (2013) shows that the Fukushima and Chernobyl releases led to a wide range of particle sizes.

Category 4: The next category is parameters that will often have some influence, but usually only a moderate one. This includes release duration, atmospheric stability class, mixing height, vertical diffusion parameters, horizontal diffusion parameters.

Release duration is rather difficult to categorise. Some models may not define it as a parameter at all, while in others it may be intrinsically linked to the source term parameter (which is itself very influential and so overwhelms any influence associated specifically with the *duration* of the release). However, in simplistic Gaussian plume models it can have a significant influence.

Atmospheric stability class will not exist as a parameter in all models, and indeed will be unnecessary in models that have sophisticated meteorological input. However, it can be an important parameter in models based on a simple Gaussian plume approach.

Mixing height was found to be influential in a number of the studies reviewed. In practice it may be closely related to other parameters such as atmospheric stability class.

Vertical diffusion parameters and *horizontal diffusion parameters* will always have some effect on a dispersing plume, but will be secondary to more fundamental considerations such as uncertainty on wind direction.

It must be emphasised that the influence of *atmospheric stability class*, *mixing height*, *vertical diffusion parameters* and *horizontal diffusion parameters* is highly dependent on the type of modelling used. A general categorisation is therefore difficult. For example, in the case of an Eulerian model being used with high-resolution NWP data, the local change in diffusivity would probably be derived from the NWP data. In that case, the uncertainty in mixing height would be unimportant because it is not required as a parameter in the model (whereas the local diffusivity would have a large influence). Conversely, in the case of a Gaussian puff model used with low-resolution NWP data, it is necessary to distinguish between above- and below-mixing-height dispersion (only two layers are considered). Consequently, mixing height would have a large influence on the results.

Category 5: The next category is parameters that were generally not found to be particularly influential in the studies reviewed (possibly with a few exceptions), but which could have some influence in certain circumstances. This category includes terrain modelling, ambient temperature, surface roughness, vertical source profile, time step, grid cell size.

Terrain modelling was mentioned only in Beyea and DeCicco (1992), which did not find it to be an influential parameter. That study related to Three Mile Island. It is likely that a study involving more complex terrain would have found the terrain-modelling parameter to be more influential; however, no such studies were found. This means that this parameter would normally be in Category 7; however, as it would clearly be highly relevant in certain circumstances, such as a release in a mountainous region, it has been assigned to Category 5.

Vertical source profile could have some influence very close to a release, but in practice many models will specify only the more influential parameter: release height.

Category 6: A further category is parameters that were found to be influential in one or more of the studies reviewed, but where it seems unlikely that such influence would apply in situations that are of interest to CONFIDENCE WP1. This might apply if the studies in question were not emergencies, or if the parameters in question were very specific to a model which is not particularly relevant to an emergency radiological release (or indeed might be rare in any model). Parameters in this category include cross-wind entrainment parameter, multi-energy index for flammable gas, uncertainty in regional background ozone, boundary conditions.

CONFIDENCE WP1 is concerned with radiological assessments in emergency situations. Studies relating to non-radiological and non-emergency releases were included in the review because of their potential benefits in understanding analogous aspects of radiological emergency releases. One of the consequences of this was the inclusion of some parameters that are not relevant in the present review. Category 6 is largely a reflection of this.

Category 7: Parameters that have not been mentioned above were not found to be influential in any of the studies reviewed. This is either because they were considered and found not to be influential or because they were not considered at all. This category effectively includes an unlimited number of parameters, so no complete list can be given. However, some examples of parameters that were mentioned in the reviewed documents but not found to be influential in any of them are: time of day, solar radiation, cloud cover, building downwash.

It is surprising that *building downwash* is not in a higher category. Category 3 might have seemed more appropriate than Category 7. Building downwash was mentioned only in Alameddine and El-Fadel (2005), which found it to have no effect. That study related to sulphur dioxide emissions from desalination plants. It is possible that a study involving a different type of release, or endpoints modelled closer to the release, might have found the building-downwash parameter to be more influential; however, no such studies were found. In general, the significance of this parameter will be highly dependent on the spatial scale of the endpoint considered. Consequently, although it intuitively seems that this parameter should be in a higher category, the present review has not been able to provide any evidence for this.

In principle, the number of parameters that exist is limitless. It is inevitable that some relevant parameters may have been missed from the lists above, particularly if they are of special relevance to a model that is not covered by the papers reviewed. Each modeller will need to be aware of this when determining which parameters are relevant in the circumstances being considered.

Moreover, the categories defined above are, to an extent, arbitrary. Other categorisations could have been devised. If further assessments of influential parameters are carried out in future, the following strategies might be considered.

> Categorisation based on modelling approaches (such as Eulerian, Lagrangian, Gaussian) and level of detail in the models and input data (such as the NWP data). The influence of parameters for these groups might be scored separately.
>
> Categorisation based on the cases to which the modelling is applied, such as maximum effect distance, duration and temporal/spatial resolution (for example, the scale of the whole of Europe versus a maximum scale of 50 km). The influence of parameters might again be scored separately for these groups.

The principal obstacles facing such categorisations are likely to be a scarcity of relevant studies and a lack of necessary detail in the studies identified.

Comment on the applicability of the categorisations to more complex models

Before drawing any general conclusions, it is important to emphasise that the classifications of input variables into categories, as has been done above, carries with it an implicit assumption that those variables exist as independent entities in the relevant models. This is most applicable in the case of simple models that take a series of individual parameters as inputs; for example, a single wind direction, wind speed and stability category. It will also be most true in the case of small domains where variables have minimal variation across the domain.

More complex models, such as Lagrangian or Eulerian models, are likely to use meteorological inputs that vary in space and time. This will become more significant as the spatial and temporal domains become larger. In addition, such input data cannot be simply divided into individual parameters such as wind speed and stability class, and in many cases it would not be meaningful to speak of varying an individual parameter in isolation. Indeed, even variables such as scavenging coefficients, deposition velocities and plume rise, which might seem more likely candidates for being considered in isolation, may also depend on meteorological data in some models.

One consequence of this is that for more complex models running on larger domains, where meteorological variables vary in four dimensions (including time), it becomes more meaningful to consider uncertainty in meteorological data as a whole when considering the effect on the dispersion results. In such modelling scenarios, the categorisations above become less useful, and a better approach for assessing uncertainty would be to use ensembles of meteorological data. This possibility is mentioned in Korsakissok et al (2013) and Périllat et al (2017).

It is perhaps surprising that this was not highlighted more clearly by the literature search itself. This may be because the use of ensembles in this way is a relatively recent development. Another reason is that the search identified both old and new documents as being relevant. Older documents tended to deal with simpler models, whereas newer documents considered a range of simple and complex models. This may have resulted in the literature review being weighted towards simpler models for which the use of ensembles would be unnecessary.

An additional finding of the review is that not much work has been done on ranking parameter uncertainties using ensembles. This is something that the next phase of the present work should focus on.

Conclusions

This review was intended to investigate the extent to which the uncertainty on atmospheric dispersion models' various input variables has an effect on the models' outputs, and in particular to determine which input variables are most influential in the sense of giving rise to the largest uncertainties on those outputs.

The review uncovered a significant number of studies in which matters of this nature were addressed; however, these covered a wide range of models, parameters and scenarios, which made it difficult to make a fair comparison among them. In addition, only a minority dealt with scenarios that were similar to those envisaged by CONFIDENCE WP1.

As a consequence, it has not been possible to determine a rigorous quantitative ranking of parameters. To have attempted to do so would not have led to meaningful results. However, the review has revealed certain patterns that have enabled parameters to be grouped in to approximate categories according to the influence their uncertainties might have on modelling results.

The categories are described below. Parameters that were mentioned in the reviewed documents have been assigned to the appropriate category. Although the categories are themselves approximately ranked (i.e. Category 1 includes more influential parameters than Category 2), any form of ranking will depend on the scenario being considered and should never be treated as absolute. More detailed explanation is given in the *Ranking and categorisation of parameters* section above.

***Category 1**: Most influential parameters*

Source term, wind direction.

***Category 2**: Often (but not always) influential; capable of having a large influence in some circumstances*

Plume rise, release height, wind speed, release timing (or time shift).

***Category 3**: Sometimes not relevant at all, but can be very influential in some circumstances*

Precipitation, scavenging coefficients, dry deposition velocity, surface resistance, particle size distribution.

***Category 4**: Often have some influence, but usually only a moderate one*

Release duration, atmospheric stability class, mixing height, vertical diffusion parameters, horizontal diffusion parameters.

***Category 5**: Generally not found to be particularly influential in the studies reviewed (possibly with a few exceptions), but which could have some influence in certain circumstances*

Terrain modelling, ambient temperature, surface roughness, vertical source profile, time step, grid cell size.

***Category 6**: Found to be influential in one or more of the studies reviewed, but where it seems unlikely that such influence would apply in situations that are of interest to CONFIDENCE WP1*

Cross-wind entrainment parameter, multi-energy index for flammable gas, uncertainty in regional background ozone, boundary conditions.

***Category 7**: Not found to be influential in any of the studies reviewed*

Effectively includes an unlimited number of parameters, but for example: time of day, solar radiation, cloud cover, building downwash.

The parameters that appear in the categories above should not be treated as an exhaustive list. In principle, there are an unlimited number of possible parameters. Some may even be unique to a single model. The present review does not claim to have been able to cover every existing model, let alone every possible parameter. Each modeller will need to be aware of this when assessing which parameters are relevant in the circumstances being considered.

As complexity of models increases, the categorisation of parameters above becomes less applicable and it becomes less meaningful to consider parameters in isolation. One way in which the next phase of the present work could address this difficulty is by using ensembles to assess uncertainties.

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